

ANFIS-BASED REAL-TIME POWER ESTIMATION FOR WIND TURBINES

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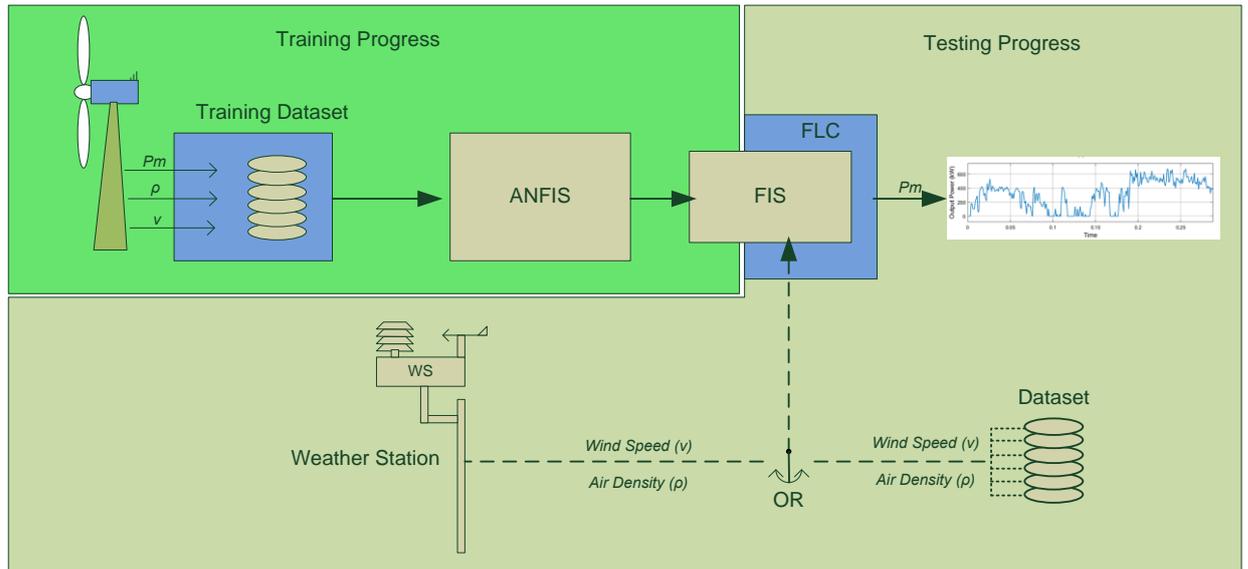
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Highlights

- Machine Learning: The method proposed in the study can estimate the output power of the wind turbine by learning with ANFIS without the need for a mathematical equation.
- Sustainability: With the proposed method, the Vestas V44-600 model is able to predict what the power curve will be like using only the atmospheric data of that region, without the need to physically install the model.
- Flexibility: The proposed method allows, with minor modifications, to estimate the output power of not only the Vestas V44-600 model, but also other wind turbine models.
- Current Trends: In terms of study results; The behavior of ANFIS, which has been applied to many areas and obtained very efficient results, proves that it also provides success in non-linear systems such as wind turbines.

Graphical Abstract



Flowchart of the proposed method



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(Geliş/Received: 06.11.2022; Kabul/Accepted in Revised Form: 10.12.2022)

ABSTRACT: In this study, it is aimed to make real-time power estimation for the V44-600 model wind turbine of Vestas company. The scope of the study is aimed to perform ANFIS-based power estimation for the V44-600 VESTAS wind turbine, which is intensely used in the wind industry, by using the wind speed and air density data of the city of Neveşehir. For this purpose, an Adaptive Network Based Fuzzy Inference System (ANFIS) trained on V44-600 wind turbine data was used. For the training and testing steps of ANFIS, wind speed, air density, and output power of the wind turbine are used as input-output parameters. As a result of the simulations and training, the percent relative error value in the widest range where the prediction value deviates from the true value is 11.86%. This value was higher than expected due to the scarcity of the data used in the ANFIS training (144) and the repetitive values in the output power. Similarly, the lowest efficiency value is 89.4%. Despite all this, it has been observed that ANFIS gives good results if the data used in the testing process is within the scope of the data used in the training. Moreover, the developed model when supported with 32-bit hardware can make real-time power estimation for a real wind turbine. The main motivation for this study; is develop a model that can predict the output power for the Vestas V44-600 model based on wind speed and air density data. In addition, it is to produce the Fuzzy Interface System (FIS) file that enables the developed model to run on embedded systems.

Keywords: ANFIS, Wind Turbine, Real-Time Power Estimation, Vestas V44-600

1. INTRODUCTION

In addition to being a rapidly increasing energy policy in the last 20 years due to its high energy potential, wide application area, and negative effects of fossil resources on the environment, wind power; has become a remarkable phenomenon in both industrial and academic research [1]. In addition to these, it came to the idea that every country should provide the energy it needs with its resources, due to the current energy crisis due to epidemics and war situations.

Although fossil fuels are easy to convert into various energy fuels, having a regional potential is one of their biggest drawbacks. For many such reasons, the interest in energy sources that can be found all over the world such as wind and solar has increased even more [2]. Although electricity generation from solar energy is very popular due to its accessibility and relatively simple structure, the energy value produced is seriously reduced in the winter months, as it is very affected by shading, dust, and dirt, and in the evening hours when the sun is not present. In addition, when it is evaluated as the rate of benefiting from solar energy, an average 1000 W/m² of energy comes to the earth's surface and when it is considered the accessible price and number of solar panels work with a maximum efficiency of 20 %, a maximum of 200 W electrical energy can be obtained from an area of 1 m² under full sun and at an appropriate angle. For this reason, to obtain a very high amount of energy by using solar panels, it is necessary to cover large agricultural areas or apply them on the sea-ocean.

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Agricultural areas or sea-ocean surfaces-floors covered with solar panels are deprived of the beneficial light and heat of the sun and cause various ecological problems.

Wind power has a major role in providing energy to industrial and local consumers, it has the largest share among other alternative energy sources [3-4]. But it also has some disadvantages like solar energy. Chief among these are mechanical problems. Because wind turbines convert mechanical energy into electrical energy, they have many moving parts. Most failures from wind turbines occur in the bearing structure [5]. Apart from that, wind energy is not always accessible like solar energy. One of the most fundamental problems in wind turbine management is the high rate of deterioration and variation in wind speed and the inability to effectively measure this variation [6]. In the generation of electricity from wind, the operation of the system is as important as the installation. Wind turbines that are not operated properly have a long payback period, and the longer this process, the higher the maintenance-repair and operating costs.

With the developing wind energy policy, the need for more and more complex control techniques on turbines is increasing [7]. Estimating the potential and power output of wind energy in large-scale applications such as wind farm is critical to the profitability and realization of the system [8]. To make maximum use of both wind and solar energy, it may be possible to shorten the payback period of the system by applying various control methods.

Producing sustainable and clean energy, creating more efficient wind turbines and maximizing system efficiency can only be possible by estimating the design parameters of WT correctly [9-10]. Moreover, it is possible to increase the efficiency of wind turbines by using ANFIS-based Maksimum Power Point Tracker (MPPT) algorithms and mechanical control methods [11]. Efficiency increases in wind turbines can be done with other methods besides MPPT. On the basis of such methods; it can be done by estimating the power that can be produced with the wind speed, air temperature, and rotation information of the turbine [12]. Making power estimation using various parameters allows early warning of risky situations that may occur in turbines and taking precautions, as well as error checking [13]. With ANFIS-based studies, not only power estimation is made, but also the speed and position estimation of Permanent Magnet Synchronous Generators (PMSGs) to provide power increase and efficiency in turbines, the excitation processes of such generators can be controlled without sensors [14].

The rest of this article is organized as follows: In Section II, a literature review of studies related to the subject of the article is addressed. In Section III, the materials and methods that enabled the study to achieve its purpose are explained. In Section IV, the simulation results are provided and discussed. Section V contains the conclusion.

2. RELATED WORKS

When similar studies in the literature are examined; [15] conducted an ANFIS-based study estimating the optimal power coefficient value for wind turbines. FLC member functions are set by using ANFIS in the simulation environment. In another study [16], they conducted an ANFIS-based study that calculates the effective wind speed for wind turbines online. Within the study, it makes an estimation using real-time wind turbine Tip Speed Ratio (TSR), mechanical power, and rotor speed information. [17], estimated the effective wind velocity value by using an ANFIS-based method in their study, TSR and blade pitch angle were used as input parameters to ANFIS.

In another study conducted within the scope of wind turbine parameter estimation [18], they carried out a method that can predict torque for Savonius-type wind turbines by using ANFIS. The obtained results were compared with the Radial Basis Function (RBF). In the study [19] for the estimation of power output in wind turbines, an estimation study including soft computing methods in which wind speed and rotor speed are used as inputs. Scope of work; they used ANFIS, Elman Neural Network (ENN), and Feed-forward Neural Network (FNN) approaches.

In another study [20], they prepared an ANFIS-based study for the safe and efficient operation of systems that generate energy from wind in variable and unpredictable natural conditions. The study aimed to estimate the power coefficient value, which is a function of tip-speed ratio and pitch angle, with ANFIS. With the study, a National Renewable Energy Laboratory (NREL) offshore 5 MW baseline wind turbine was simulated. The proposed method is more reliable, computationally intelligent, and easy to implement for rapid estimation of power efficiency.

In another study [21], in which rotor speed, turbine output power, and pitch angle were used, wind speed estimation was made. ANFIS was used as an estimation tool within the scope of the study. They used ANFIS to estimate output power for Diffuser Augmented Wind Turbine (DAWT), which is more efficient in overcoming the negative effects of the naturally variable behavior of wind speed [22]. Output power, rotor speed, and output torque data are used in the training of ANFIS. The performance and analysis of the intelligent forecasting system researches done in the simulation environment.

3. MATERIAL AND METHOD

In this section; details of the real-time power estimation study tested on the Nevşehir province data are explained by making ANFIS training on the Vestas V44-600 model wind turbine data.

3.1. Model and operation of wind turbine

Wind turbines are systems that first convert kinetic energy into mechanical energy and then into electrical energy. A simplified block diagram of the process of generating electricity from wind turbines is given in Figure 1.

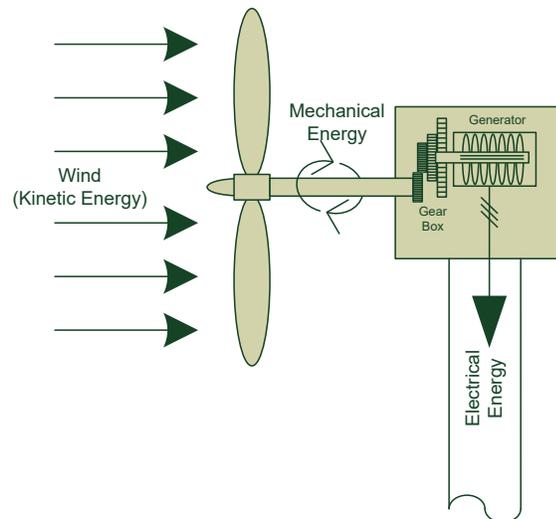


Figure 1. Block diagram of power conversion in wind turbines

According to the block diagram in Figure 1; wind hitting the turbine blades creates a lifting force on the blades due to the aerodynamic structure of the blades. This lifting force acting on the wings turns into a rotational force due to the fact that the wings are fixed on the rotor. The resulting rotational force is applied to the electric generator directly or via the transmission mechanism such as the gearbox. At the end of all these processes, wind energy in the form of kinetic energy is converted into electrical energy. It is possible to calculate the power that can be obtained from the wind turbine with Equation 1. The mechanical power obtained from the turbine is calculated with Equation 2.

$$P = \frac{1}{2} A \rho V^3 \quad (1)$$

$$P_m = \frac{1}{2} A \rho V^3 C_p(\alpha, \beta) \quad (2)$$

$$C_p = \frac{P_m}{P} \quad (3)$$

Wind turbines, the conversion of the kinetic energy of the wind to mechanical energy is also called the efficiency of the wind turbines and is calculated with Equation 3.

Where;

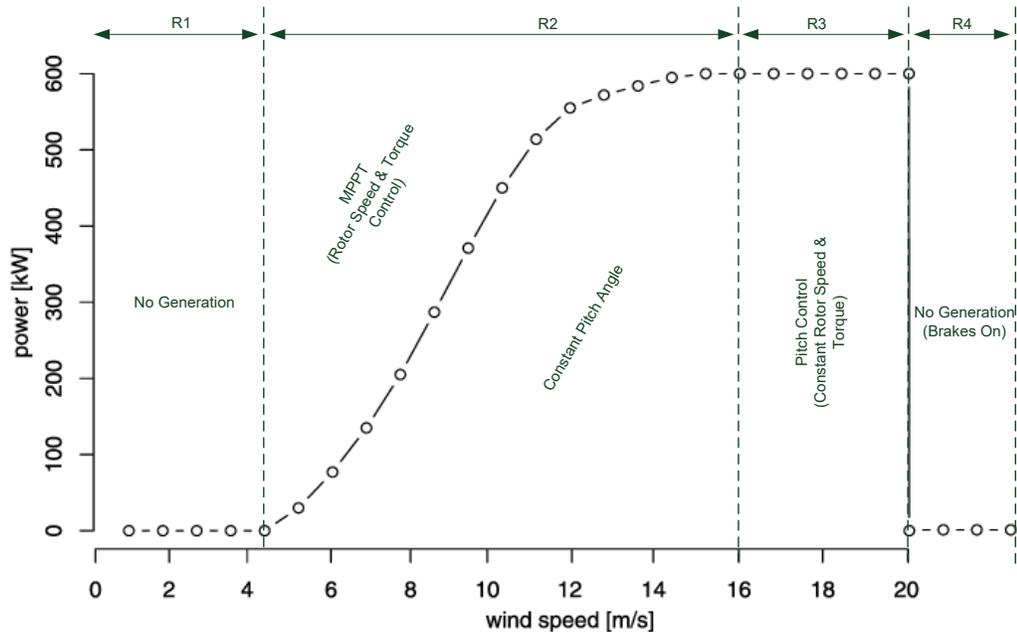
- A : Rotor swept area in m^2
- V : Wind speed in m/s
- ρ : Air density in kg/m^3
- C_p : Power coefficient
- P_m : Wind turbine output power in w
- α : Tip Speed Ratio (TSR)
- β : Blade pitch angle in $^\circ$

In the study, the data of the V44-600 model, which is a commercial product of Vesta's, has been investigated. The company has published various data on its products as open access. The electrical and mechanical parameters of the V44-600 model are given in Table 1.

In wind turbines, the energy conversion process and the control of the turbine are carried out according to the amount of wind speed. Wind turbines; it is an energy conversion system that is costly to install and has operating costs due to the mechanical components in their structure. Companies investing in the field of energy expect these systems to cover their installation costs as soon as possible. The healthy operation and sustainability of wind turbines can only be possible if the stages in the energy production process are carried out properly and their maintenance is carried out at appropriate intervals. Operating wind turbines outside of the appropriate wind speeds or in areas with insufficient energy potential will do more harm than good. The wind speed and turbine output power graph of the V44-600 model, whose data were used within the scope of the study, is given in Figure 2.

Table 1. Electrical data of the V44-600 wind turbine in the study [23].

Parameter	Value	Unit
Rated Power	600.0	kW
Rated Wind Speed	16.0	m/s
Survival Wind Speed	52.0	m/s
Cut-in Wind Speed	4.50	m/s
Cut-out Wind Speed	20.0	m/s
Rotor Diameter	44.0	M
Swept Area	1521.0	m ²
Number of Blades	3	Pieces
Rotor Maximum Speed	28.0	U/min
Tipspeed	65	m/s
Rotor Material	GFK/Epoxy	-
Gear Box Ratio	1:51	-
Generator Type	Asynchronous	
Gen. Maximum Speed	1650	U/min
Generator Voltage	690	V
Grid Connection	Thyristor	-
Frequency	50	Hz

**Figure 2.** Wind speed and output power graph of V44-600 model.

When we examine the areas on the graph:

Region 1: It is the area where the wind speed is too low to generate power or is much lower than the desired value. According to the manufacturer, the wind turbine is disabled at wind speeds below 4.5 m/s, and according to the company, the lower wind cut value of the V44-600 model is 4.5 m/s.

Region 2: The wind speed in this area is higher than the lower cut value and less than the optimum value. In other words, the wind speed varies between 5-16 m/s. In this area, it is possible to produce mechanical

power and therefore electrical energy. The wind turbine is constantly controlled by various methods in this area, and it is aimed to produce maximum power from the turbine. This field is also called the MPPT field.

Region 3: This is the area where the wind turbine produces the highest power and energy. The rotor speed of the wind turbine is fixed in this area, ensuring that the power produced is at the maximum rate. The rotor speed of the turbine is fixed by methods such as blade angle control, variable TSR, and variable Cp.

Region 4: This area is the wind speed area determined by the manufacturer and includes the risks if the wind turbine continues to operate. If the wind speed exceeds 20 m/s, the braking process is activated, preventing structural damage to the components under pressure or to the wind turbine.

A. *Training and Testing Data*

ANFIS is a widely used learning approach today and is trained using data stacks with input and output parameters and aims to reach the desired output value by using various input data [24].

With this aspect, ANFIS can be used in many places to solve the problem [25]. It is possible to study and predict wind energy with both single and hybrid ANFIS [26]. In order to make real-time output power estimation of the wind turbine with ANFIS, historical data to be trained beforehand is needed.

The wind speed (V), air density (ρ), and output power (P_m) values of the V44-600 model used in the ANFIS training are given in Table 2.

Table 2. Wind and power data of the V44-600 wind turbine in the study (thewindpower).

Power (kW)	<i>Air Densiyt (kg/m³)</i>								
	<i>1.06</i>	<i>1.09</i>	<i>1.12</i>	<i>1.15</i>	<i>1.18</i>	<i>1.21</i>	<i>1.225</i>	<i>1.24</i>	<i>1.27</i>
<i>4.5</i>	0	0	0	0	0	0	0	0	0
<i>5</i>	24.7	25.8	26.8	27.8	28.9	29.9	30.4	31.0	32.0
<i>6</i>	65.2	67.4	69.6	71.8	74.0	76.2	77.3	78.4	80.6
<i>7</i>	115	119	123	126	130	134	135	137	141
<i>8</i>	176	181	187	192	198	203	206	209	214
<i>9</i>	246	253	261	268	275	283	287	290	298
<i>10</i>	320	329	338	348	357	366	371	375	384
<i>11</i>	393	404	415	425	436	445	450	454	463
<i>12</i>	461	471	482	492	503	511	514	518	525
<i>13</i>	517	525	534	542	551	556	558	560	565
<i>14</i>	557	563	568	573	579	581	582	584	586
<i>15</i>	581	584	587	589	592	593	594	594	595
<i>16</i>	593	594	595	596	598	598	598	598	599
<i>17</i>	598	598	598	599	599	599	600	600	600
<i>18</i>	599	599	600	600	600	600	600	600	600
<i>19-20</i>	600	600	600	600	600	600	600	600	600

The values given in Table 2 were taken into operation with the block diagram given in Figure 3 and ANFIS training was carried out. Neural network in ANFIS adjusts the input parameters of the membership function in the fuzzy inference system.

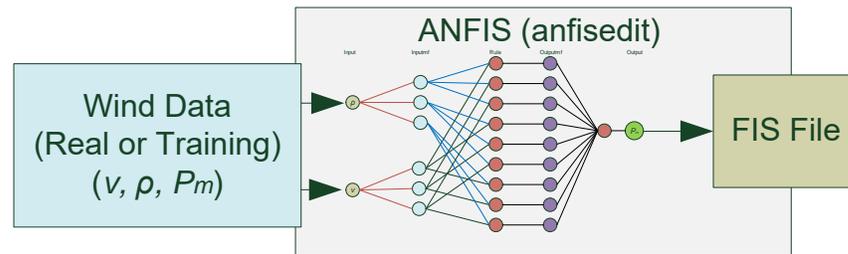


Figure 3. Block diagram of the ANFIS training process

The wind turbine data given in Table 2 were trained with ANFIS and the FIS file required for FLC was produced. The layers and members of the generated FIS file are given in Figure 4.

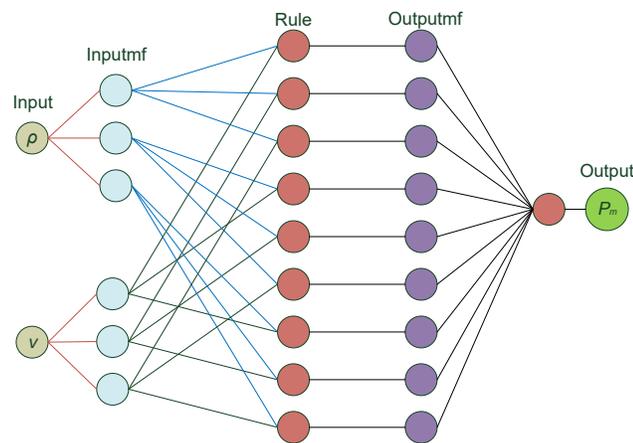


Figure 4. Layer and relationships graph of the FIS file created in the study

According to the diagram given in Figure 4, the air density (ρ) and wind speed (V) parameters are used as inputs and the turbine output power is calculated as a result of the relations between the layer and the members.

3. RESULTS AND DISCUSSION

The simulations are performed to make real-time power estimation on the Vestas V44-600 model. For this purpose, first of all, ANFIS training was conducted over the wind speed, air density, and power output values of the turbine provided by the company in Table 2. In this context, the graph of the data obtained from Table 2 is given in Figure 5 and ANFIS was trained using these data. The data stacks obtained from Table 2 were applied to the simulation model given in Figure 6, and the training data tested and verified.

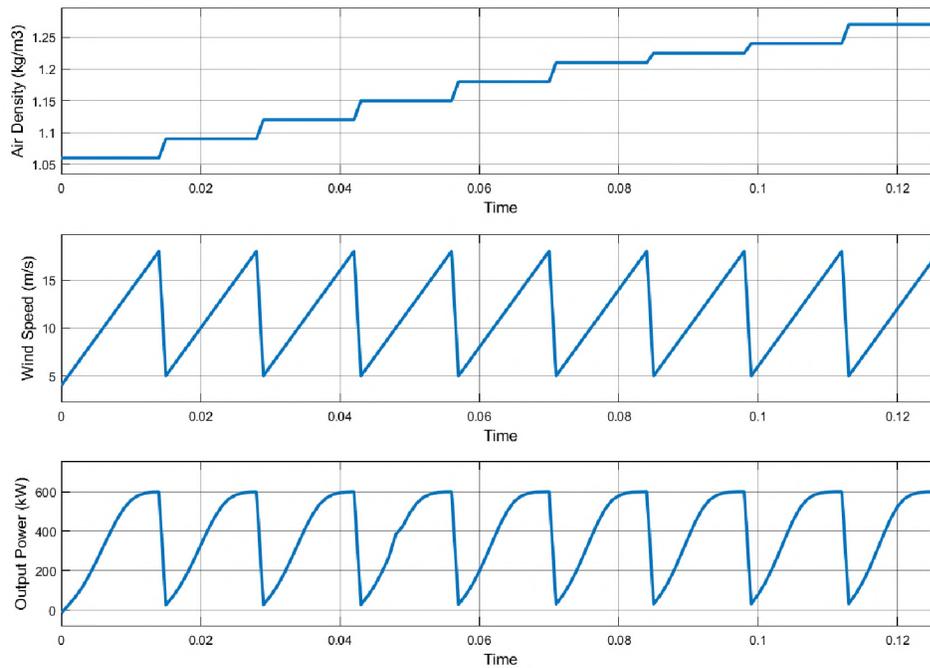


Figure 5. Graph of data used for ANFIS training.

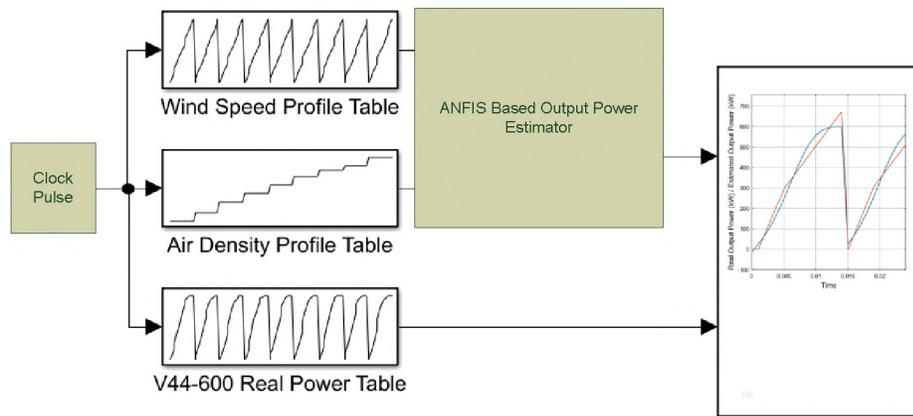


Figure 6. A simulation model in which data used for ANFIS training is tested and verified.

The graph given in Figure 7 was obtained from the test study carried out through the model given in Figure 6. The black graph shows the power data used in the training, and the blue graph shows the predicted power data made by ANFIS.

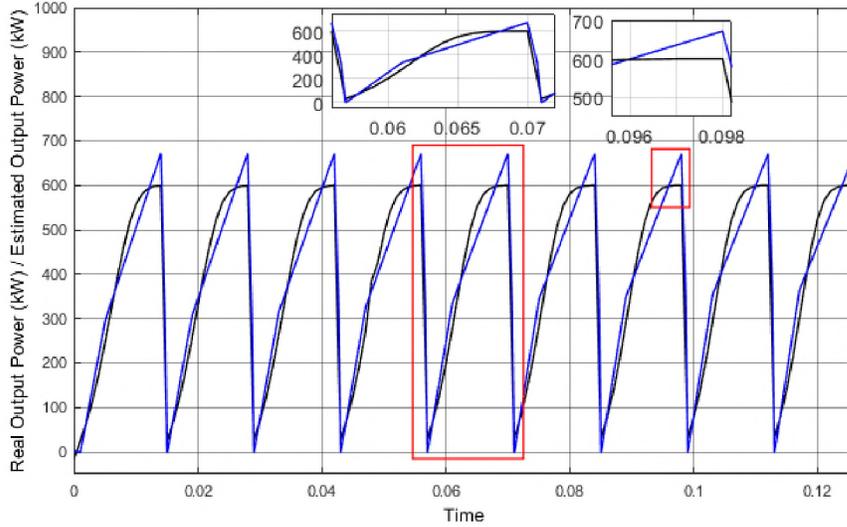


Figure 7. Comparison graphs of data used for training and testing.

As a result of the simulations and training, the estimated power value was found to be 671.2 kW while the actual power value was 600 kW in the widest range where the estimated value deviated from the true value. The reason for this situation is the small number of data (144 items) in Table 2 used in ANFIS training and the repetitive values in the output power. The percent relative error value of this difference is 11.86%. Similarly, the lowest efficiency value is 89.4%. Within the scope of the study, the model created to make the output power estimation with ANFIS over the wind speed and air density data of Nevşehir province is given in Figure 8.

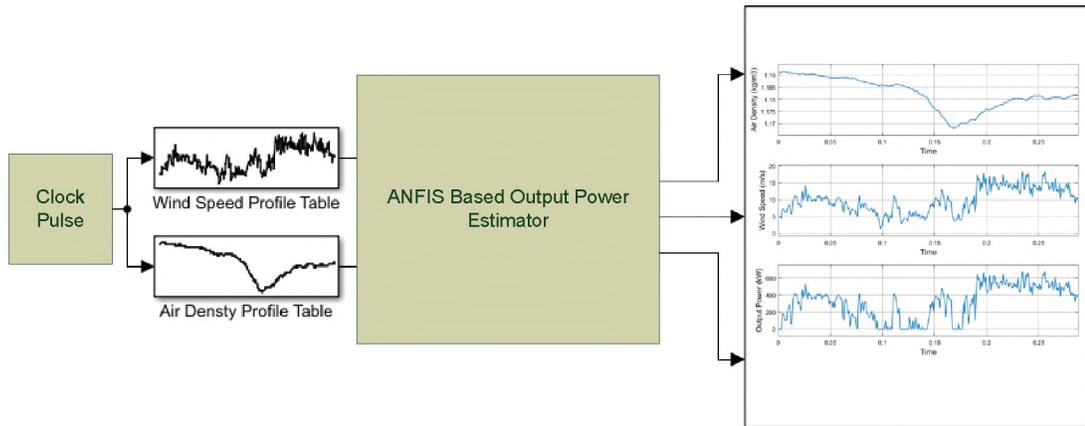


Figure 8. Block diagram of the model that enables the use of Nevşehir province data.

By using the model given in Figure 8, the wind speed and air density data of Nevşehir province were used as input, the output power of the Vestas V44-600 model was estimated and its graph was created. The wind speed, air density, and estimated output power graph of the V44-600 model for Nevşehir are given in Figure 9.

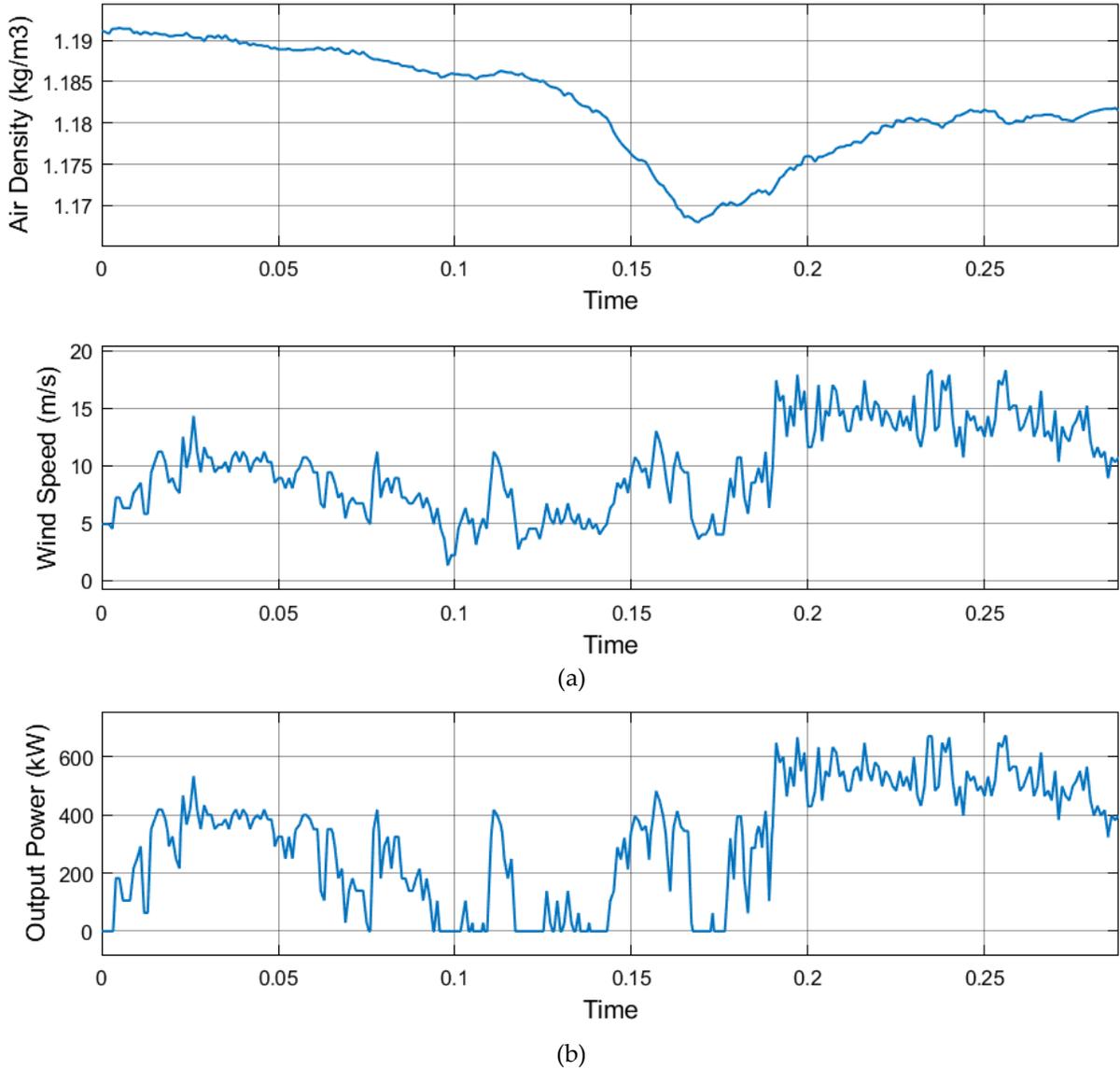


Figure 9. Wind data of Nevşehir province and estimated output power graph

The graph of the wind speed and air density data set for Nevşehir province is given in Figure 9 (a). The testing process of the FIS file obtained as a result of the ANFIS training was carried out on this data set. The graph of the data set of the estimated power value obtained as a result of the test process is given in Figure 9 (b). Detailed analysis of the estimated output power value versus the wind speed value is given in Figure 10.

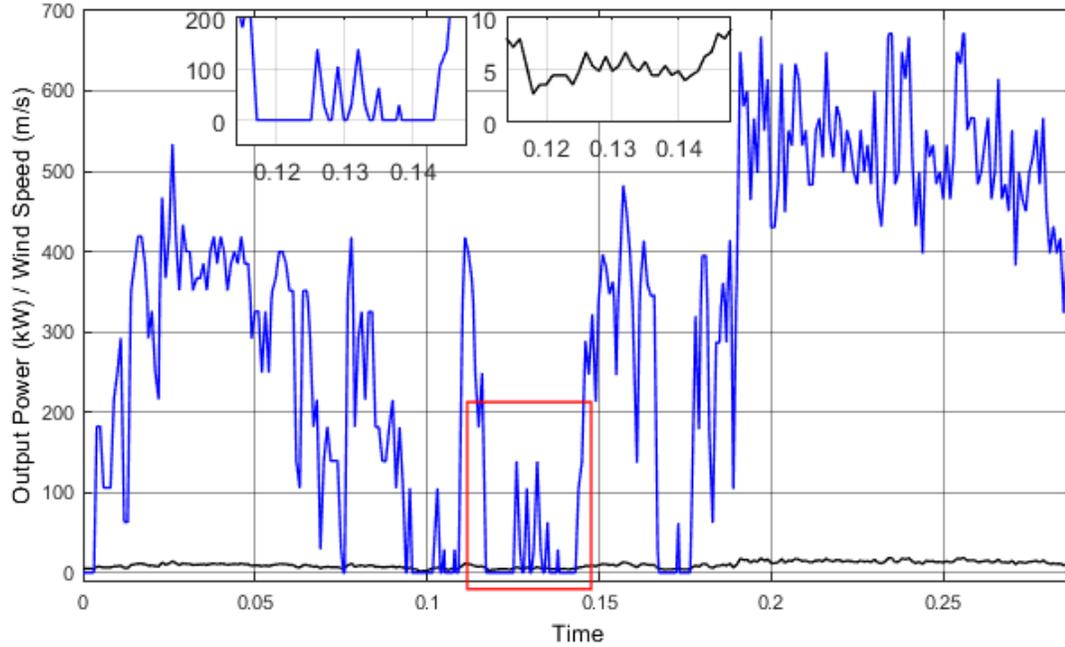


Figure 10. Analysis graph of the estimated output power value versus the wind speed value

When the graph in Figure 10 is carefully examined, it can be seen that the Vestas V44-600 model behaves in accordance with its characteristics and cannot generate power at wind speeds below 5 m/s.

4. CONCLUSION

In this paper, we proposed an ANFIS-based power estimation forecasting approach to make real-time power estimation for the V44-600 model wind turbine of Vestas company. The scope of the study is aimed to perform ANFIS-based power estimation for the V44-600 VESTAS wind turbine, which is intensely used in the wind industry, by using the wind speed and air density data of the city of Nevşehir. Firstly, real data from the V44-600 model were used in the ANFIS training. Wind speed, air density, and output power of the wind turbine are used as input-output parameters. Using the real data values given in Table 2, ANFIS training was carried out. After that Neural network in ANFIS adjusts the input parameters of the membership function in the fuzzy inference system. As a result of the simulations and training, the estimated power value was found to be 671.2 kW while the actual power value was 600 kW in the widest range where the estimated value deviated from the true value. The reason for this situation is the small number of data (144 items) in Table 2 used in ANFIS training and the repetitive values in the output power. The percent relative error value of this difference is 11.86%. Similarly, the lowest efficiency value is 89.4%. When the graph in Figure 10 is carefully examined, it can be seen that the Vestas V44-600 model behaves in accordance with its characteristics and cannot generate power at wind speeds below 5 m/s. It has been observed that ANFIS gives good results if the data used in the testing process is within the scope of the data used in its training. Moreover, the developed model can be transferred to an embedded system with an embedded coder. When the developed model is supported with 32-bit hardware, it can make real-time power estimation for a real wind turbine. The main motivation for this study; To develop a model that can predict the output power for the Vestas V44-600 model based on wind speed and air density data. In addition, it is to produce the Fuzzy Interface System (FIS) file that enables the developed model to run on embedded systems.

Declaration of Ethical Standards

Author agree and commit to abide by all ethical guidelines, including authorship, citation, data reporting, and original research publication.

Credit Authorship Contribution Statement

Author agree to CRediT (Contributor Roles Taxonomy). The manuscript is not the product of a project or group work so there in no need to recognizing individual author contributions.

Declaration of Competing Interest

There is no conflict competing Interest such as the validity of research or financial gain.

Funding / Acknowledgements

There are no funding or research grants (and their source) received in the course of study, research or assembly of the manuscript.

Data Availability

There in no research data or a data repository in available.

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