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# Wind power forecasting: A case study in terrain using artificial intelligence

**Ph.D Ali Saygın[1], Ph.D (Candidate) Alper Kerem[2]**

[1]*Gazi University, Faculty of Technology, Department of Elecrtical and Electronic Engineering Ankara, Turkey*
[2]*Osmaniye Korkut Ata University, KVHS, Department of Electricity and Energy Osmaniye, Turkey*

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**Abstract -** *The rapidly increasing world population and developing technology bring about the need for energy. Limited reserves of fossil fuels and the damages caused on the environment by these fuels have necessitated the move towards renewable energy sources such as wind. Wind energy is at the top among renewable energy resources as a type of economical and rapidly improving form of energy production. Wind, which as an intermittent and stochastic structure may change momentary changes and this situation makes it difficult to estimate its power accurately. It is crucial to accurately estimate wind power to calculate energy unit costs beforehand and ensure safe connection with the power grid. The purpose of this study is to accurately estimate wind power at 61 m at the wind measurement station by using 25,926 units of real-time data including data on wind power, wind direction, temperature, humidity and pressure at 31 m. For this purpose, 100 artificial neural networks were trained and tested using the method of Multilayer Perceptron (MLP). The system's error rates were analyzed, and the lowest rate of error was at the MLP 6-24-1 network with 6 inputs, 24 hidden layers, exponential hidden activation, and output activation as identity.*

***Key Words***: Artificial neural networks (ANNs), Multilayer perceptron (MLP), Wind, Wind power forecasting

## 1. INTRODUCTION

Wind energy is a type of renewable energy which is rapidly developing [1] non-consumable, environment-friendly, free [2] with the most commercially economical and widespread field of usage [3]. However, by its nature, it has an intermittent and stochastic structure [4]. This situation makes it highly difficult to estimate wind power.

Because of wind farms are rapidly spreading, effective energy market, real-time power grid connection, technical service demand and cost, competitive quality of power, power system quality and reliability, transmission capacity and interconnected network operations are becoming increasingly difficult. However, advanced wind estimation operations are some of the most effective methods to overcome the mentioned problems [3], [5], [6]. Additionally, estimation of wind power has a very important role in the optimal management of revenue and risks of wind farms [7] reducing risks of energy transformation efficiency and surges [8] determining the locations of new wind farms to be established [9] as well as facility maintenance and energy planning [10].

Wind power estimation research is studied under two main categories as physical and statistical. Physical wind power estimation methods are based on physical parameters, and they include meteorological estimations. The statistical method involves wind power estimations to be produced by using previous wind data [11], [12], [13]. While the physical method is successful for long-term estimations, the statistical method is highly effective for short-term estimations [14], [15].

In the literature reviews conducted, it was seen that various estimation algorithms are being used for wind power estimations. Zhang et al [16] developed a hybrid forecasting methot which is named IFASF (Interval Forecast-ANFIS-SSA-Firefly Algorithm) to obtain daily average wind power. End of the process, they observed satisfactory prediction results for different wind farms. Carpinone et al [11] used the real wind data they obtained for making very short wind power estimations in the Markov Chain model. Akdağ et al [17] used the method of power density (PD) to estimate Weibull parameters in wind energy implementations. They reached the conclusion that the PD method is a highly successful and capable method for estimating Weibull parameters, and added that it may be a much more suitable method than others. Catalão et al. [18] developed a genuine and efficient hybrid model consisting of wavelet transform, particle swarm optimization, and an adaptive-network-based fuzzy inference system for sort-term wind power estimation in Portugal. They showed that this model is a suitable one for short-term wind power estimations. Liu et al. [19] developed a hybrid relevance vector machine model for wind power estimation in China. They demonstrated that this proposed model provided much more capable and accurate results than each of the single-kernel models. Saleh et al. [20] developed a hybrid neuro-fuzzy model. As a result of estimations, they showed that this model is an accurate and practical one. Aghajani et al. [21] developed a new model consisting of wavelet transform, hybrid neural networks and imperialist competitive algorithm for energy protection in wind farms. In estimation results, they obtained much lower error rates than those of the all component methods. Kirbas et al. [22] used the multilayer perceptron (MLP) and radial basis function (RBF) methods to estimate wind speed at 61 m. They trained artificial neural networks and conducted a performance analysis. They used 25,777 units of real data in their study. The wind speed at 61 m estimated with significant success using artificial neural networks.

In this study, 100 artificial neural networks were trained to make short-term wind power estimations. In the developed model, 6 input parameters, 1 hidden layer containing 4 to 60 nodes, and a single output parameter were created. The performance of the multilayer perceptron (MLP) method was tested on data obtained from real-time measurements, and error rates were analyzed.

## 2. MATERIALS AND METHODS

### 2.1. Data Monitoring

The coordinates where the wind measurement station would be mounted were determined in the light of criteria included in the literature. In this context, the tower was mounted as shown in Table -I at UTM E 263254 and N 4173479 coordinates with 1313 m altitude to cover an area with a radius of 50 m, using steel ropes. The tower was balanced by setting the foundations of these ropes at 40 m and 50 m distances. The measurement tower consisted of 21 3-m-high modules and had a total height of 63 m.

**Table -1:** The data informations of measurement station

| Geographic Coordinates | Elevation | 31m Wind Speed (m/s) | | | Temperature (ºC) | | |
|---|---|---|---|---|---|---|---|
| | | min | average | max | min | average | max |
| UTM E 263254 N 173479 | 1313 m | 0 | 5,89 | 25,81 | 1,831 | 9,73 | 22,59 |

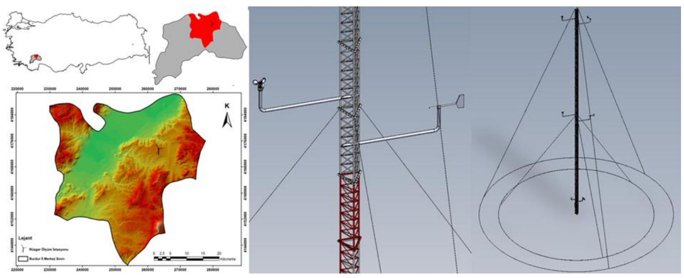

**Fig -1:** Geographical location and 3D models of wind measuring station

A total of 6 sensors including 2 wind gauges at 30 m and 61 m, 2 wind direction sensors at 28 m and 59 m, 1 pressure sensor at 3.5 m, and 1 temperature and humidity sensor at 4 m were mounted. Schematic illustration of the wind measuring station and mounting of devices are shown in figure 2.

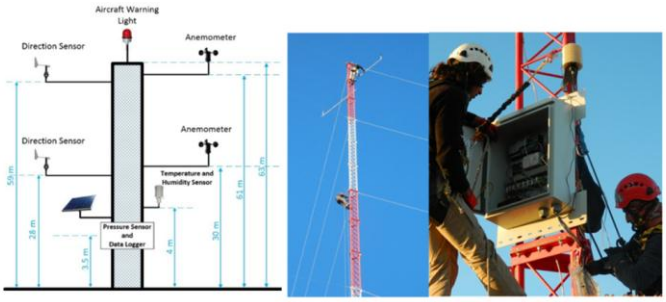


**Fig -2:** Schematic illustration of the wind measuring station and mounting of devices

The data on the Istiklal Campus were recorded by a data logger device every 10 minutes. This is demonstrated in figure 3. The tower was powered by a 20 W solar panel and a 12 V dry accumulator, independent from the power grid. While the tower and the sensors were protected against lightening by a ground line, the system was protected from danger by an aircraft warning light.

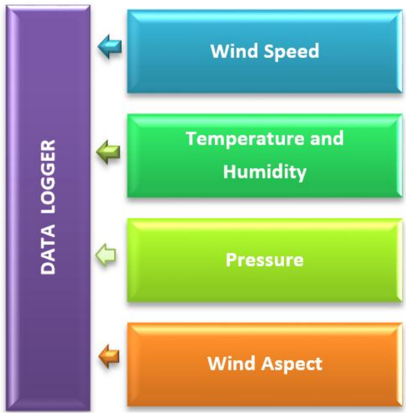


**Fig -3:** Schematic illustration of data gathering.

Considering the importance of wind speed in energy production, it may be understood that the process of measurement it highly important. Making point measurements in the land planned to be used for wind energy plants on an altitude making energy production possible, will also help obtaining real wind speeds. As measurement of wind speed with an error of 10% will affect the amount of energy to be produced by a rate of 30%, this is an issue that needs to be carefully assessed [23].

The power that can theoretically be obtained from wind is calculated [24] using equation (1).

$$P = \frac{1}{2}\, \rho_a . A_T . V^3 \text{ Watt} \qquad (1)$$

where $\rho_a$ is the air density (kg/m$^3$), $A_T$ is the wind mill area perpendicular to the wind (m$^2$) and V the wind speed (m/s).

The temperature, atmospheric pressure, slope and components of the air are effective on air density. If the temperature (T) and the altitude (Z) of an area is known, the air density may be calculated using the equation (2).

$$\rho_a = \frac{353.049}{T} \cdot e^{\left(-0.034\frac{Z}{T}\right)} \qquad (2)$$

In this study, the measured data of real temperature and altitude information were considered while calculating air density.

The relationship of wind power with pressure and temperature is shown in figure 4, its relationship with humidity and temperature is shown in figure 5, its relationship with wind direction (59 m) is shown in figure 6, and its relationship with air density is shown in figure 7 as diagrams. These diagrams were created using the real data obtained from the wind measurement station.

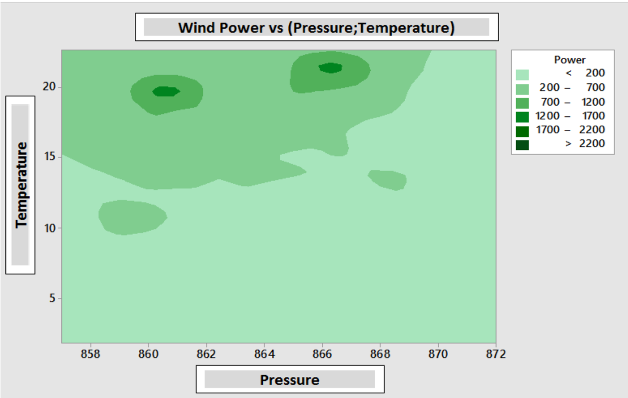


**Fig -4:** Wind power vs (pressure; temperature) relationship

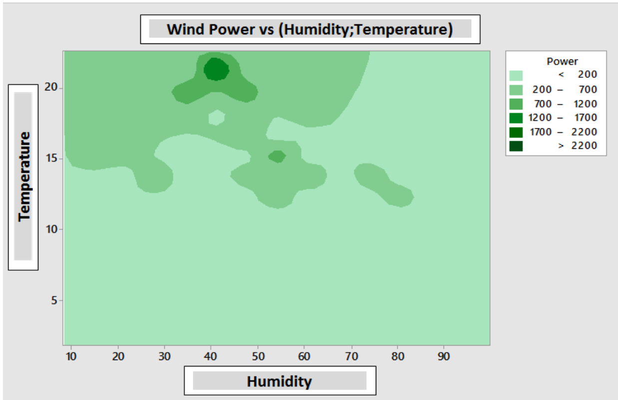


**Fig -5:** Wind power vs (humidity; temperature) relationship

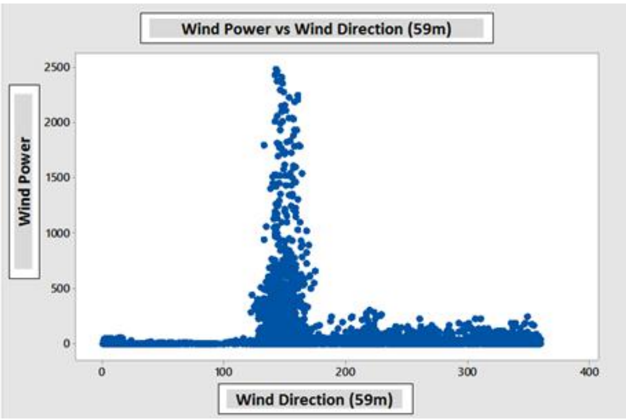


**Fig -6:**Wind power vs direction (59m) relationship

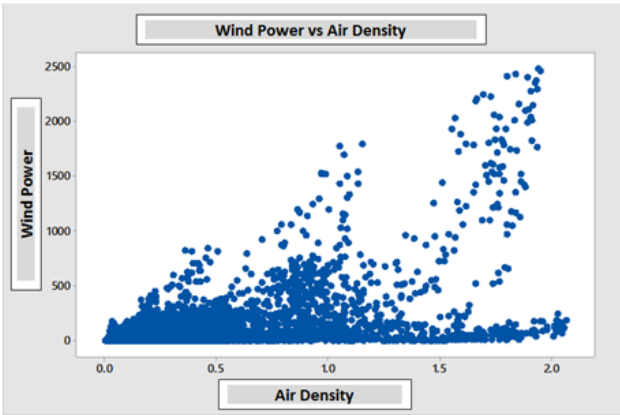


**Fig -7:** Wind power vs air density relationship

**Table -2:** Results of regression analysis for data

| | Coefficient | Standard Error | t Stat | P-value | Low %95 | High %95 |
|---|---|---|---|---|---|---|
| Intersection | 0 | 0 | 0 | 0 | 0 | 0 |
| 61m wind speed (average) | 33,715855 | 13,56709605 | 2,485119504 | 0,012988422 | 7,117371031 | 60,31433898 |
| 31m wind speed (average) | 63,31737142 | 14,36202631 | 4,408665604 | 1,0654E-05 | 35,1604154 | 91,47432744 |
| 59m angular aspect | -0,125766259 | 0,100840604 | -1,247178751 | 0,212399681 | -0,323465692 | 0,071933174 |
| 29m angular aspect | 0,21617298 | 0,103037935 | 2,097994102 | 0,035963704 | 0,014165649 | 0,418180311 |
| Humidity (average) | -3,195305617 | 0,364939062 | -8,755723761 | 2,86474E-18 | -3,910773818 | -2,479837417 |
| Pressure (average) | 0,053936603 | 0,04587649 | 1,175691589 | 0,239783035 | -0,036004905 | 0,143878112 |
| Temperature (average) | -20,64976099 | 1,83403224 | -11,25921373 | 5,2772E-29 | -24,24540717 | -17,0541148 |

In regression study for data, $R^2$ value is obtained 0,602494338 and statistical values are given in Table 2.

### 2.2. Multilayer Perceptron Networks (MLP)

Multilayer Perceptron (MLP) is a feed forward neural network model which adapts input data into a set of suitable output data. In this model, neurons are divided into 3 categories as input, hidden and output layers. Backpropagation algorithm is used in training MLP networks as it is easy to understand and mathematically provable [25], [26]. This algorithm was named backpropagation as it aims to reduce errors backwards from the output to the input [26]. In MLP, every node in a layer is connected to each node in the previous layer with a certain weight w_ij. equation (3). is used to calculate output layer [21].

$$y_i = f\left(\sum_{j=1}^{m} w_{ij}x_j + b_i\right) \quad (3)$$

MLP is a highly successful method in overcoming some different and hard to solve problems. In this technique, the training algorithm used is usually the Error Backpropagation algorithm. The output in each neuron model on the network contains non-linearity. It is important point here is that non-linearity has smoother transition in comparison to the function used in Rosenblatt's perceptron which has sharp transition. One or more hidden neurons in the network do not belong to input or output. The network is able to learn complicated tasks with the help of these hidden neurons. Each neuron is interconnected in the network. An alteration of the connections results in change in synaptic connections and weights. The backpropagation algorithm's development has broken a new ground in the usage of neural networks [27]. Table III shows the activation and output function types used in the networks.

**Table -3:** The evaluated hidden activation and output activation functions

| Function Name | Equation |
|---|---|
| Identity | $f(x) = x$ |
| Logistic | $f(x) = \frac{1}{1+e^{-x}}$ |
| Exponential | $f(x) = e^{-x}$ |
| Tanh | $f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$ |
| Sinusoid | $f(x) = \sin(x)$ |
| Gausian | $f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]}$ |

The parameter values in artificial neural networks have high levels of influence on the results. Selection of the number of nodes forming the network structure and the activation function which facilitates the relationship between nodes and output functions is crucial [22].

It is a very difficult operation to estimate which parameter value will provide the best result. Therefore, various neural networks were tried in this study and the best ones were selected. For calculation of the error rates of the trained networks, sum of squares error function was used. Equation (4) shows the error function used, were dk is the target value for dimension k.

$$E(t) = \frac{1}{2}\sum_{k=1}(d_k(t) - y_k(t))^2 \quad (4)$$

## 3. PERFORMANCE ANALYSIS

In this study, 100 artificial neural networks consisting of different hidden layers, activation functions and output functions were used to make an accurate wind power estimation in matlab. The data randomly selected from among 25,926 units of real-time data were divided into three groups to be used for training, validation and test purposes, respectively by 70, 15 and 15%. The performances of the data used for training, validation and test purposes through neural networks were ranked from the most successful to the least successful. It was observed that the 10 most successful MLP networks showed a 99% success in terms of training performance, validation performance and test performance values. This situation is shown in chart 1.

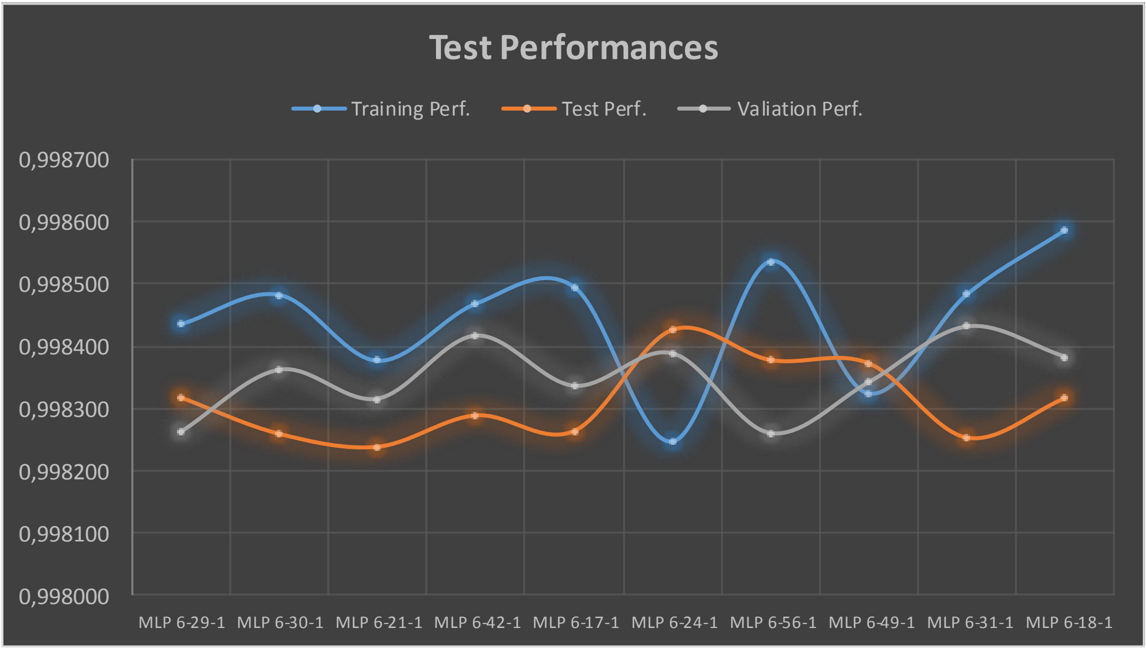


**Chart -1:** Structural properties and performance results

**Table -4:** Structural properties and training results of the best 10 results for ANNs

| Index | Network | Training Error | Test Error | Validation Error | Algorithm | Hidden Activation | Output Activation |
|---|---|---|---|---|---|---|---|
| 1 | MLP 6-29-1 | 122,0637 | 146,8586 | 156,2461 | BFGS 208 | Tanh | Tanh |
| 2 | MLP 6-30-1 | 118,5224 | 151,4235 | 149,3255 | BFGS 168 | Logistic | Logistic |
| 3 | MLP 6-21-1 | 126,6347 | 158,9903 | 150,1923 | BFGS 93 | Logistic | Exponential |
| 4 | MLP 6-42-1 | 119,4107 | 154,2005 | 141,8027 | BFGS 279 | Logistic | Identity |
| 5 | MLP 6-17-1 | 117,8510 | 154,7481 | 149,5503 | BFGS 125 | Logistic | Exponential |
| 6 | MLP 6-24-1 | 136,6520 | 137,6605 | 150,6857 | BFGS 164 | Exponential | Identity |
| 7 | MLP 6-56-1 | 114,1541 | 146,0365 | 156,9282 | BFGS 123 | Tanh | Exponential |
| 8 | MLP 6-49-1 | 130,5974 | 142,9577 | 152,9676 | BFGS 205 | Exponential | Identity |
| 9 | MLP 6-31-1 | 118,9654 | 152,2221 | 144,6383 | BFGS 108 | Tanh | Logistic |
| 10 | MLP 6-18-1 | 110,2584 | 151,2787 | 145,3357 | BFGS 126 | Tanh | Exponential |

The error rates for the created neural networks were analyzed. The lowest rate of error was at the MLP 6-24-1 network with 6 inputs, 24 hidden layers, exponential hidden activation, and output activation as identity. It was understood from the obtained results that estimation of wind power at 61 m using artificial neural networks had a success rate of 99%. The comparison of the data estimated by artificial neural network and the real data measured at the wind measurement station is given chart 3.

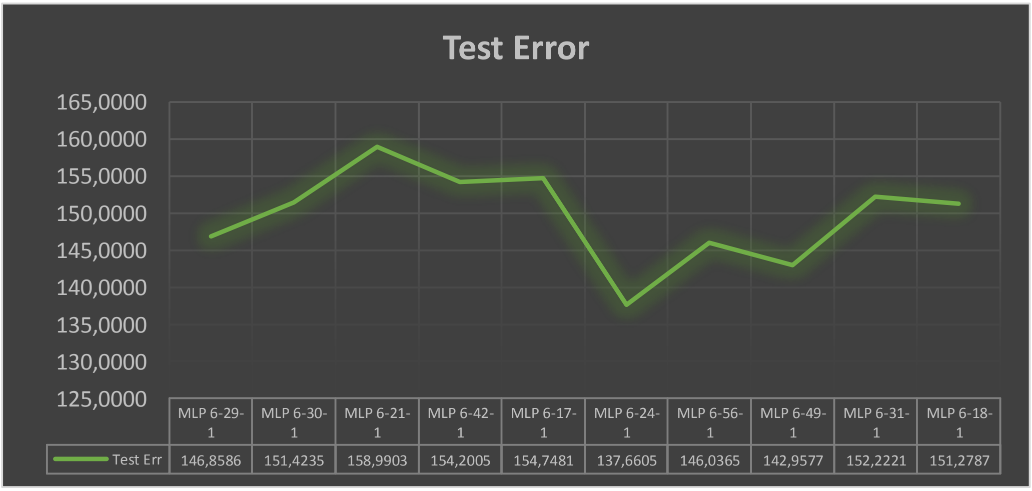


**Chart -2:** Test error evaluation for MLP networks

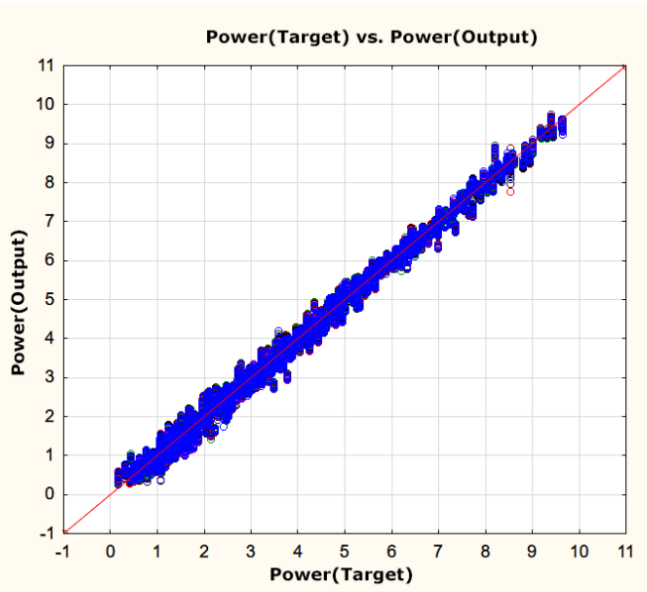


**Chart -3:** Wind power at 61m target and output for the best MLP

## 4. CONCLUSION

In this study, analyses were conducted on real data obtained from the wind measurement station mounted at an altitude of 1313 at the coordinates UTM E 263254 and N 4173479. The main purpose here was to get the wind power to be obtained at 61 m estimated as accurately as possible using the data (wind speed, wind direction, temperature, humidity, pressure) collected at 31 m. This operation of estimation is highly difficult because wind naturally has an intermittent and stochastic structure. This estimation task carries great importance for determining the total power of the wind farm planned to be established at this altitude, pre-planning of unit electricity costs, safety of the grid, etc. With this purpose, 100 artificial neural networks were tested on 25,926 real-time data for the month of April 2014. MLP method was preferred because of its success in overcoming problems that are hard to solve, and 4 different activation and output functions comprising tanh, exponential, logistic and identity were used. Considering the test results, the lowest rate of error was observed at the MLP 6-24-1 network with 6 inputs, 24 hidden layers, exponential hidden activation, and output activation as identity. It was determined that the 10 most successful MLP networks had a 99% success in terms of training, validation and test performance values.

The success rate obtained in this study will provide inspiration for long-term wind power estimation. Moreover, it is considered that performance of recurrent neural network (RNN) can be tested and performances comparisions of RNN and ANN can be analysised in future study.

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**BIOGRAPHIES**

Ali SAYGIN, PhD
He's an Asist. Prof. Dr. at Gazi University,
Department of Electrical and Electronics Engineering
Ankara, Turkey

Alper KEREM, PhD(Candidate)
He's a lecturer at Osmaniye Korkut Ata Univ, KVHS,
Department of Electricity and Energy
Osmaniye, Turkey