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# Implementing Modern Estimation Methods for Long-Term Wind Speed Estimates in the Province of Şanlıurfa in the Southeastern Anatolia Region

Umut Saray[1*],Tolga Yücehan[2],Sadık Önal[1]
[1](*Turhal Meslek Yüksekokulu/ Gaziosmanpaşa University, Turkey)*
[2](*Dazkırı Meslek Yüksekokulu/ Afyon Kocatepe University, Turkey)*
*Corresponding author: Umut Saray**

**Abstract:** In recent years, studies on wind energy have accelerated, due to developments and incentives in renewable energy. Wind speed has a significant role in generating electricity through wind energy. Wind speed estimation poses an important issue in determining the electric potential to be generated and in bringing the wind plants into an interconnected system. In this study, the use of Adaptive Neuro Fuzzy Inference System (ANFIS) and three artificial neural networks, namely feedback Levenberg-Marquardt learning algorithm (BPLM) and Radial Basis Network (RBN) models, were used for wind speed estimation in the Siverek district of the province of Şanlıurfa in the Southeastern Anatolia region of Turkey. In this application, meteorological data, including temperature, humidity, pressure, and wind speed in Siverek district were received from Turkish General Directorate of Meteorology and simulated in the MATLAB program. The temperature, humidity and pressure data for 2000 – 2009 were entered, the monthly average of the wind speed values for 2009 were estimated, and a 3-input, 1-output network structure was used in the three network models. The success of the BPLM, RBN, and ANFIS networks was realized by calculating the mean square errors (MSE) and root mean square error (RMSE) values' wind speed estimates acquired using these networks.
**Keywords:** Artificial neural networks, Adaptive Neuro-Fuzzy Inference System, Backpropagation, Radial Basis Network, Wind speed estimates

## INTRODUCTION

Population growth and industrial developments increase the global need for energy day by day. The diminishing lifetime of fossil fuels is a matter of common knowledge. Therefore, energy savings, efficient use, recovery, and research for new energy sources have become increasingly important worldwide. The negative effects of carbon dioxide emissions of fossil fuels on climate and damage to the ozone layer have proven that clean energy is an important necessity for the world [1].

One of the most widespread sources renewable energy is wind energy. The wind energy sector has become important in terms of employment, due to the investments that have been made in this field worldwide. About 2% of the solar energy that reaches the Earth's surface is converted to wind energy. Therefore, wind energy is a sustainable and important source. Wind energy is supported by several countries through government incentives. China, Brazil, Canada, USA, Denmark, Japan, and Turkey are among these countries [2].It is believed that wind energy use goes back to 2800 BC and that it was first used in the Middle East. Wind energy, which was used in Mesopotamia for irrigation purposes in the 17th century BC under the administration of Babylonian king Hammurabi, is claimed to be used during the same period in China, as well. Windmills, which were developed for purposes such as grinding agricultural products and pumping water, swept through Europe until the Industrial Revolution. At the beginning of the 1890s, the development of the first wind turbine in Denmark caused wind energy to gain significance again

Although wind energy was not popular during the period of cheap petrol, it became a more discussed topic after the petrol embargoes between 1974 and 1978. The research and development activities carried out in the 1980s under the leadership of the International Energy Agency had a significant impact on the development of wind energy. Today, modern wind energy systems have replaced the old models of wind generators. Wind energy conversion systems have become widespread throughout the world and they are expected to be even more widespread in the future.

Wind speed is very important in terms of potential electrical energy to be converted in wind turbines. Since this effect is proportional to the third power of wind speed, performing studies on wind speed estimation models became necessary for wind plants [3]. In this way, the systems can be activated at the times when high wind speeds are projected, and maximum energy conversion can be ensured.

Several methods have been used for estimating wind speed. Some of these methods include: autoregressive moving average (ARMA) [4], autoregressive integrated moving average (ARIMA) [5], Regression analysis [6], fuzzy logic [7], genetic algorithm [8], ANN multi-layered feedback network [9], and the RBN network [10].

Lapedes and Farber estimated wind speed through an ANN multi-layered feed-forward model and observed significant fluctuations in the results that were obtained [11]. Hocaoğlu and Kurban estimated wind speed for the province of Eskişehir using fuzzy logic [12], while Gong and Jing did it for the city of Hannaford using artificial neural network feedback multi-layered network [9]. As Ghanbarzadeh et al. used an ANN multi-layered network on temperature, pressure, and humidity inputs for Manjil city of Iran [13], Nogay and Akıncı carried out long-term wind speed estimations for the district of Amasra in the province of Bartın employing artificial neural networks [14]. Civelek et al. used genetic algorithms [15]; Gnana and Deepa used pressure, temperature, and humidity inputs and the ANN-RBN model [16]; Ata and Koçyigit employed the ANFIS approach in wind turbines for wind speed estimations [17], while Zhiling Y et al. estimated lost wind data through the ANFIS method [18]. Long-term wind speed estimations aid in determining the location for wind plants. On the other hand, short-term wind speed estimations aid in determining the possible amount of power generation and taking the wind plants in or out of the interconnected system.

In this study, wind speed estimation was performed comparatively using the ANFIS, BPLM, and RBN network structures.

## WIND ENERGY

### 1.1 Wind Energy in the World

Almost 55 GW of wind power capacity was added during 2016, increasing the global total about 12% to nearly 487 GW. Gross additions were 14% below the record high in 2015. [19]. The growth rate of wind energy in the whole world in 2015 is more than in previous year. Growth rate which is 16.4% in 2014 reached 17.2% in 2015. Also, power of installed wind farm reached nearly 435 GW levels in the whole world in 2015. In the best 15 countries about wind investment Especially China, Brazil, Poland and Turkey were shown the fastest growth by capturing powerful growth rate. In 2015, China was continued leadership position as in 2014 by adding 33 MW new capacity. China possess %51.8 of wind energy investment of the whole world in 2015. When look at data of wind energy in USA, the highest growth rate was observed in 2015 since 2012. The powerful growth was provided with new 8.6 MW wind farm capacity. In recent years, declining oil price have negatively affected to wind investments. In 2015, Germany beat the new record in itself by supplying 13% of energy demands of German State with establishing new 4.9 MW wind farm [20]. Wind Power Global Capacity and Annual Additions are listed in Table 1.

**Table 1:** Wind Power Global Capacity and Annual Additions, 2006-2016 [19]

| Year | World Total Capacity end [GW] | Added Capacity [GW] |
|---|---|---|
| 2016 | 487 | 55 |
| 2015 | 433 | 64 |
| 2014 | 370 | 52 |
| 2013 | 319 | 36 |
| 2012 | 283 | 45 |
| 2011 | 238 | 41 |
| 2010 | 198 | 39 |
| 2009 | 159 | 38 |
| 2008 | 121 | 27 |
| 2007 | 94 | 20 |
| 2006 | 74 | 15 |

## METHODS

The attributes such as wind speed, direction, and number of hours wind are assessed for wind energy. Wind speed increases proportionally with height, while power increases in proportion to the wind speed cubed [21]. According to the theory established by Dr. Albert Betz, kinetic energy should be calculated in order to define wind potential. Wind is actually air in motion, and therefore its kinetic energy is expressed as follows:

$$E_k = \frac{1}{2} m_h v_r^2 \quad (1)$$

where

$E_k$: The kinetic energy of wind (J)

$v_r$: The wind speed at the measurement elevation (m/s)
$m_h$: The mass of air (kg)
The mass of air ($m_h$) is calculated as follows:

$$m_h = p_h \, v_h \tag{2}$$

where
$p_h$: The density of air (kg/m$^3$)
$v_h$: The volume of air (m$^3$),

$$v_h = v_r \, At \tag{3}$$

where
$v_r$: The wind speed at the measurement elevation (m/s)
$A$: Rotor sweep area (m$^2$)

$t$: Measured time (s). Thus, if the kinetic energy equation is rearranged using equations (2) and (3), wind energy (*$E_r$*) in Joules is defined by equation (4).

$$E_r = \frac{1}{2} \rho_h A v_r^3 t \tag{4}$$

In this equation, if it is assumed that t = 1, then the energy per unit time, in other words the instantaneous power of wind, becomes:

$$P_r = \frac{1}{2} \rho_h A v_r^3 \tag{5}$$

In accordance with the Betz law, 59.3% of the incoming wind's kinetic energy can be transferred to the turbines as mechanical energy [22].
The wind input and output at the wind blade, turbine power;

$$P_t = \left(\frac{1}{4}\right) \rho_h \, A\left(V_r + V_{r_2}\right)\left(V_{r_2} - V_{r_2}^2\right) \tag{6}$$

Defined by equation [23].

### 1.2 Artificial Neural Networks

Artificial Neural Networks (ANN) are computer software systems that perform the human brain's higher functions, such as establishing new information by learning and discovery without assistance from outside the system. ANN is the type of software used to carry out functions similar to that of a human brain, such as learning, recollection, forming new information, and making generalizations. ANN has important characteristics such as being nonlinear, parallel, local information processing, fault tolerance, learn ability, generalization, adaptability, hardware and speed, and analysis and ease of design.

In a basic ANN cell, the inputs (Xn), weights (Wn), summation function (NET), activation function threshold value (b), activation function (f), output value (o) are as shown in Fig. 1.

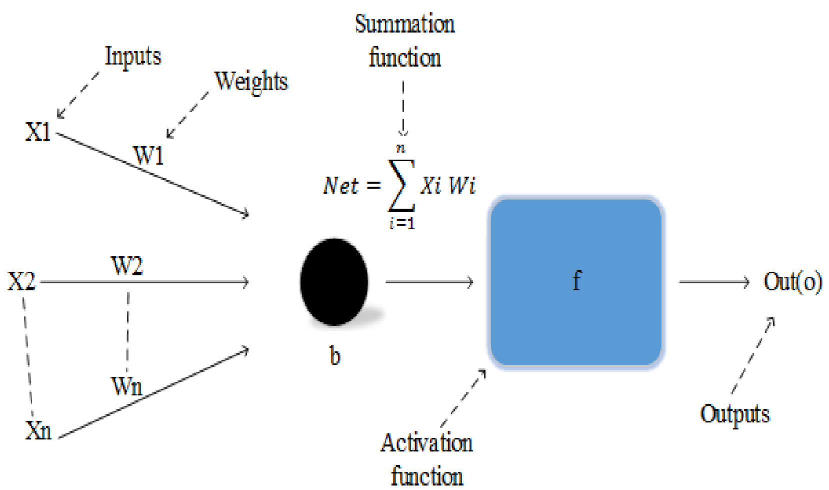


**Fig. 1** : The basic structure of ANN

Data received from outside the cell is connected to the neuron, taking weights into account. The net input is formed by multiplying the weights by inputs and adding the threshold value. The net input is processed in the activation function to give the cell's output.

$$o = f\left(\sum_{i=1}^{n} w_i\, x_i + b\right) \tag{7}$$

Several functions are used in ANN cells. These functions might also be linear or nonlinear mathematical structures. The tangent hyperbolic function is used in this study [24]. The tangent hyperbolic function uses the following equation:

$$F(NET) = \frac{e^{NET} + e^{-NET}}{e^{NET} - e^{-NET}} \tag{8}$$

Several network structures such as BPLM, RBN, Elman network, Hopfield network, LVQ, and Adaline are widely used in ANN. BM, BPLM, and RBN structures were used in this study.

**1.3 Backpropagation Algoritması**

Backpropagation algorithm is one of the most popular algorithms for network education due to its advantages such as ease and feasibility. While calculating the weights, the error signal between the inputs and outputs is found and the weights are updated using this error signal. The error e(k), is the difference between the desired output (y(k)) and the neural network's output (o(k)) .

$$e(k) = y(k) - o(k) \tag{9}$$

A feed-forward multi-layered artificial neural network, in which several neural cells are interconnected, is shown in Fig. 2. The layer or layers between the input layer and the output layer is/are called hidden layer(s). The number of hidden layers to be used in neural networks and the number of neurons each hidden layer should hold has yet to be determined; these attributes change depending on the problem, and are found by trial and error.

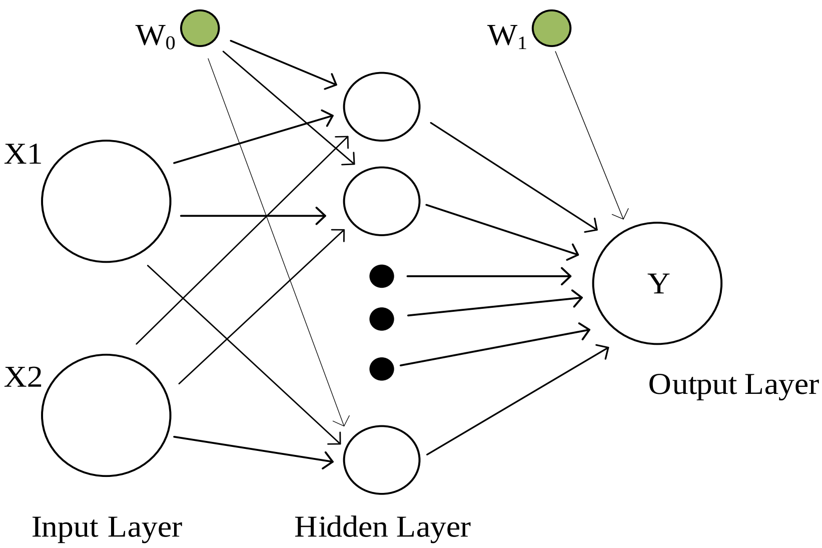


**Fig. 2: Feed-forward and feedback multi-layered neural network.**

Considering about multilayer neural network in Fig. 2 [15];
the net input for i. units in k+1 layers is:

$$n^{k+1}(i) = \sum_{i=1}^{Sk} w^{k+1}(i,j)\, o^{k}(j) + b^{k+1}(i) \tag{10}$$

The output of unit i would be as follows:

$$o^{k+1}(i) = f^{k+1}\left(n^{k+1}(i)\right) \tag{11}$$

If a network having M layers is expressed as a matrix;

$$o^{0} = x \tag{12}$$

$$o^{k+1} = f^{k+1}\left(W^{k+1} o^{k} + b^{k+1}\right) \qquad k = 0.1, \ldots, M-1 \tag{13}$$

The fundamental task of the network is to learn the relation between the input-output pairs.

$$\{(x_1, y_1),(x_2, y_2),\ldots,(x_n, y_n)\} \tag{14}$$

The network performance is as follows:

$$E=\frac{1}{2}\sum_{q=1}^{Q}(y_q-O_q^M)^T\left(y_q-O_q^M\right)=\frac{1}{2}\sum_{q=1}^{Q}e_q^T e_q \tag{15}$$

where $O_q^M$ is the network's output when q. input becomes $X_q$ , and $e_q = y_q - O_q^M$ is the error in input q. The approximate step reduction algorithm is used for the standard backpropagation algorithm. Performance index is used in the approximation as follows:

$$E=\frac{1}{2}e_q^T e_q \tag{16}$$

Here the sum of squares is substituted by square error for a single input-output pair. Afterwards, the approximate step (slope) reduction algorithm becomes:

$$\Delta w^k(i,j)=-\propto\frac{\partial E}{\partial w^k(i,j)} \tag{17}$$

$$\Delta b^k(i)=-\propto\frac{\partial E}{\partial b^k(i)} \tag{18}$$

where $\propto$ is the learning rate and is defined as follows:

$$\delta^k(i)=-\propto\frac{\partial E}{\partial n^k(i)} \tag{19}$$

The precision of the performance index is changed net input for the unit i. of on layer k.

$$\frac{\partial E}{\partial w^k(i,j)}=\frac{\partial E}{\partial n^k(i)}\frac{\partial n^k(i)}{\partial w^k(i,j)}=\delta^k(i)\,o^{k-1}(j) \tag{20}$$

$$\frac{\partial E}{\partial b^k(i)}=\frac{\partial E}{\partial n^k(i)}\frac{\partial n^k(i)}{\partial b^k(i)}=\delta^k(i) \tag{21}$$

The precision adequacy can be also expressed with the following recursive relation:

$$\delta^k=F^k\left(n^k\right)W^{k+1}\delta^{k+1} \tag{22}$$

Here;

$$F^k\left(n^k\right)=\begin{bmatrix} F^k\left(n^k(1)\right) & 0 & \ldots & 0 \\ 0 & F^k\left(n^k(2)\right) & \ldots & 0 \\ \ldots & 0 & \ldots & \ldots \\ 0 & 0 & \ldots & F^k\left(n^k(Sk)\right) \end{bmatrix} \tag{23}$$

and

$$f^k(n)=\frac{df^k(n)}{dn} \tag{24}$$

$$\delta^M=-F^M\left(n^M\right)\left(y_q-o_q\right) \tag{25}$$

In all learning algorithms, generally the following steps are taken: First, the input is propagated forward by using (12) and (15), then propagated backwards using (25) and (22), and finally recalculated using weights and equilibrium (17), (18), (19) and (20) [25]. Several learning algorithms are available in ANN. The algorithms such as Gradient-Descent, Resilient, Levenberg-Marquardt are a few. The Levenberg-Marquardt algorithm has become a very popular algorithm in recent years. The Levenberg-Marquardt learning algorithm was used in this study. The Levenberg-Marquardt algorithm is a method that is technically based on the nonlinear least squares method used in updating weights. The weight updates are performed via the following operations:

$$W_{ij}(t+1)=W_{ij}(t)+\Delta W_{ij}(t) \tag{26}$$

Thus, the Levenberg-Marquardt difference from the Gauss-Newton method is shown in the following equation.

$$\Delta W_{ij}=-\left[\mathrm{J}^{\mathrm{T}}(\mathrm{w})\,\mathrm{J}(\mathrm{w})+\mu\mathrm{I}\right]^{-1}\,\mathrm{J}^{\mathrm{T}}(\mathrm{w})\,\mathrm{E}(\mathrm{w}) \tag{27}$$

where $W_{ij}$ represents the weights, J the Jacobian matrix, μ a constant, I the unit matrix and E(w) the error function [12].

**1.4 Radial Basis Network**

The Radial Basis Network (RBN), is a network type that was first developed in 1988 inspired by the action-reaction behaviors in neural cells [26]. RBN training is a curve fitting problem that involves finding the best fitting surface in multi-dimensional space. It has a three-layer structure composed of an input layer, an intermediate layer and an output layer. The RBN network structure is shown in Fig. 3 [27].

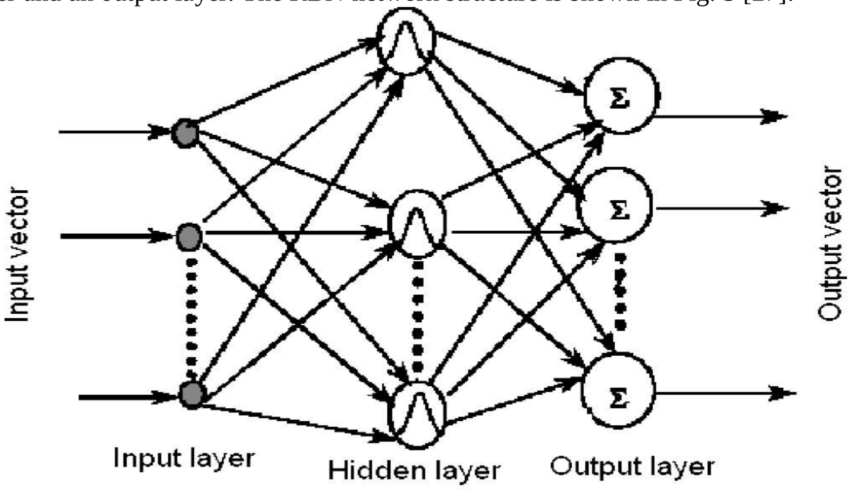


**Fig. 3 : General RBN structure [27]**

The radial basis activation functions are used for the neurons in the intermediate layer. Some of those are functions, such as linear, cubic, and Gauss. In this application, the Gauss function is used as the activation function.
Gauss activation function becomes:

$$\varphi_j(x) = \exp\left(-\frac{x - C_j^{\ 2}}{2\sigma_j^2}\right) \tag{28}$$

Here x represents the input vector, $C_j$ the center, and $\sigma_j$ the bandwidth (28) is a Gaussian curve. The equation for the neuron j on the output layer is:

$$s_j(x) = \sum_{i=1}^{K} w_{ij}\varphi_i(X) + b_j \tag{29}$$

Where $w_{ij}$ is the weight coefficient between the hidden neuron i and the output neuron j [10].

**1.5 ANFIS**

In 1965 L. A. Zadeh introduced the fuzzy sets method to the literature by publishing an article titled "Fuzzy Sets" that explains a new mathematical method, in the magazine Information and Control. This method enabled obtaining fuzzy sets such as "short man", "beautiful woman", or "real numbers that are greater than 1". Since then, the fuzzy sets theorem has been studied and developed rapidly by Zadeh and numerous other researchers.

Adaptive-Network Based Fuzzy Inference Systems (ANFIS) is a hybrid artificial intelligence method that uses parallel processing, the learning ability of artificial neural networks, and the inference attribute of fuzzy logic. The ANFIS model, developed by Jang [28] in 1993, uses a Sugeno-type fuzzy inference system and a hybrid learning algorithm. It is composed of directly connected nodes. Each node represents an operation. By using backpropagation or the least squares method, FIS (Fuzzy Inference System) membership functions can be determined. Therefore, the data modeled using this method enables the fuzzy system to learn.
Some features of the ANFIS controllers are as follows:

- The ability to learn,
- Parallel processing,
- Representation of structured information,
- Better integration with other control design methods.

The learning algorithm is directed forward and backwards. While calculating the resulting parameters, the parameters of the membership functions are held constant and these parameters are calculated using "the least squares" method. Furthermore, to calculate parameters of the membership functions, the resulting parameters are kept constant and the membership functions are adjusted by the "backpropagation algorithm" [29].

In order to explain the formation of fuzzy inference system in the ANFIS structure easily, if two inputs called x and y, and an output called f are assumed, then the fuzzy IF THEN possible rule for the first degree Sugeno-type fuzzy model becomes the following:

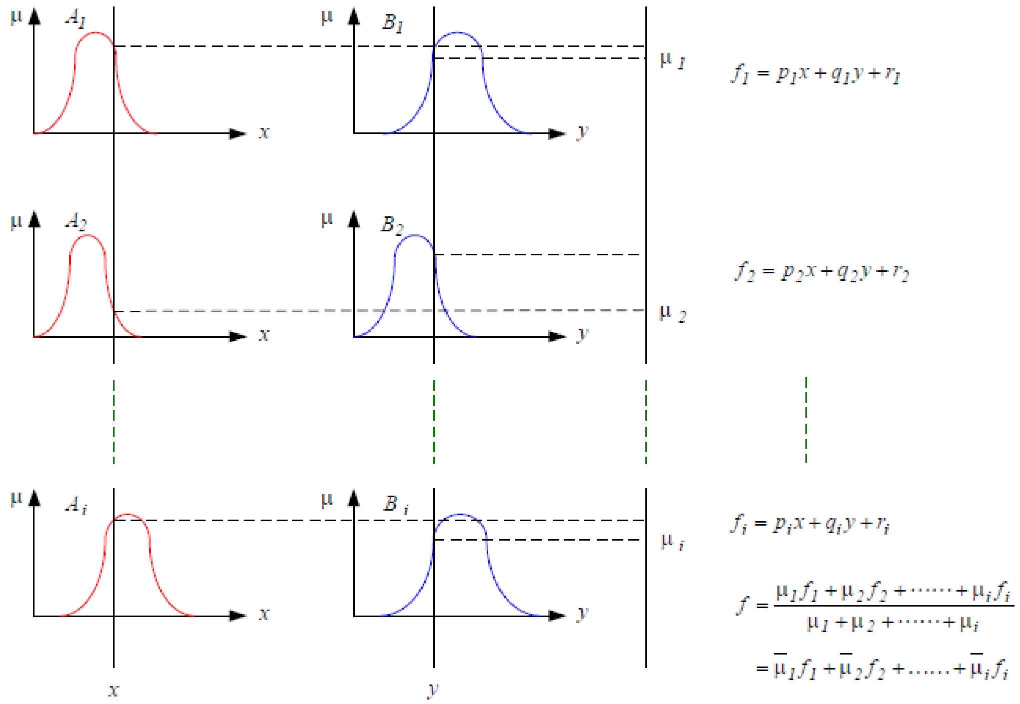

**Fig. 4 : Sugeno type fuzzy inference [29]**

$$Rule\ 1:\ if\ \ x = A_1 and\ \ y = B_1 then\ f_1(x,y) = p_1x + q_1y + r_1 \tag{30}$$

$$Rule\ 2:\ if\ \ x = A_2 and\ \ y = B_2 then\ f_2(x,y) = p_2x + q_2y + r_2 \tag{31}$$

If the membership value for any set of the date is close to 1, then it is included in that set, and if it is close to 0 it is considered out of the boundaries of that set. The Sugeno model was established by using the system above, considering the generalized input rules as given in Fig. 4. The ANFIS model corresponding to this Sugeno model is shown in Fig. 5.

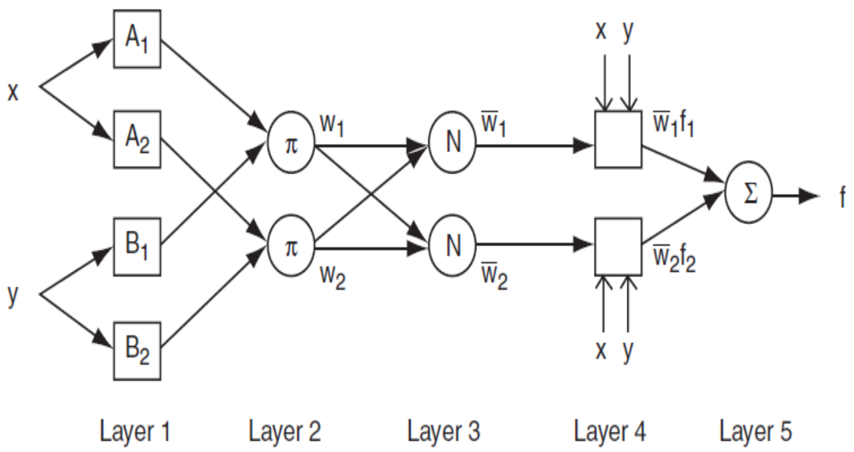


**Fig. 5 :** ANFIS structure [30]

## APPLICATION

In this study, the temperature, pressure, humidity, and wind speed data at 10 m elevation for the Siverek district of the province of Şanlıurfa received from the state meteorology station were used after arranging them into monthly average data from 2000- 2009. Three different methods were employed to estimate wind speed using the temperature, humidity, and pressure inputs. All applications have a 3-input, 1-output network structure. The wind speed was estimated using BPLM in the first application, using RBN in the second application, and using ANFIS in the third application. The success rates of these networks were calculated via root mean square error (RMSE) and mean square error (MSE) values. In each application, all data were normalized, networks were trained, and all achieved results were denormalized to calculate the RMSE and MSE values.

### 1.6 Normalization

Normalization is carried out in order to minimize the period of the input data to ensure that outputs are affected as little as possible from the data fluctuation. All data used in this study were normalized. The following equation was used for normalization:

$$xn = \left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) * 0,8 + 0,1 \tag{32}$$

Root mean square error (RMSE) and mean square error (MSE) values were calculated for the estimates.

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (Y_t - F_t)^2} \tag{33}$$

$$MSE = \frac{1}{T} \sum_{t=1}^{T} (Y_t - F_t)^2 \tag{34}$$

$Y_t$ : Measured value
$F_t$ : Predicted value [1]

**Table 2 : The maximum and minimum values used in normalization**

| | Minimum(m/s) | Maksimum(m/s) |
|---|---|---|
| Temperature | 1,1 | 33,6 |
| Pressure | 908,6 | 927,6 |
| Humidity | 25,4 | 87,5 |
| Wind speed | 0,4 | 3,2 |

The monthly average pressure, temperature, and relative humidity graphs for the parameters used in the application are shown in Fig. 6, Fig. 7, Fig. 8. In all applications, the temperature, pressure, and humidity data were assigned as the input data and the wind speed data as the target data. The temperature, pressure, and humidity data between 2000 and 2008 were given as the input data for ANFIS, BPLM, and RBN methods. The wind speed values for 2000-2008 were assigned as the target. As test data, the temperature, pressure, and humidity data for 2009 were given and the wind speed values for 2009 were estimated. In the first application, BPLM was employed; 10 neurons were used in the first intermediate layer, and 8 neurons were used in the second intermediate layer. Moreover, the tangent hyperbolic function was chosen for this network. After the application, the values RMSE = 0.1289 and MSE = 0.0166 and the graph in Fig. 9 were achieved. In the second application, the RBN network was employed and the best result was obtained for a distribution coefficient of 2.2 during the training, where this value ranged from 0.1 to 3.0. For a distribution coefficient of 2.2, the values RMSE = 0.1752 and MSE = 0.0307 and the graph in Fig. 10 were achieved. The ANFIS editor was used in the application employing fuzzy logic. "Grid partition" was selected while creating a FIS file in this application. Moreover, backpropagation was chosen as the optimization model. The “gaussmf” function was used as the function. The values RMSE = 0.1960 and MSE = 0.0384 and the graph in Fig. 11 were achieved.

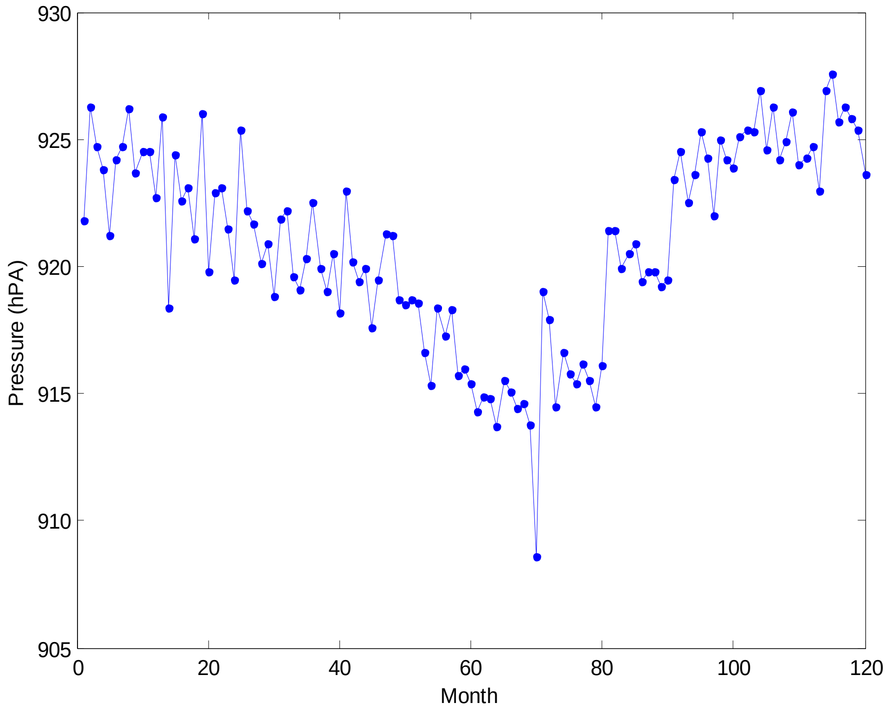


**Fig. 6:** Pressure data for Siverek

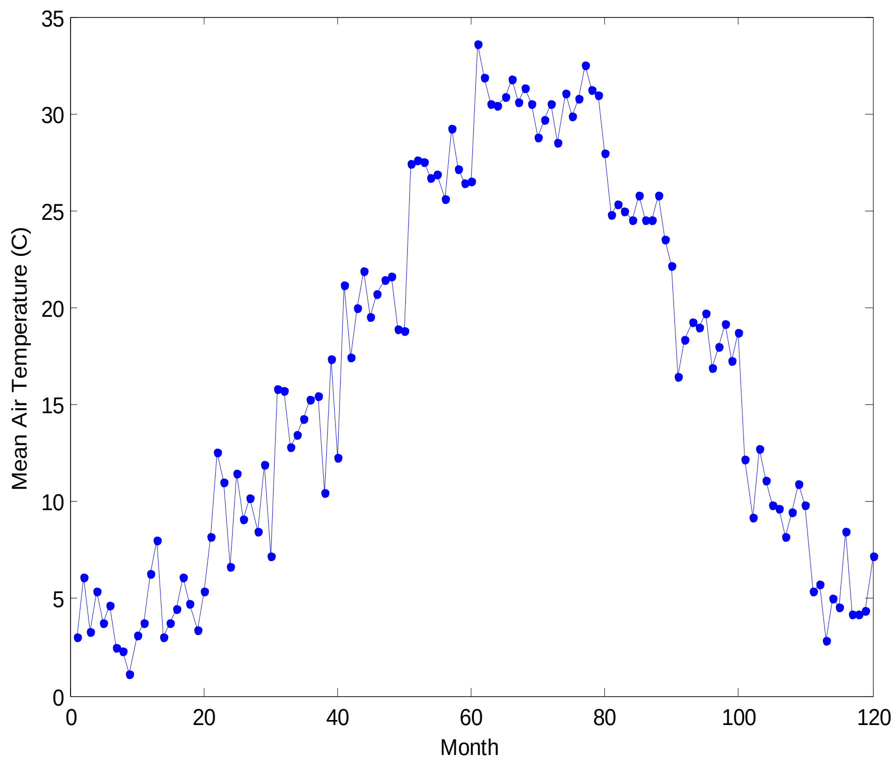


**Fig. 7 : Temperature data for Siverek**

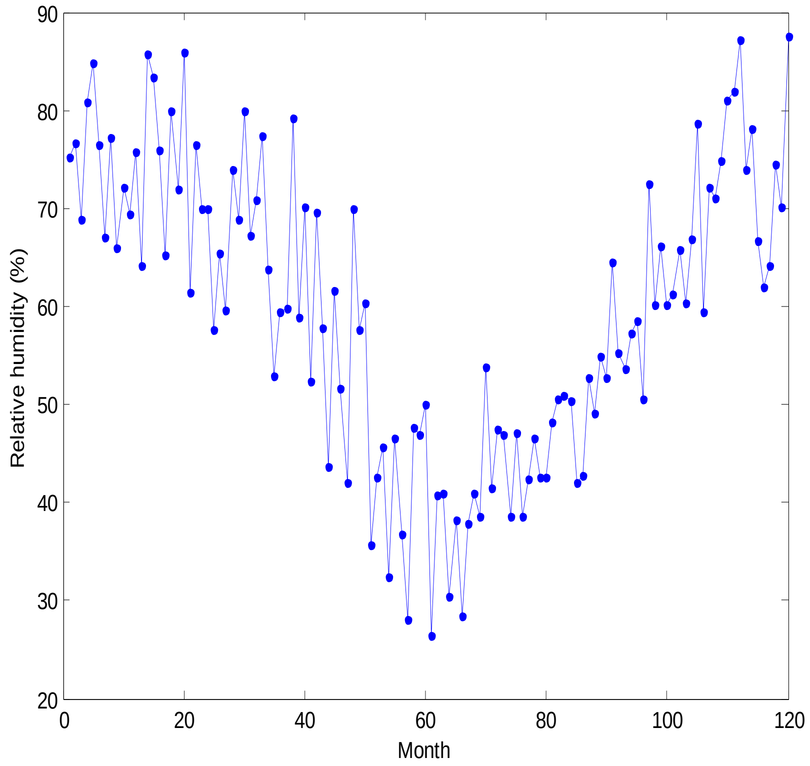


**Fig. 8 :** Humidity data for Siverek

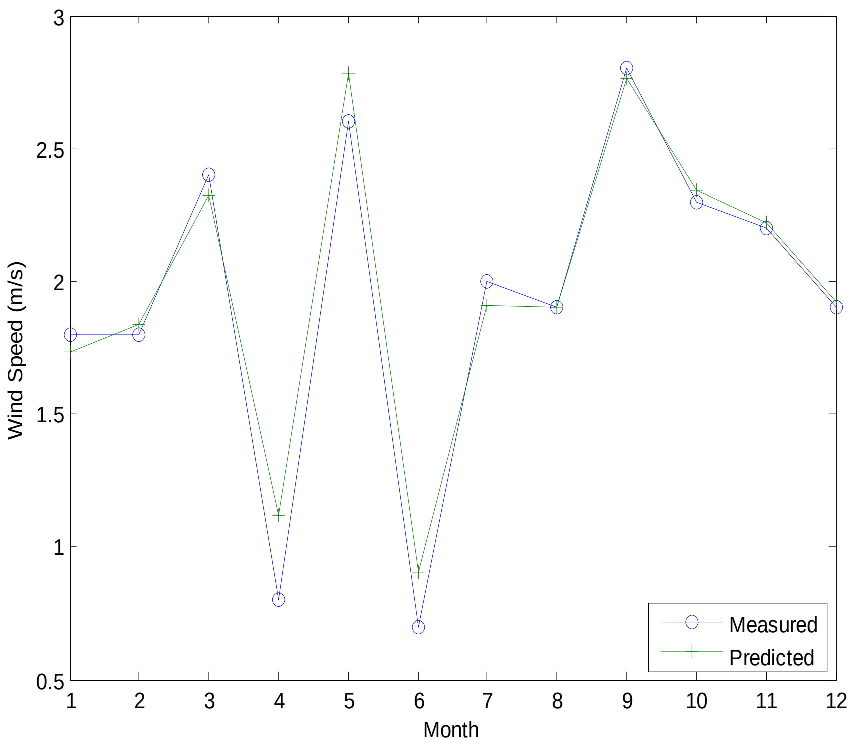


**Fig. 9 :** Estimation graph achieved using BPLM

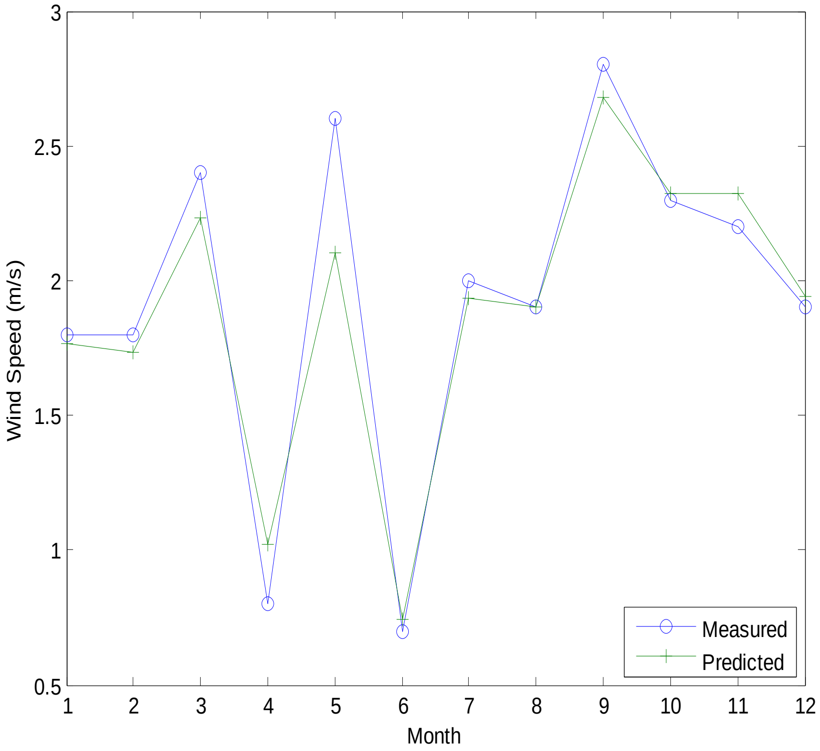


**Fig. 10 :** Estimation graph achieved using RBN

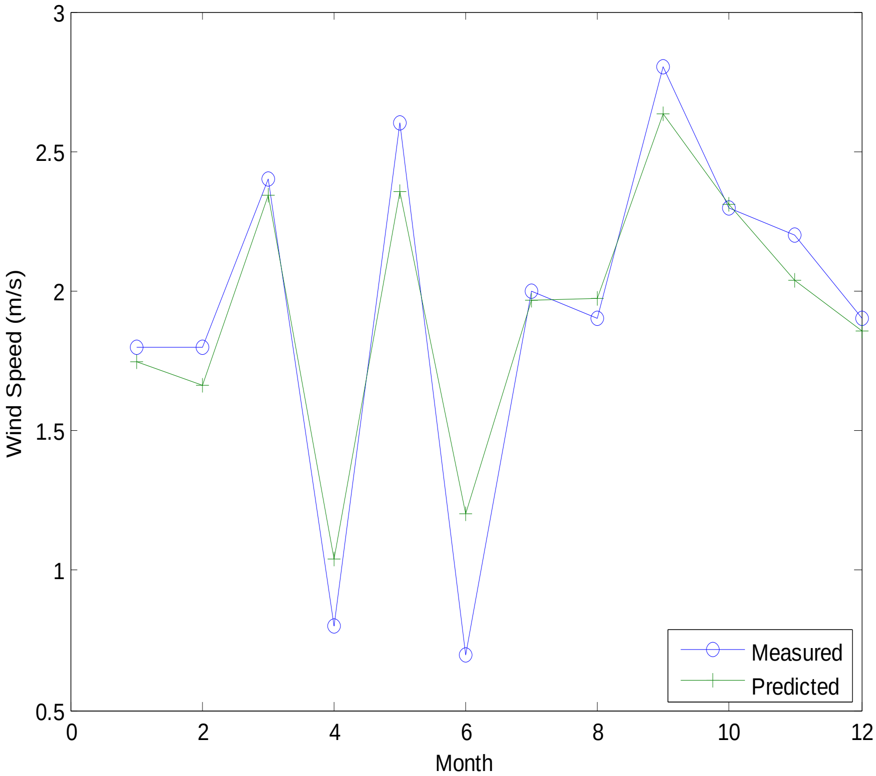


**Fig. 11 :** Estimation graph achieved using ANFIS

## CONCLUSION

In this study, the wind speed was estimated for the Siverek district of the province of Şanlıurfa for 2009. To obtain the estimates, the data collected using BPLM, RBN, and ANFIS on the temperature, pressure, and humidity inputs were analyzed. The best results obtained by RBN, BPLM, and ANFIS methods are listed in Table 3.

**Table 3 :** RMSE and MSE results

| | RMSE | MSE |
|---|---|---|
| BPLM | 0,1289 | 0,0161 |
| RBN | 0,1752 | 0,0307 |
| ANFIS | 0,1960 | 0,0384 |

As seen in Table 3, the best results were achieved using the BPLM algorithm (RMSE = 0.1289 and MSE = 0.0161). In this application, the BPLM model was found to be more successful than the RBN and the ANFIS network models. The values RMSE = 0.1752 and MSE = 0.0307 were achieved using the RBN model. The RBN model was observed to give better results than the ANFIS model, but the difference was not very significant. As given in Table 3, the values RMSE = 0.1960 and MSE = 0.0384 were obtained using the ANFIS model. Moreover, in this study, where we used 10-year data, shows that the temperature, pressure, and absolute humidity inputs could be used to estimate the wind speed. For the RBN model, the best result was achieved for the distribution coefficient of 2.2. For the BPLM model, it was observed that a 3-layer network structure could be used in order to estimate the wind speed, and that the tangent hyperbolic function could be chosen as an estimation algorithm. For the ANFIS model, the "gaussmf" function was found to be appropriate for estimates. The significance of wind speed was stressed and the advantages of three of the methods used for estimating the wind speed were compared to each other. The parameters for these methods (such as the number of neurons and the type of the function) were assessed. The objective of this study was to determine the installation locations for wind plants and to estimate the amount of energy likely to be generated.

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