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Determination of Wind Potential of a Specific Region using Artificial Neural Networks

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Abstract: There is a widespread trend in alternative energy sources in today's world. Achieving energy without harming the environment has been the most important target of the countries in recent years. For this reason, it is necessary to make utmost use of natural energy sources such as wind, sun and water. Among these sources, wind energy is the most utilized. Because it was cheap and quickly return to investment it is carried out many studies in this area. However, the most important problem is the continuity when the wind energy is obtained. The first thing to do before a wind power plant is installed in a region is to calculate the wind potential of the area concerned. This process is long-term under normal conditions. Artificial Neural Networks (ANN) is one of the most frequently used methods for determining a wind power potential in a short time period. In this study, it is aimed to estimate the wind potential of a certain region within the boundaries of Osmaniye province. ANN was used to estimate the wind power potential. As a result of comparing the statistical values of the forecast values with the measured actual values, the performance of the method applied is indicated. The meteorology station at Osmaniye Korkut Ata University using data has been successfully estimated wind potential.

Keywords: *Artificial Neural Networks (ANN), Wind Potential, Estimation, Wind Power.*

1. Introduction

Nowadays, fulfilling increasing energy needs, the most important target has become to obtain clean energy without damaging the environment we live in. Oil and coal-based resources are a known fact that affects living environments and the quality of life of living things in a negative way. For this purpose, many of the countries around the world have brought renewable energy sources to an important position in meeting their energy needs by revising their energy policies. Among renewable sources, wind energy is one of the areas where countries invest the most and produce the cheapest electricity compared to other renewable energy sources. Thanks to improvements in wind energy technology around the world, wind energy is the first to come to mind when it comes to clean energy and to make a significant contribution to the growth of the market [1].

By the end of 2015, the world's electric energy from the wind has reached about 4% of total global electricity. According to various forecasting scenarios in 2020, it can be better understood by countries, energy generated from renewable energy sources will be around 26% of the world's contribution to electricity on a global scale, and wind energy will rise to about 7% by 2020 [2].

Obtaining efficiently electrical energy from the wind and ensuring its continuity are the very important problems. Because the wind energy is not a stable source of energy. It is an energy source that cannot be fully controlled due to fluctuations in its structure. Intermittent blowing in a zone and depending on many parameters, such as seasonal, meteorological, and terrain conditions, affects the wind speed. Therefore, energy potential generated by the wind speed is also influenced. Accordingly, before establishing a power plant in a zone, it is absolutely necessary to calculate the wind potential of the relevant site. Calculation of the wind potential is a process and requires many years. Furthermore, the installation of the devices to be measured is costly and difficult to operate. The devices require high precise calibration. The carelessness and wrong installation affect measurement results. So, if it is aimed to achieve healthy and reliable measurement results, the data of expert institutions in the field should be utilized. In these measurements, the main goal is to determine the wind speed characteristic of the relevant zone and to calculate the wind power [3, 5].

The factor directly affecting production in wind-driven power plants is wind power. Power is converted to electricity in power plants. Providing the continuity of electricity is one of the most important factors. One of the most widely used methods today is to estimate wind speed or power in order to plan for energy production in one place, to calculate efficiency level and to determine investment situation. Decreasing the errors according to the actual measured values of performance ratios in forecasting methods has increased confidence among these investors. When you look at the literature, a number of methods are used to estimate the wind power in a region. It is possible to classify these methods as statistical methods and machine learning approaches in general. In both methods, some meteorological data (such as wind speed, wind direction, air pressure, temperature and density) based on the past are used. Some of these are obtained from wind turbines currently in active while others are obtained from weather forecasting stations, some of which are numerically measured in the state or private institutions that are established in a region. Autoregressive Moving Average (ARMA) and Kalman Filter Method are widely used in statistical methods. Machine learning approaches are defined as methods

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that have increased usage rate in recent years and give more accurate results in terms of reliability compared to statistical methods. It is widely used especially in the estimation of short period wind power. These methods can be arrayed as Artificial Neural Network (ANN), Fuzzy Logic, and Support Vector Machine. ANN is one of the most used methods in machine learning approaches [4-8].

In our study, we did not use any data set obtained from a meteorological measurement station belonging to the state or a private institution compared to other studies and aimed to estimate the wind potential of a region determined by the ANN method. It was aimed to estimate short period wind power by using Multilayer Feed-Forward Backpropagation neural network method with the help of data obtained from the meteorological station which was established at Osmaniye Korkut Ata University. Firstly, the data received from the station are determined and arranged. Secondly, in order to maximize the performance of the Artificial Neural Network to be applied, the data is subjected to normalization processing and the best prediction performance is obtained by using the Levenberq-Marquardt(LM) backpropagation algorithm in order to train the generated network.Using the data from our own measurement station, the wind potential was successfully calculated by the ANN method. With this study, it is aimed to benefit the wind based work done on the region.

2. Structure Of Wind Power

Wind power is one of the most important parameters that need to be known and calculated which directly affect electricity production. As can be seen in the formula given in Eq.(1), wind power is directly proportional to the cube of wind velocity (v). In addition, the air density (ρ) directly affects the wind power. The wing areas of the wind turbines specified in the formula (A) are another variation that has an effect on power. Calculation of this value can be neglected as homogenous blades are only used when power calculation is performed [5, 7].

$$\text{Power} = \frac{1}{2}\rho A v^3 \qquad (1)$$

In the above equation, it is obvious that the most important parameter directly affecting power is speed. It seems that the smallest change over speed causes great differences in power. Therefore, factors affecting wind speed have a similar effect on wind power. While calculations of power performance are made in wind turbines, changes in speed are based on the year. Turbine layout designs are made in such a way that the wind speed in a zone will produce minimum and maximum power during the season. In this way, the efficiency of the wind power plant is ensured by obtaining as much efficiency as possible from the wind. A wind turbine starts to move when average wind speed is in between 2.5-3.5 m / s. If it is over 4 m / s speed, it starts producing energy by going through production. When the wind speed exceeds 20 m / s, braking systems are switched on to shut itself off or give no damage the system [11].

3. Estimation Method Of Wind Power

It is known that many methods and techniques are used when wind power is predicted. It is possible to classify the commonly used methods in the literature in two approaches. These are Statistical and Physical approaches [9, 10].

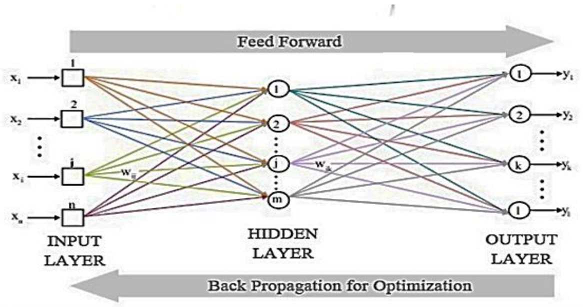
3.1. Physical Approaches

These approaches are generally defined as methods involving powerful and complex mathematical formulas used in predicting future meteorological phenomena by taking account of various meteorological and physical properties such as the atmospheric conditions and the terrain structure in a region, various obstacles, temperature, pressure, wind speed, direction. At this point, wind speed can be estimated in the future for any region. It is also known as the Numerical Weather Forecast (NWF). NWF is a structure based on providing precise results to estimators by considering multiple physical states. It is usually used by meteorologists and the performance is poor in short-term estimates. But, its usage in medium and long-term estimation is widespread. There is a need for computers called supercomputers in order to operate properly of NWF. So it cannot be used anywhere and cannot be measured [3, 7, 9, 10, 11].

3.2. Statistical Approaches

Statistical approaches are known as approaches that are easy to use, inexpensive, successful and quick to achieve, without complex mathematical models used to predict wind power and speed. They are widely used compared to physical approaches. In these approaches, it is aimed to estimate for the future by calculating the difference between meteorological data measured and predicted in the past. Time series and Artificial Neural Networks (ANN) methods can be divided into two subcategories [8, 9]. Auto-Regressive Moving Average (ARMA) is one of the most commonly used methods in time series. However, methods such as Kalman Filters Model are also used [10, 11].

ANN is one of the most frequently used and most successful techniques within statistical approaches. This structure is the computer modeling of the biological brain nerve cell, which is the basis of human spiritual structure. With ANN, it is usually aimed at reaching the goal from existing information for the solution of any problem. Widely used in the solution of events such as classification and prediction. An artificial neural network model has been developed for different types of problems. It is best known as the Perceptron network. When a network is being trained, the main goal is to try to minimize the difference between the input and output values as much as possible. When this is achieved, the problem is learned at a high rate by the computer. They are closely estimated by the computer to real measured values or approximated values when different input values of a similar type are entered on the computer. In this way, relations between input and output values, result impact levels and future prediction situations can be learned by using past data [7, 18, 19].



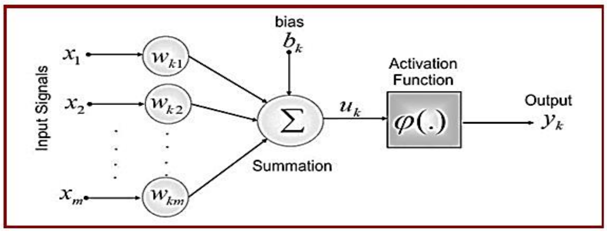


Fig. 1.A simple Multilayer Feed Forward Back Propagation Artificial Neural Network structure.

Basically, the neural network model consisting of more than one hidden layer from the input and output layers is shown in Fig. 1. The values in the input layer (x) represent the data to be used to solve a problem. The choice of data and the relationships between each other are largely influential on the outcome performance. The value (y) or values in the output layer is the result of the prediction in the network. When the estimation result is reached, hidden layers are used. Each layer of the network has structures called nerve node points, which are processed nonlinearly and in parallel. These nodes are designed by network builders. The weight (w) and threshold (b) of each node are processed on the mathematical equation given in Eq.(2) until the target output value is reached [1, 3, 4, 13, 16].

$$yk = f\left(\sum_{k=1}^{N} (w_{ik}x_k + b_k) \right) \quad (2)$$

Weights are randomly given at the beginning. As the data is processed in the network, these values are changed so that the output result reaches the desired level. Finally, the first step of learning the network is realized by inserting it into an activation function (f). The mathematical structure used as an activation function has an important role in network performance and is a linear or non-linear function in accordance with the natural structure of Artificial Neural Networks [8, 12, 15].

4. The Estimation Method Used And Measurement Of Accuracy

In this study, multi-layer neural network was used for prediction. Networks only consisting of input and output layers cannot perform complex structure calculations. Thus, there is a need for at least one intermediate layer to be able to predict the wind power successfully [12, 15]. Therefore, a three-layer Feed-Forward Backpropagation ANN model was developed using the Matlab R14a program.

4.1. The Selection of Learning Algorithm

One of the other issues that the developers refer to when developing models is the learning algorithms used during network training. Learning algorithms are influential on the performance of the network in the first place. There are many learning algorithms used in the ANN structure. They are divided into two parts, supervised and unsupervised. Commonly used supervised backpropagation learning algorithms [12, 13, 17]. The Levenberg-Marquardt learning algorithm was used because contribution of the estimation we made is higher than the other learning algorithms used in this study.

4.2. Data Selection and Preparation

The meteorological data to be used in estimating the wind power is measured by the Vantage Pro2 meteorological measuring instrument installed at Osmaniye Korkut Ata University. The coordinates of the station, which is 120 meters above sea level, are 37.05 north latitude and 36.14 east longitude in the northern hemisphere. Distance to the sea is 20 km and height is 20 m from the ground level [14].

Wind speed, density and humidity data were taken from the measuring station to estimate the wind power in the first six months of 2013 meteorological data. It is a known fact that immediate use of raw data within ANN will reduce the performance of the network. Therefore, the data are rearranged using the Min-Max normalization technique. This technique is linearly normalized between 0-1 values. The mathematical formula is as shown in Eq.(3) [15, 17].

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

After the values are normalized, power values are calculated using the power formula given in Eq.(1). The calculated power values are then compared with the predicted power values.

4.3. The Certainty of Prediction Results Detection Methods

Especially in academic studies it is necessary to test the accuracy of the result when ANN is reached with any other method. These methods are often defined as statistical error detection methods. More than one method is used in the literature. The most frequently used statistical error detection methods are the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) methods when the wind base literature is investigated. Equations for both methods are given below [4, 7, 8,15].

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{P_i - O_i}{P_i} \right| *100 \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=i}^{n} (P_i - O_i)^2}{n}} \quad (5)$$

Using statistical methods more than one way, a result can be achieved on the estimation performance of a model. The only MAPE formula given in Eq.(4) is a more advanced error-finding method than any other statistical error method [15]. In formulas Eq.(4) and Eq.(5), P_i is used for estimates, O_i is also used the calculated actual values.

Decision making using statistical error methods is not commonly used for a developed ANN model without simple linear regression analysis (R^2). As a result of R^2 calculation, the performance status of the model is between 0 and 1. It can be said that the calculated actual values and predicted values are almost the same [12].

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y'_i)}{\sum_{i=1}^{n} (y_i - \bar{y})} \quad (6)$$

Using the R^2 formula given in Eq.(6), the predicted values are compared with the values produced by the model. The y, y'and $\bar{y}$ values used in the formula represent the Real, Estimated and Mean values, respectively.

5. Results And Discussion

In order to estimate the wind power, the first 6 month short period data set from January to June of 2013 was used. In network was determined Wind Speed, Humidity and Density as input, Wind Power as output. Input variables are measured every five minutes in the active station. The hourly averages of these data are calculated. Then the hourly wind power was calculated using the formula given in Eq.(1). Input and Output data are normalized to increase network performance.

Using Matlab R14a program, 3-input 1-output Multilayer Feedforward Backpropagation neural algorithm network model was designed in Fig. 2. In the developed ANN model, 4344 data set was used. 3624 data of these values were used for training purposes and 720 data were also used for testing purposes. More than one hidden layer is used in the model. Models with 6, 9, 12, 15, 30, 60 neurons were tested between 0 and 1000 epoch values for use in hidden layers. The most successful performance was achieved after the result of 213 epoch, it is shown in Fig. 3.

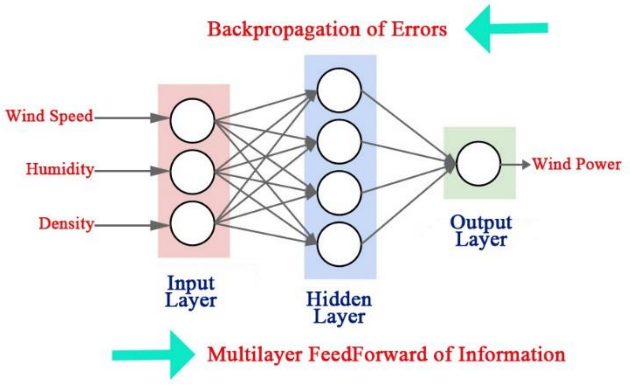


Fig. 2. Graphical design of the ANN used in the study.

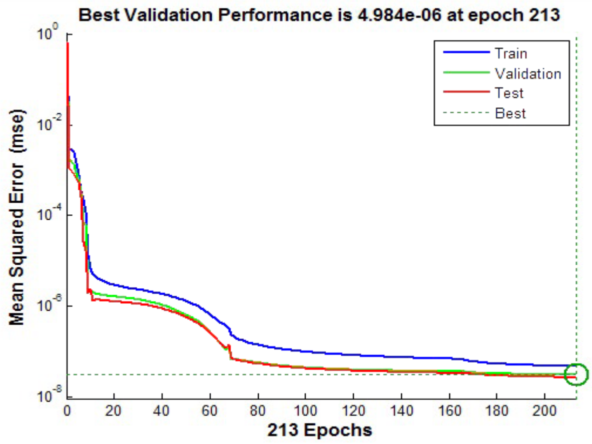


Fig. 3. The performance graph MSE.

The MSE performance of the developed model is estimated to be approximately 0.000005. Fig. 4 shows the test, training and validation regression plots of the corresponding model generated from the Matlab program.

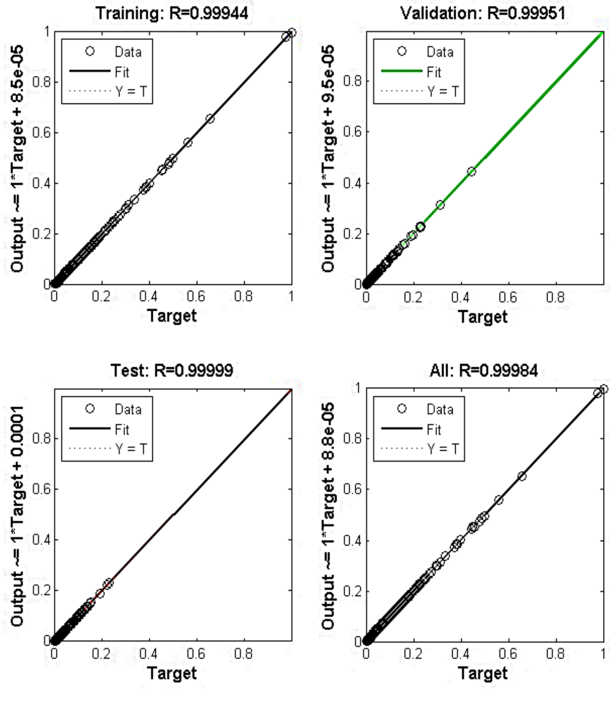


Fig. 4.ANN Regression performance graph.

It can be concluded that the developed model predicts the wind power very successfully according to the regression performances in Fig. 4.The 3624 training data entered are divided into three parts, which are defined by ANN as test, training and validation. Learning the problem happens at this stage. When the values are close to 1, it means that the estimated performance of the developed model is higher.

Predicted results from the ANN model calculated real wind power values were compared statistically and then the performance of the developed model is shown in Table 1.

Table 1. Statistical evaluation of prediction model

R^2	RMSE	MAPE
0.997754	0.002397	7.88

As can be seen from this table, the MAPE value is below 10%. This shows us that the effect on the results of the developed model gives a very good level. Looking at the results of the RMSE and R^2 values, it can be said that the performance of the prediction model is at a fairly good level.

Comparison of the estimated wind power with ANN for five days which are chosen randomly is given in Fig. 5. As can be understood from this figure, the network result success and prediction performance according to a data set which has never been seen before is a level that can be considered excellent when compared with calculated power values.

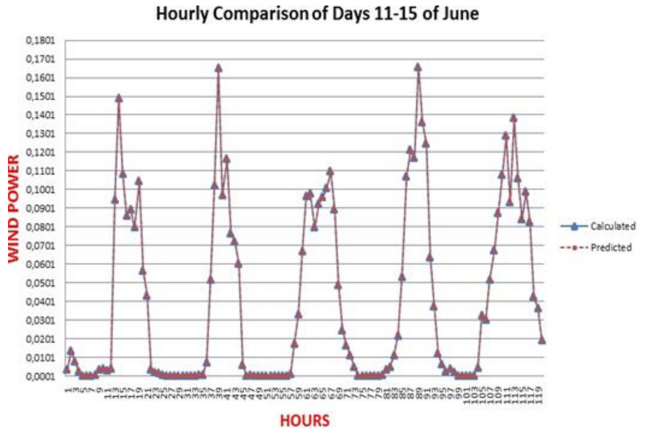


Fig. 5. Compare the Five-Day Hourly Values for June.

Hourly forecast and calculated wind power values for the month of June is given Fig. 5.using the 5-day (11, 12, 13, 14, 15 Days). A total of 120 data have been utilized in the Fig. 5. Monthly windpower potential in June is presented in Fig. 6.

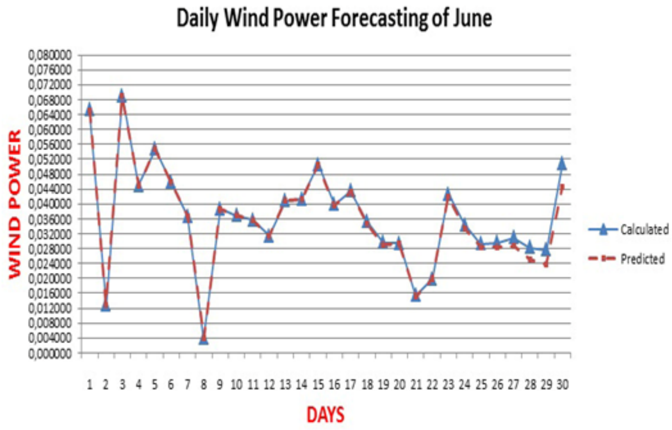


Fig. 6. Comparison of Daily Calculated and Predicted Results for the Month of June.

As can be understood from this figure (Fig. 6), average values of calculated and predicted power potentials of the month of June are calculated by using the ANN method and the daily values are compared. The difference between the estimation results and the actual power values calculated is very close. This shows us that the model established with ANN is a very useful model for predicting wind power by using wind speed, humidity and density values for Osmaniye province.

6. Conclusion

In this study, some measurements taken at the meteorological station of Osmaniye Korkut Ata University were tried to calculate the wind power potential. There are many meteorological data affecting wind power. The wind power has been successfully estimated with Multilayer Feed-Forward Backpropagation method which considers wind speed, humidity and density values. The LM backpropagation learning algorithm used for the success of the prediction model is important for the network to be used during the training phase. The wind power forecasting potential for Osmaniye province is clearly explained by both the statistical calculation results and the graphical comparison method. In this way, the wind power for June was successfully modelled and predicted.

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