15th "International Scientific Conference"
RE & IT - 2016, SMOLYAN - BULGARIA

APPLICATION OF ANN FOR SHORT TERM FORECASTING OF WIND POWER DENSITY

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Abstract: *Short-term wind power density forecasting of a region is an important aspect in order to affect all the decisions to be taken with regard to the power stations to be constituted and developed within the scope of the development plan to be arranged for the mentioned region. Forecasting wind power density by any means whatsoever is important, different from wind speed, with regard to the assessment of the size, type, wing shape, and wing size of the wind turbine which is essential for use in a power station to be constituted in the region. In this study, wind power density obtained from a wind turbine which is suitable for the regional conditions was forecasted in connection with the future constitution of a wind station in Siverek District of Sanliurfa, a Southeastern Anatolian Province of Turkey. Respectively, multi-layered Artificial Neural Networks (ANN) model was used. ANN model in use at the study was developed in order to forecast wind power density directly. ANN model was trained by making use of back propagation learning algorithm. So as to have ANN model trained, a data set was organized by making use of time series of wind speed data. ANN model was trained by means of 80% (7028) of 8784 wind speed data having been used in the study. In accordance with the approach (R) value, training thereof was realized by 99.83%. Having ANN model tested by 10% of the data set, a success rate of 99.79% was attained.*

Key words: *wind power density, artificial neural network, forecasting, wind speed*

1. Introduction

Recyclable energy resources in the world are becoming increasingly attractive day by day. For a region to benefit from wind power, and cover its energy requirements by having a wind station constituted, atlas of the mentioned region is to be charted. Southeastern Anatolia Region of Turkey is the second productive region of Turkey after Marmara Region in terms of wind speed. However, the same region is also noteworthy as being the region with the harshest geographical and natural conditions in Turkey. Located in the mentioned region with its fully mountainous and bumpy land conditions, Siverek District of Şanlıurfa Province has weather forecasting stations in which wind forecasts may be conducted regularly and accurately as well. Short-term wind speed forecasting in Southeastern Anatolia Region of Turkey is quite important in order to enable the constitution of a wind station in the region in the future. Enabling the wind speed forecasting in a region is essential in terms of producing the energy potential thereof. Electric power being attained from wind speed is called *wind power density*. Wind power density is changeable, depending on the type of the wind tribune to be used in the station, the shape of the wings thereof, as well as the size of the area being swept by the tribune wing. It is possible to have wind power density forecasted simply by having the wind data reviewed, or having the same density calculated over the same data. On the other hand, having a region’s future wind power density calculated by the future value of the wind speed data thereof forecasted is quite critical with regard to the wind station to be constituted in the mentioned region, as well as the overall development thereof. A number of methods are in use for prospective wind speed forecasts. The most common among these is the artificial neural networks method. Artificial neural networks method is generally limited with wind speed forecast of a region. Potential wind power to be attained from the same wind in the respective region is calculated thereafter. In this study, a little bit different from what is normally done in other studies, a multi-layered artificial neural network model has been developed in order not to forecast wind speed, but for direct forecasting of the wind power density of the region. Making use initially of time series method respectively, so as to review wind speed data attained from the region, and the wind power density, sought for, was thereafter calculated by making use of the mentioned speed data. Whereas conditions of the wind speed from different times were used as inputs into artificial neural networks by means of time series, their concurrent wind power densities were used as outputs wherefrom. A total of 8784 data were used in the system. 878 of the mentioned data were used in order to test the operation of the system. Another 878 were used to validate the operation of the system. The results attained from artificial neural networks method compared with wind power density results attained from the respective calculations, these two result sets were seen to be quite harmonious with and close to each other [1].

2. Arrangement for the Wind Speed Time Series

Time series are the series in which observation results were distributed in terms of time. They notify the values of a variable observing in varying times. In an ANN forecasting system, ANN's input variables are critical in the accurate forecasting of the outputs. Therefore, prior to having a forecasting model set up, input variables are to be ascertained and analysed properly. Wind speed time series are comprised of hourly average wind speed data, calculated in Siverek. Real data is comprised of data, calculated from 10m of height in intervals of 10 minutes. This is a study, in which a single variable is made use of. This variable is the wind speed. In systems with single variables, auto-correlation curve gains critical importance. In models with single variables, performance is in direct relation with auto-correlation function. Auto-correlation functions distinguish the dependencies in a data set. Besides, auto-correlation function analysis plays a critical role in the determination of the input variables of Artificial Neural Networks model. In figure 1, auto-correlation function of the wind speed time series is revealed. Qualitative analysis of the curve gives information about whether short-term or long-term forecasting is suitable for the region. In view of the qualitative analysis of the curve shown in Figure 1, it may be said that short-term forecasting model tends to display a better performance than that of long-term forecasting model. Besides, auto-correlation curve of the 48-hourly series is seen to have another period of twenty four hours after the initial peak value. This behaviour of the auto-correlation curve in Figure 1 characterizes the seasonality of the wind according to the time of the day [2-5].

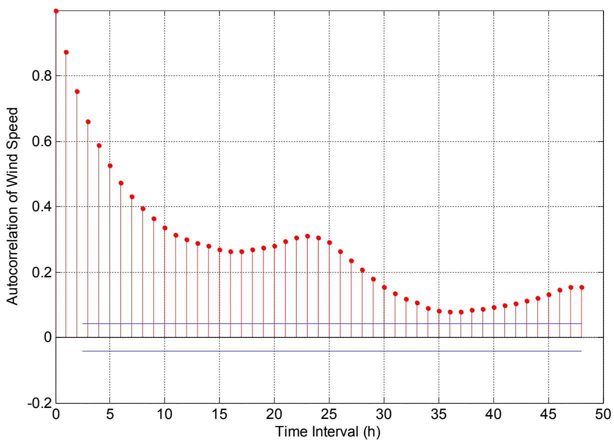


Fig 1 *Autocorrelation function of the wind speed time series*

3. Wind Power Density (WPD)

V90-1.8 MW Turbine power and models used in this analysis. The turbine projected to operate at a height of 80 m. Therefore, the wind speed time series is measured at 10 m, hence, the input and output patterns used to adjust and train the forecasting model is depends on this height. For this reason, the model accomplishes wind speed prediction at a reference height of 10 m. Before transforming the wind speed forecasting into WPD forecasting using the wind turbine manufacturer's power curve, it is necessary to convert the wind speed forecasting from the height of 10m to the turbine height of 80 m. Power curve graphics of the turbine is given in Fig.2. The potential WPD, P/A, available on a unit area oriented normal to the wind of speed *V* is given Eqs.1

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

Air density depends on the atmospheric conditions (temperature, pressure, humidity, etc.). Wind speed analysis are widely used data obtained from the observatory per hour. This data can be measured from 10 meters and 50 meters in height. For wind potential analysis, the most important feature for statistical accuracy, the data are derived from data collected over many years. Also Weibull statistical distribution should be carried out for analysis. The wind power plant to be established in an area, it will be dealing with wind potential of the surrounding area. Regional wind speed data to be analysed in detail, and all data must be calculated. In the calculations, average wind power density will be one of the most important factors. The average wind power intensity is calculated by the following formula (Eq.2).

$$\frac{P}{A} = \frac{1}{2N}\rho_{avg}\sum_{j=1}^{m} n_j u_j^3 = \frac{1}{2}\rho_{avg}\sum_{j=1}^{m} f_j u_j^3 \qquad (2)$$

The average air density is based on the monthly average of temperature and pressure recorded at each location [3].

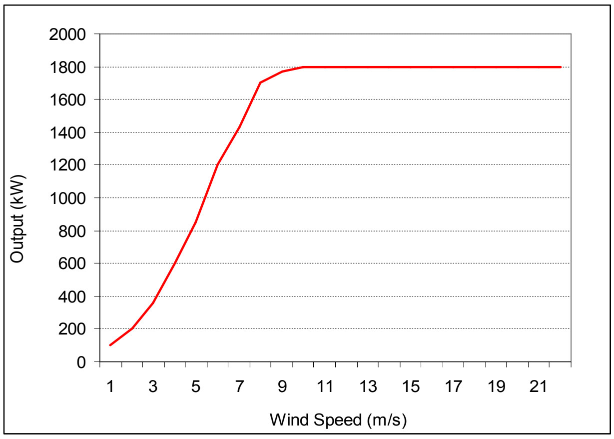


Fig 2 *Power Curve of Wind Turbine (V90)*

4. Development of the Forecasting Model

4.1. Artificial Neural Network

Artificial neural networks are being used nowadays in various fields. One of these fields is forecasting. There are artificial neural networks models functioning in forecast. The most popular among these models is the multi-layered artificial neural networks model which is trained with back-propagation learning algorithm. Back propagation algorithm is a very effective method for multi-layer feed-forward networks. Such a network model is designed as shown in Fig.4. [4]. It is given by Equation 3 in order to calculate each neuron of the input layer. Here, the output can be calculated for each neuron.

$$n_i = o_i \qquad (3)$$

Where n_i is the input of neuron i, and o_i is the output of neuron i. For each neuron in the output layer of the architected, the neuron inputs are given by Eqs.4.

$$n_k = \sum_{j=1}^{N_j} w_{kj} o_j \qquad k = 1,2,3,\ldots,N_k \qquad (4)$$

For the neurons in the hidden layer, the inputs and the outputs are given by in Eqs. (4) and (5), respectively.

$$o_k = \frac{1}{1+\exp[-(n_k+\theta_k)]} = f_k(n_k,\theta_k) \qquad (5)$$

The connection weights of the feed-forward network are reproduced from the input–output types in the training set by the implementation of generalized delta code. The algorithm is settled on minimization of the error function on each type p by the use of steepest drop method. Ep is defined as the error function. This function consists of the total of squared errors. Each error function is calculated by equation 6 in the formula.

$$E_P = \frac{1}{2}\sum_{k=1}^{N_k}\left(t_{pk} - o_{pk}\right)^2 \qquad (6)$$

Here, tpk is the target output for output neuron k, and also opk is the calculated output for output neuron k. The overall measure of the error for all the input–output types is given by Eqs.7.

$$E = \sum_{p=1}^{N_p} E_p \qquad (7)$$

Np is the number of input–output designs in the training set. When an input design p with the target output vector tp is given, the connection weights are updated by using the following Eqs. (8-11). Here are η: learning rate and α: momentum constant.

$$\Delta w_{kj} = \eta\delta_{pk} o_{pj} + \alpha\Delta w_{kj}(p-1) \qquad (8)$$

$$\delta_{pk} = \left(t_{pk} - o_{pk}\right) o_{pk}\left(1 - o_{pk}\right) \qquad (9)$$

$$\Delta w_{ji} = \eta\delta_{pk} o_{pj} + \alpha\Delta w_{ji}(p-1) \qquad (10)$$

$$\delta_{pj} = o_{pj}\left(1 - o_{pj}\right)\sum_{k=1}^{N_k}\delta_{pk} w_{kj} \qquad (11)$$

Artificial neural network applications, the number of neurons in layer and activation function (purelin, tansig, logsig) should be set for the simulator. ANN designing process involves five steps. Artificial neural network design consists of 5 stages. These are: gathering the data, normalizing the data, selecting the ANN architecture, the network training, and validation-testing. In this research, the data are normalized accordance with (12), also shown in [8], whose values ranged from 0.1 to 0.9.

$$\overline{X}(t)=\frac{0.1\cdot(X_{max}-X(t))-0.9\cdot(X_{min}-X(t))}{X_{max}-X_{min}} \quad (12)$$

Here, X and $\overline{X}$ indicate un-normalized and normalized wind speed time series respectively. The part denominator in the formula are the absolute minimum and the absolute maximum value of the wind speed time series [4-8].

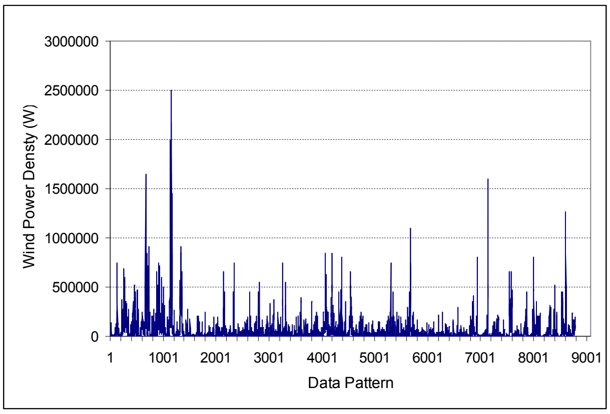


Fig 3 *Wind Power Density in Siverek*

B. Selecting and Training the ANN Architecture

In this study, results obtained in the analysis of wind speed data input and output patterns are given in Fig.4. The best number of neurons in the hidden layer that better adapted to the dataset is chosen among different neural architectures. The artificial neural network architecture with 20 hidden nodes is presented with the smallest margin of error on the validation set during the trainings. Hence, the architecture of the selected ANN is 5 -20 -4. The ANN model is improved by using Multilayer Perceptron neural network system with three layers: the input layer, hidden layer, and the output layer. In this analysis, Hyperbolic tangent sigmoid function is used for all of the layers [8-11].

Artificial Neural Networks, predicting output, is quite successful by using sample data. It has the ability to forecast nearest results with a statistical approach. In this analysis ANN is trained with the back propagation (Levenberg-Marquardt) algorithm training.

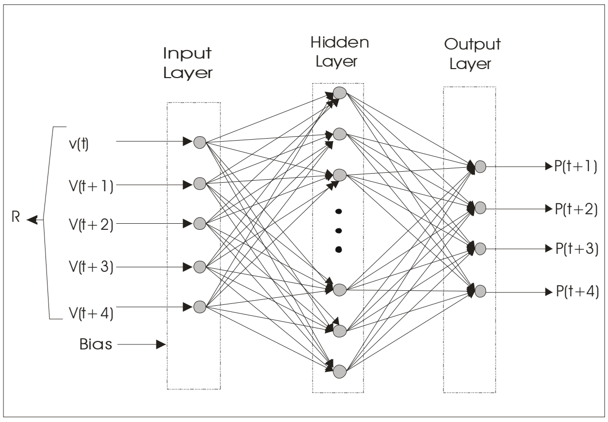


Fig 4 *Proposed ANN Architecture*

At the end of the study, real output is compared with trained output. Training of artificial neural network model consists of 5 inputs and 4 outputs. The number of data is 8784. 80% of these data are used for training. Artificial neural network is set up with random sets of weighting coefficients. In the analysis training, process is stopped when the error has become stable. Training and simulation results are given Fig.5 [8-11].

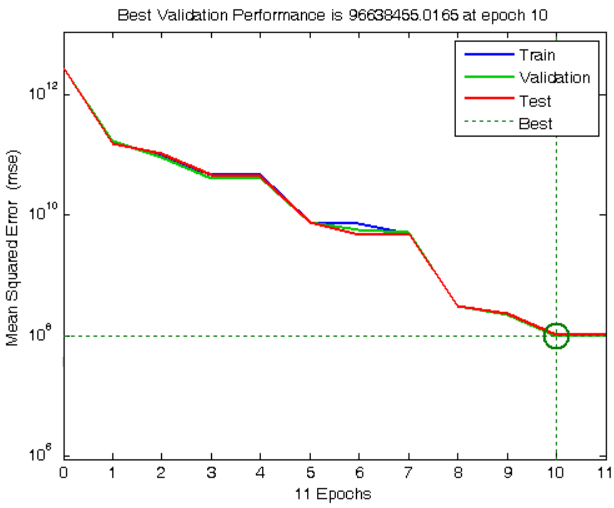


Fig 5 *Validation Performance of the ANN Model*

5. Results and Discussion

In the test of the first stage in this study, thus, the output generated by ANN is calculated from an unknown input data. In addition to this study, linear regression is performed between the target and neural network output. The results of the calculations, in the regression analysis, it is observed that they are quite compatible with the ANN. Regression analysis graph is given in Figure 6. 878 data are used in order to test ANN model. In order to compare the output of ANN model with the result sought for by means of the graphic to be attained by 878 data, the difference between the two curves may not be fully discerned, for the mentioned difference is to be quite little. Therefore, in order to have the difference between the two curves reviewed more easily, the graphic, attained from only the first 50 of 878 test data, is given in Figure 7. Even in Figure 7, the small difference between the two curves may hardly be discerned. In other words, forecasting model has reached its target [12, 13].

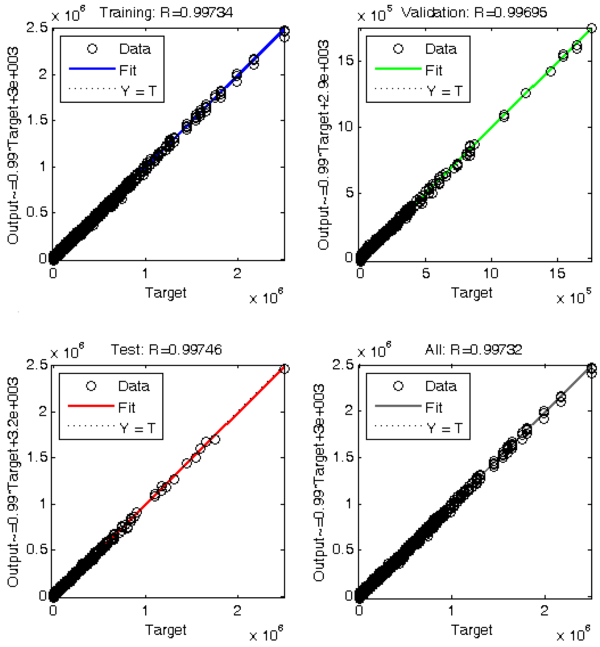


***Fig 6** Regressions of ANN model*

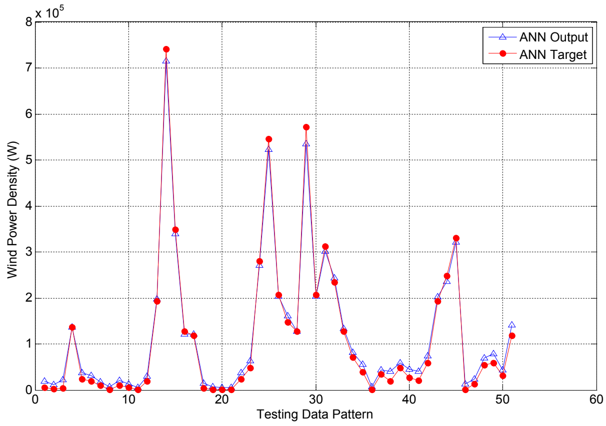


***Fig 7** Comparisons of the ANN Output and Target*

Figure 7 reveals only $P_{(t+1)}$ output. Whereas there are 3 more outputs other than $P_{(t+1)}$ output in ANN model used in the study. 3-D graphic, comprising all outputs, is being shown in Figures 8 (a) and 8 (b).

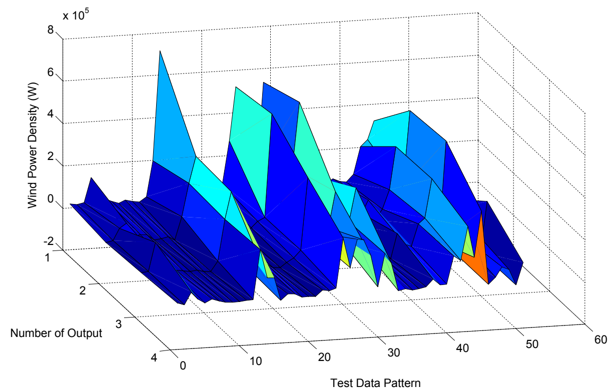
Success rate of the forecasting model, having been developed for the study, may also be seen from Table 1. Table 1 also includes RMSE values. This table may also be extended by such data as MAPE, MAE, etc. The smaller Mean-Square Error (MSE) value is the greater success of the system becomes. In Table 1, despite of the fact that MSE values are being seen quite great, the system is successful anyway. The reason is that power density values forecasted are quite big in numeric point of view. I.e., it is seen from Fig.8 that the highest power density value is 7.5×10^5 [14, 15].

TABLE 1 ANN RESULTS

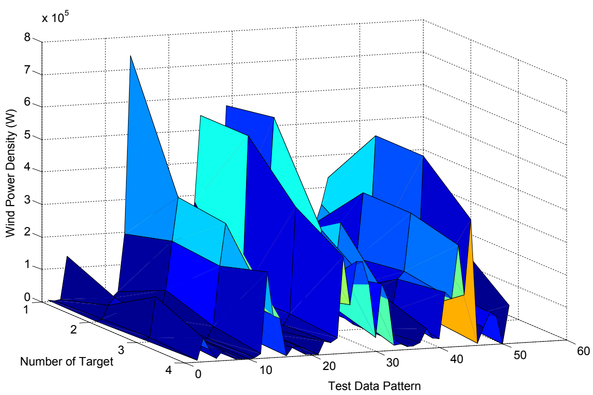
	Training	Validation	Testing
Samples	7028	878	878
MSE	98875394.6920	96638455.0164	101732109.342
RMSE	9943.61074	9830.486001	10086.233654
R	0. 99734	0. 99695	0. 99746

6. Conclusion

In this study, a wind power density forecasting as being among the initial stages of the constitution of a wind station in the future was conducted in Siverek District of Southern Eastern Anatolian Region of Turkey.



(a)



(b)

***Fig 8** Variation of the ANN testing data (a) Output, (b) Target*

Having a wind tribune chosen primarily, and having annual wind speed data for the year, 2009 was used by taking this chosen wind tribune as a basis for the electrical energy to be generated via a tribune, namely, the wind power density was calculated. Calculated wind power density values comprise the output of the data set in order to make a short-term prospective wind power density forecasting of the region. The data set which was developed was reviewed by means of time series analysis. Multi-layered ANN model, developed for forecasting, was trained via data set. Success of ANN model after the training was tested by means of test data. As a result of the test, outputs of ANN forecasting model and the targets (calculated power density values) were seen to be quite harmonious with, and close to each other [8,16, 17].

List of symbols and abbreviations

A. Symbols

n_i :Input of neuron i
o_i :Output of neuron i
*wkj:C*onnection weight between neuron j and neuron k
*Nj :*The number of neurons in the hidden layer
Nk :The number of neurons in the output layer
θk :Threshold of neuron k, and the activation function
fk :Activation function
Ep: Sum of squared errors
P : Input–output patterns
Tpk :Target output for output neuron k
opk :Calculated output for output neuron k
Np :The number of input–output patterns in the training set
tp :Target output vector
η :Learning rate
α :Momentum constant
i :Input layer neuron
j :Hidden layer neuron
θ :Threshold of each neuron
P :Electircal power (W)
R :Average density of the air (kg/m^3)
A :Area perpendicular to the wind speed vector (m^2)
V :Wind speed (m/s)
N :Total number of observations
ρ_{avg} :Average air density for the period,
n_j :Number of observations in the j_{th} class,
f_j :Frequency of occurrence of winds in the j_{th} class
u_j :Wind speed at the midpoint of the j_{th} class.
X :Wind speed time series non-normalized
$\overline{X}$:Wind speed time series normalized,
X_{max} :Maximum absolute value of the wind speed time series
X_{min} :Minimum absolute value of the wind speed time series

B. Abbreviations

ANN : Artificial Neural Network
MSE : Mean Square Error
RMSE : Root Mean Square Error
MAE : Mean Absolute Error
MAPE : Mean Absolute Percentage Error
rms : Root-Mean-Square
TSMS : Turkish State Meteorological Service

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