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# Application of artificial neural networks for short term wind speed forecasting in Mardin, Turkey

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***Abstract.***
*Artificial neural network models were used for short term wind speed forecasting in the Mardin area, located in the Southeast Anatolia region of Turkey. Using data that was obtained from the State Meteorological Service and that encompassed a ten year period, short term wind speed forecasting for the Mardin area was performed. A number of different ANN models were developed in this study. The model with 60 neurons is the most successful model for short term wind speed forecasting. The mean squared error and approximation values for training of this model were 0.378088 and 0.970490, respectively. The ANN models developed in the study have produced satisfactory results. The most successful among those models constitutes a model that can be used by the Mardin Electric Utility Control Centre.*

*Keywords: artificial neural network, back propagation, forecasting, wind speed*

## 1. Introduction

Accurate wind speed forecasting of wind farms is necessary because of the intermittent nature of wind. Also it can relieve or avoid the disadvantageous impact to the electric network. For developing the exact wind speed prediction, a lot of studies have been performed. The mathematical model of the human brain was obtained, inspired by its neurophysical structure; with the consideration that in order to model the whole behaviour of the brain the physical components had to be modelled correctly, and various artificial cell and network models were developed. Thus, a new scientific field called Artificial Neural Networks, which is widely different from the algorithmic calculation methods of the computers used today, was born. Because of their structure, their difference in processing data and their fields of application, Artificial Neural Networks are used by many scientists from various disciplines ranging from engineering to medical sciences as an efficient method. There are a lot of prediction methods for wind speed estimation. Weibull and Rayleigh distributions, weather ensemble predictions, Kernel density estimation techniques and ANFIS are some of the wind speed prediction methods. ANN, compared to traditional methods, offers very efficient and different solution methods in the solution of complicated real world problems. It is a mathematical method that presents contemporary applications, which are pretty hard to predict and calculate, in terms of absolute solutions (Nogay, 2007), (Nogay, 2011).

The ability to predict accurately the future is fundamental in planning and decision making in any activity; and the inherent nonlinear structure is useful to manage the complex relations in problems of diverse disciplines. Also, ANN has demonstrated high capacity in the modelling of time series for different applications.

The models for wind forecasting and power generation are valuable support tools to support the operators of the General Directorate of Electrical Power Resources Survey and Development Administration (EIE). The measurements of the wind speed are generally reported in the form of time series (minutes, hours, months, etc.), which are adequate to use ANN for prediction purposes. Although in Mardin, there is not any wind power installed and it is expected to be set up in the next decade, the EIE has not yet a mathematical model in order to predict accurately the short term wind velocities and an adequate electricity supply. Because of this, it is important to develop a model that can be used confidently for this purpose. Also the methodology showed in this work can be used to generate other models in different sites of Turkey and other countries (DeLurgio, 1998; Lei, 2009).

In this paper, diverse configurations of ANN that have different numbers of neurons were generated and compared through error measures, guaranteeing the performance and accuracy of the chosen models. A model for every month of the year was developed. Four different configurations of ANN of two layers (with different number of neurons) were proven determining their statistical error in order to obtain the best model for every month. Finally, the ANN model was evaluated for the forecasting using data not considered previously during their training stage. Because of the best configuration of the ANN consisting of sixty neurons was always the same (with exception of the weights) for the 12 months, just the results for the month of January are presented (Mohandes, 1998).

## 2. Artificial neural networks

One of the latest products of humanity efforts about research and imitation of nature is artificial neural network technology. Artificial Neural Networks are programs designed to simulate behaviour of the simple biological nervous system. An Artificial Neural Network is shaped by structuring a foreseen number of artificial neural cells in certain architecture in order to process data. This structure usually consists of a few layers, which are numbered. The first layer is the entry layer and is often not numbered. The reason for this layer to be excluded from enumeration is that the elements in the entry layer that don't have weighting multipliers and activation functions and thus cannot perform any other process but data entry.

The common name of the other intermediate layers, which can differ in number according to preference, is hidden layers. The exit layer is the last layer. The Artificial Neural Network model with backpropagation is the most widely used multi-layered prediction model. Such a network including three layers of perceptrons is shown in Figure 1.

By the algorithmic approach known as Levenberg-Marquardt back propagation algorithm, the error is decreased repeatedly. Some ANN models employ supervisory training while others are referred to as none-supervisory or self-organizing training. However, the vast majority of ANN models use supervisory training. The training phase may consume a lot of time. In the supervisory training, the actual output of ANN is compared with the desired output. The training set consists of presenting input and output data to the network. The network adjusts the weighting coefficients, which usually begin with a random set, so that the next iteration will produce a closer match between the desired and the actual output. The training method tries to minimize the current errors for all processing elements. This global error reduction is created over time by continuously modifying the weighting coefficients until the ANN reaches the user defined performance level. This level signifies that the network has achieved the desired statistical accuracy for a given sequence of inputs. When no further training is necessary, the weighting coefficients are frozen for the application. After a supervisory network performs well on the training data, then it is important to see what it can do with data it has not seen before. If a system does not give reasonable outputs for this test set, the training period is not over. Indeed, this testing is critical to insure that the network has not simply memorized a given set of data, but has learned the general patterns involved within an application (Barbounis, 2006); (Tomonobu, 2006); (Bose, 1996); (Kariniotakis, 1996).

## 3. Time series model

Time series are strings formed by sequencing the observation values of an event according to time. Time series analysis is a method that aims at modelling the stochastic process that yields the structure of an observed series of an event that is observed in certain intervals, and making future predictions via the observation values belonging to past intervals. Figure 2 shows the time series used in the models which consist of 744 data in total, corresponding to daily mean data for each of the 31 days of the last January. The training set with 670 data was used for the models' training and the prediction set consisting of 37 data as validation and 37 data as test were used to verify their accuracy during the prediction stage (Box, 1970), (Hagan, 1996).

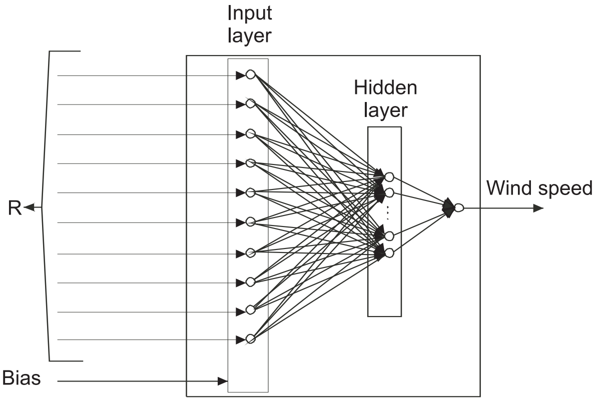


**Figure 1: Multilayer feed forward network**

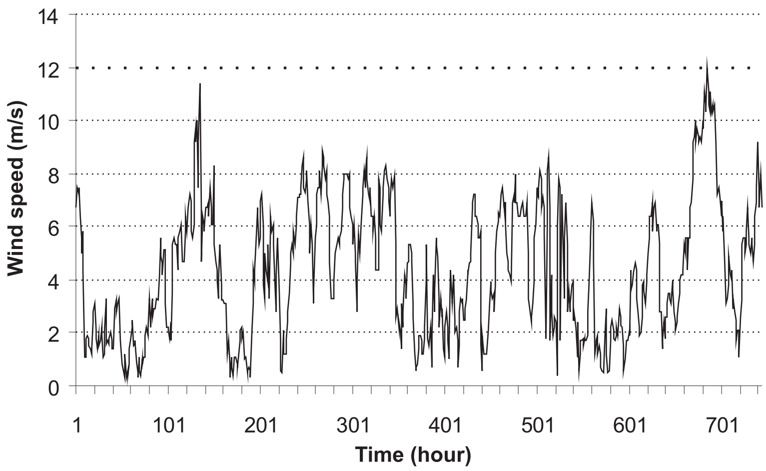


**Figure 2: January mean daily values in Mardin**

## 4. Performance of the models

The performance of a network is measured by the intended signal and error criterion. The output of the network is compared to the intended output to obtain the margin of error. An algorithm called backpropagation is used to calibrate the weights in order to reduce the margin of error. The network is trained by repeating this process a number of times. The goal of the training process is to reach the optimum solution in terms of performance measurements.

Some error analyses have to be performed in order to be able to evaluate the performance and prediction results of the model more correctly. The mean squared error (MSE) and mean absolute error (MAE) are among those error values.

If it is the actual observation for a time period t and Ft is the forecast for the same period, then the error is defned as:

$$e_t = y_t - F^t \quad (1)$$

The standard statistical error measures can be defned as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \quad (2)$$

and the mean absolute error as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \quad (3)$$

where n is the number of periods of time (Erasmo, 2009).

## 5. Proposed models

Choosing the number of layers and the number of processing elements per layer to a feed forward back propagation topology is the art of the ANN designer. There is no quantifiable, best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture to their problems.

The first rule states that if the complexity in the relationship between the input data and the desired output increases, then the number of the processing elements in the hidden layer should also increase. The second rule says that if the process being modelled is separable into multiple stages, then additional hidden layer(s) may be required. The result of the tests has shown that the optimal number of neurons in the hidden layer can be chosen as 80, and the activation function has been chosen as a hyperbolic tangent sigmoid function for all of the layers. ANN simulators have been trained through the 19, 13, 14, 14 epochs with 15, 30, 45, 60 neurons respectively. The training process has been stopped when the error has become stable. Variation of the total absolute error through the epochs is for Model 4 (with 60 the number of neurons) shown in Figure 3 (Kua-Ping, 2005).

In order to use the ANN simulator for any application, first the number of neurons in the layers, type of activation function (purelin, tansig, logsig), the number of patterns, and the training rate must be chosen. Normalization of data is a process of scaling the numbers in a data set to improve the accuracy of the subsequent numeric computations and is an important stage for training of the ANN. Normalization also helps in shaping the activation function. For this reason, [+1, -1] normalization function has been used.

It is commonly used for short forecast horizons in situations where the one-lag correlation is dominant over other lag correlations. In Table 1, number of neurons in the hidden layer is illustrated. The summery of the data set is illustrated in Table 2 (Viharos, 2002), (Ho, 1992).

**Table 1: Designated models**

| | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|
| Attribute | 1ann15 | 2ann30 | 3ann45 | 4ann60 |
| Input neuron number | 11 | 11 | 11 | 11 |
| Hidden layer neurons | 15 | 30 | 45 | 60 |
| Output neurons | 1 | 1 | 1 | 1 |

**Table 2: Dataset summary**

| | *Parameters* | *Min.* | *Max.* |
|---|---|---|---|
| *Input* | Soil temperature (5 cm) | -3.7 | 4.6 |
| | Soil temperature (10 cm) | -1.2 | 4.6 |
| | Soil temperature (50 cm) | 4.2 | 7.2 |
| | Relative humuditiy (7 H) | 8 | 88 |
| | Relative humuditiy (14 H) | 5 | 90 |
| | Relative humuditiy (21 H) | 7 | 94 |
| | Air pressure (B) | 882.8 | 907.9 |
| | Sunshine duration (H) | 0 | 1 |
| | Air temperature | -6.9 | 11 |
| | Hour | 0 | 23 |
| | Day | 1 | 31 |
| *Output* | Wind speed (m/s) | 0.3 | 12 |

## 6. Results and discussions

Mean squared error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Figure 3 shows the evolution of the minimum error for Model 4. In this Figure, it can be seen how the error decreases rapidly for training, testing and validation and then remains almost constant from the iteration 14.

Figures 4, 5, 6 and 7 compare the results obtained using the model 1, 2, 3, and 4 respectively with the real data. It can be seen how the model predicts in a reasonable way the randomness of the

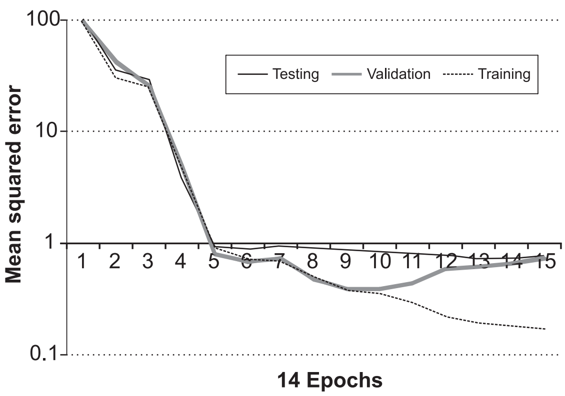


**Figure 3: Variation of the total absolute error through the Epochs for Model 4**

data. Comparison of the models for mean squared error and regression values can be observed clearly in Table 3. In this table, it can be seen that the best model is the last one, consisting of two layers with four input neurons and one output neuron and sixty neurons in the hidden layer. The other models predict the behaviour of the wind but with a gap at high velocities. As expected, the lowest statistical errors were obtained with the model 4. Once the best model was obtained to reproduce the real data, it is important to verify its accuracy utilizing the data outside the sample. This means using the last 74 data not considered during the training of the ANN, corresponding to the month of January 2008.

The most commonly used ANN prediction model is multi-layer perceptron, and the most commonly used learning algorithm is back propagation learning algorithm that is, Levenberg – Marquart learning algorithm. ANN models with the hidden layer model to compare with each other just to make this work as private, not for the purpose of the study and again for the production of artificial neural network models is unlikely to be necessary.

**Table 3: Mean squared error and regression values for the models**

| | MSE | Regression | Models |
|---|---|---|---|
| Testing | 0.8117791 | 0.931592 | 1ann15 |
| | 0.8514021 | 0.947441 | 2ann30 |
| | 0.5630057 | 0.959937 | 3ann45 |
| | 0.6660152 | 0.958667 | 4ann60 |
| Validation | 10.175.721 | 0.927951 | 1ann15 |
| | 0.6256824 | 0.931965 | 2ann30 |
| | 0.8426829 | 0,957923 | 3ann45 |
| | 0.3963228 | 0.953035 | 4ann60 |
| Training | 0.768223 | 0.937806 | 1ann15 |
| | 0.622887 | 0.951265 | 2ann30 |
| | 0.522270 | 0.958467 | 3ann45 |
| | 0.378088 | 0.970490 | 4ann60 |

## 7. Conclusions

In the test, an unknown input pattern has been presented to the ANN, and the output has been calculated. Linear regression between the ANN output and target is performed. In the particular case of Mardin, it was decided to begin the analysis with a model with neurons, according to the recommendations of diverse authors, nevertheless, the model with sixty neurons was the best for both the training and forecasting stages, which reflect the persistency of the wind in the site.

The selection of the suitable model using ANN implies a process of careful analysis that depends on the characteristics of the problem; for short term wind speed forecasting this technique responds in a satisfactory way to the necessities of precision and accuracy required to support the operators of the Electric Utility Control Centre.

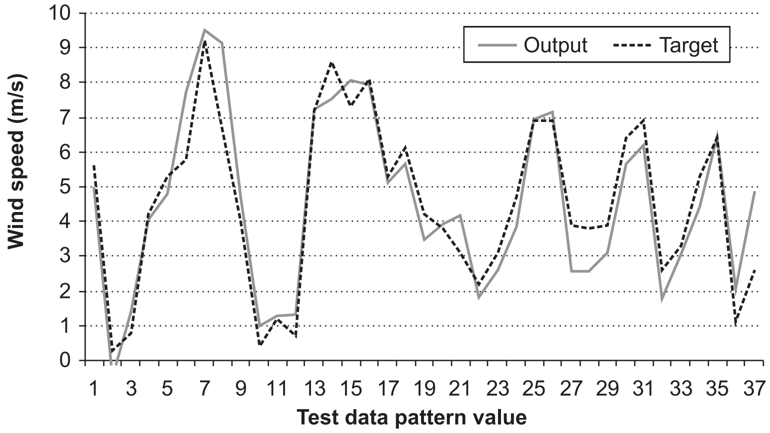


**Figure 4: Comparison of the real data with the results obtained using the model 1**

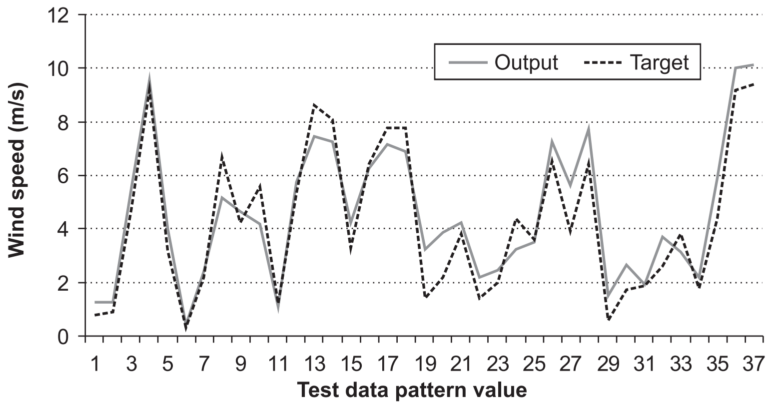


**Figure 5: Comparison of the real data with the results obtained using the model 2**

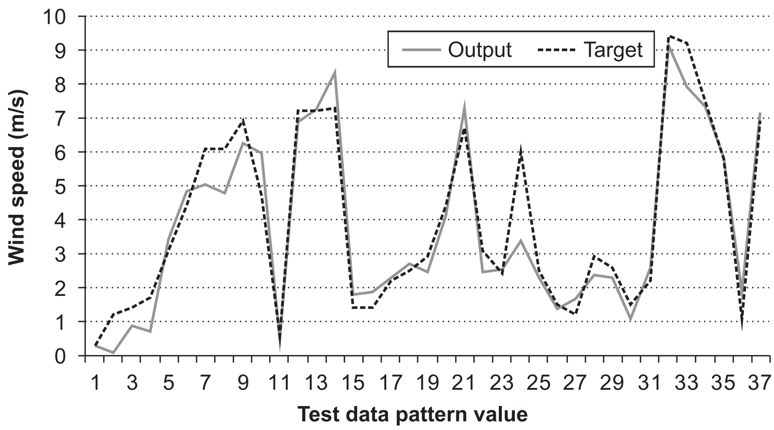


**Figure 6: Comparison of the real data with the results obtained using the model 3**

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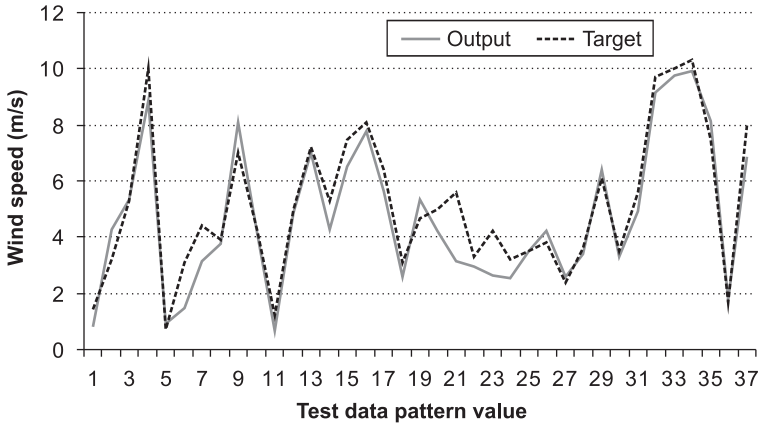


**Figure 7: Comparison of the real data with the results obtained using the model 4**


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