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Prediction of Wind Speed and Power in the Central Anatolian Region of Turkey by Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Ertuğrul ÇAM, Osman YILDIZ
Kırıkkale University, Faculty of Engineering,
71451, Campus, Kırıkkale-TURKEY
ertugrul_cam@yahoo.com

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Abstract

An adaptive neuro-fuzzy inference systems (ANFIS) model was used for predicting regional average wind speed and power values in the Central Anatolian region of Turkey. In model development, longitude, latitude and altitude of wind stations and wind speed measurement height were taken as input variables, while wind speed and power values were taken as output variables for 4 different surface roughness characteristics. After a successful learning and training process the proposed model produced reasonable mean errors ranging from 0.19% to 2.89% and negligible root mean square errors in training and testing wind speed and wind power data. Overall, the study results suggest that the ANFIS model can be used as an effective tool to estimate average wind speed and power values in the study area.

Key words: Wind speed, Wind power, Adaptive neuro-fuzzy inference systems (ANFIS), Central Anatolian region, Turkey.

Introduction

For centuries wind has been exploited for various purposes, such as for grinding grain at mills by the ancient Persians and Chinese (Stover, 1995). As a clean energy source wind is considered an alternative to fossil fuels, which actually accelerate global warming. The first scientific research to utilize wind for generating electricity was initiated by the Danish in the 1960s. The 1973 oil crisis forced many governments to realize the value of wind as a renewable and independent energy source (Hanağasıoğlu, 1999).

By 2001, Turkey had a share of installed wind power capacity of only 0.11% in Europe. The installed capacity of the country's wind energy had increased from 9 MW in 1998 to 19 MW by 2001, a small fraction of the total potential. The capacity is likely to grow rapidly as new projects have been submitted for an additional 600 MW energy production (TÜSİAD, 1999). The majority of wind energy projects are concentrated in the Aegean and Mediterranean regions. Turkey has the highest share in technical wind energy potential in Europe with 160 TWh per year, which is about twice as much as the current electricity consumption of the country (Kaygusuz and Sarı, 2003).

An effective utilization of wind energy entails having a detailed knowledge of the wind characteristics at a particular location. Reliable estimations of wind speed and power data are extremely important for a suitable design of wind turbines. Feasibility studies are required to figure out the economic aspects of such projects (www.strategis.ic.gc.ca, 2002). For these purposes, wind atlases are generally used to provide statistical data on regional mean wind speed and power densities. To make reliable decisions, the dynamic characteristics of the wind site should be evaluated using wind observations and statistical wind data (Ackermann and Soder, 2000).

Several studies have been performed to estimate the wind potential in different parts of the world using different methods such as Artificial Neural Networks (ANN) and Autoregressive Moving Average (ARMA) models (Troen and Petersen, 1989; Alexiadis, 1998; Sfetsos, 2002). The rapidly increasing population and industrialization have created an awareness of the renewable energy resources in Turkey. In this respect, several studies have been performed to estimate the wind potential of different parts of the country. Tolun et al. (1995) used 3-year data at 4 different locations on the island of Gökçeada to estimate the potential of wind energy in the northwestern part of Turkey. For each station, they performed an extensive analysis to find the monthly average wind speed and its distribution and they showed that the Weibull distribution fits well. Şen and Şahin (1998) proposed a standard regional dependence function (SRDF) based on the concepts of semivariogram and, especially, cumulative semivariogram. The authors implemented the proposed methodology for some wind velocity measurement stations in Turkey. They measured the reliability of their methodology through the cross validation procedure, showing that the procedure was valid with less than 5% error. Öztopal et al. (2000) presented wind velocity, topography and wind energy variation maps for Turkey with local and regional interpretations. Şen (2001) used the Point Cumulative Semi-Variogram (PCSV) concept to determine the wind energy potential of an airshed. The author applied the concept to wind speed and topographic height records at a set of irregularly scattered sites over Turkey. Çam et al. (2005) estimated average wind speed and wind power values in 7 geographic regions in Turkey using ANN. They utilized 50 years of wind data for training and testing their model and showed that the network successfully predicted the required output values for the test data, and mean error levels for regions differed between 3% and 6%.

Due to different characteristics of point locations a meaningful approximation mechanism for spatial distribution of wind data is required. Obviously, this needs a number of observation stations at different points, which is costly. Therefore, numerical methods are employed to obtain reliable wind data with minimum cost. In this study, an adaptive neuro-fuzzy inference systems (ANFIS) model was developed for predicting average wind speed and power values within the Central Anatolian region, where 7 wind speed measurement stations are located.

Study Area and Data Description

With a land surface area of 774,815 km^2, Turkey has advantages of comprehensive use of renewable energy sources such as wind, solar and hydro due mainly to its geographic location and typical Mediterranean climate predominant over most of its coastal areas. The country is surrounded by the Black Sea to the north, the Marmara and the Aegean seas to the west and the Mediterranean Sea to the south with a coastline of nearly 8500 km (www.egetek.org, 2002; Rahman, 2003). Local micro-climates can vary on a large scale from the regional averages because of the highly variable terrain and exposure to hot and cold winds (Rahman, 2003). As a matter of fact, wind occurrences depend on different cooling and heating phenomena within the lower atmosphere and over the Earth surface. In this respect, Turkey is considered to have a high wind energy potential.

The region under study is located at 30-39 °E longitudes and 37-40.5 °N latitudes with 7 wind measurement stations (Figure 1). The region is surrounded by the Northern Anatolian mountain ranges to the north, the Taurus Mountains to the south, and the Eastern Anatolian mountain ranges and high plateaus to the east. The region is generally characterized by highlands in the north and east and by lowlands in the west and south, with an average altitude of 1150 m. In order to show the wind profile of the region average wind speed values at 10 m measurement height at 7 stations across the region are shown in Table 1. The 10-year average wind speed data (1989-1998) at 5 different measurement heights (i.e. 10, 25, 50, 100 and 200 m) with 4 different roughness levels named as RL0, RL1, RL2 and RL3 were utilized in the model development and verification. The data were obtained from the wind atlas of Turkey prepared by the Electricity Works and Studies Department (EİE) and the State Meterology Service (EİE & DMİ Press, 2002).

ANFIS Model Application

As compared to conventional methods, fuzzy logic (FL) has 2 important advantages in data analysis. First, it reduces possible difficulties in the modeling and analysis of complex data. Second, it is appropriate for incorporating the qualitative aspects of human experience within its mapping rules, which provide a way of catching information. Artificial neural networks (ANNs) have also been used to identify

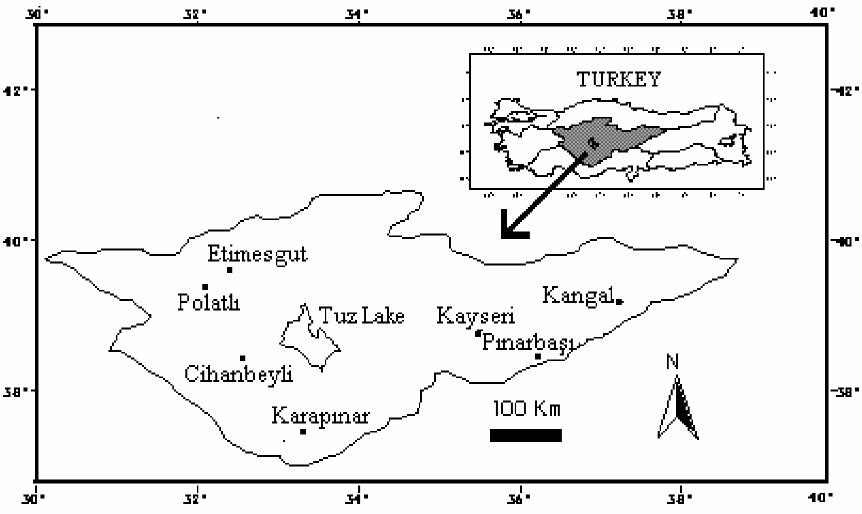

Figure 1. The study region with the wind measurement stations.

Table 1. Wind measurement stations used in the study.

Station Number	Station Name	Latitude (Deg.)	Longitude (Deg.)	Altitude (m)	Average Wind Speed at 10 m Measurement Height (m/s)			
					RL0	RL1	RL2	RL3
1	Cihanbeyli	38.39	32.56	968	5.5	3.9	3.4	2.7
2	Etimesgut	39.57	32.41	800	4	2.8	2.5	2
3	Kangal	39.14	37.23	1512	5.3	3.7	3.3	2.5
4	Karapınar	37.42	33.31	1004	5.7	4	3.5	2.8
5	Kayseri	38.73	35.48	1093	4.1	2.9	2.6	2
6	Pınarbaşı	38.43	36.23	1500	6.7	4.7	4.1	3.2
7	Polatlı	39.35	32.09	885	5.4	3.8	3.3	2.6

models of complex systems. For the same purpose, ANNs and FL are combined, referred to as ANFIS, to take advantage of the learning capabilities of ANNs and modeling superiority of FL. A detailed description of ANFIS model development is given in the following paragraphs.

The fuzzy model is based on a first-order Sugeno polynomial that is generally composed of r rules of the form:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$);

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$);

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, and p_i,q_i and r_i are the design parameters that are determined during the training process.

ANFIS has a 5 layer feed-forward neural network. Layer 1 has some adaptive nodes. Their outputs are composed of the fuzzy membership grade of the inputs, which are given by

$$O_i^1 = \mu_{A_i}(x), \quad i = 1, 2$$

$$O_i^1 = \mu_{B_{i-2}}(y), \quad i = 3, 4 \tag{1}$$

where $\mu_{A_i}(x)\, and\ \mu_{B_{i-2}}(y)$ are membership grade functions. The current study utilized the bell-shaped membership function defined as follows:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left(\frac{x - c_i}{a_i} \right)^2 \right\}^{b_i}} \tag{2}$$

where a_i, b_i, and c_i are the membership function parameters. The bell-shaped membership function was selected because it provided relatively better results. Fixed nodes are in the second layer. The number of nodes is equal to the number of fixed nodes, which are used as a multiplier. Their outputs, the firing strengths of the rules, are given by

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2 \tag{3}$$

and normalized in the third layer. The outputs of the third layer are represented by

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{4}$$

In the fourth layer, the nodes are adaptive nodes and they are generally first-order Sugeno type polynomial. The outputs of this layer can be defined by

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \quad i = 1, 2 \tag{5}$$

The last layer has a single fixed node and thus outputs of the layer or the model itself are written in the following form:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{6}$$

In the model, a_i, b_i, and c_i(i.e. premise parameters), andp_i, q$_i$, and r$_i$ (i.e. consequent parameters) are important for the learning algorithm in which each parameter is set to an appropriate value in order to match the output data to the training data. As soon as the values of the premise parameters are determined, the output of the model can be expressed as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{7}$$

Equation (7) can also be expressed in the following form by substituting Eq. (4) into Eq. (7):

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{8}$$

Finally, the model output can be rearranged using the fuzzy if-then rules as

$$f = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \tag{9}$$

In the current study, the following steps, in summary, are used in the development of the proposed model:

- the wind data were divided into 2 groups for training and testing;
- a fuzzy model was created using the ANFIS editor and data training was carried out;
- the test data were utilized for the validation of the model.

A hybrid ANFIS algorithm based on the Sugeno system improved by Jang (1993) was used for acquiring optimal output data in the study. The algorithm consists of the least-squares method and the back-propagation algorithm. The first method was used for optimizing the consequent parameters, while the second method in relation to fuzzy sets was employed to arrange the premise parameters (Übeyli and Güler, 2005).

In the model application, the longitude, latitude and altitude of stations, and wind speed measurement heights were taken as input variables, while wind speed and wind power values were taken as output variables for 4 different surface roughness characteristics. Eighty-one rules determined by the ANFIS model were applied for training and testing data. The membership functions of the model outputs were selected to be Gaussian (gaussmf). For the given surface roughness levels 4 wind speed ANFIS models and 4 wind power ANFIS models were employed.

Model Results and Discussion

For the evaluation of model performance root mean square error (RMSE), coefficient of determination (R^2) and mean percent error (MAPE) defined by Eqs. (10)-(12) were computed from the results produced by the proposed ANFIS model:

$$RMSE = \left((1/p) \sum_j |t_j - o_j|^2 \right)^{1/2} \tag{10}$$

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \qquad (11)$$

$$MAPE = \frac{1}{p} \sum_j \left(\frac{t_j - o_j}{t_j} * 100 \right) \qquad (12)$$

where t is the target value, o is the output value, and p is the number of data items.

Referring to Table 2, the mean percent errors for training wind speed data are very small, ranging from 0.19% to 0.35%. They are relatively higher for testing wind speed data but still remain in an acceptable range from 0.92% to 2.72%. From the same table, the mean percent errors for training and testing wind power data are below 3%. The RMSE values for both training and testing are negligible and the coefficients of determination are very close to unity.

Figure 2, which compares the actual and the ANFIS model outputs of wind speed for roughness level 2, was selected to illustrate the model performance. It is observed from the figure that the regression lines for both training and testing are close to straight lines. This indicates that the ANFIS model is suitable for predicting regional wind speed and wind power values in the region. As an example Figure 3 shows average wind speed and wind power predictions of the ANFIS model at the stations for each roughness level separately.

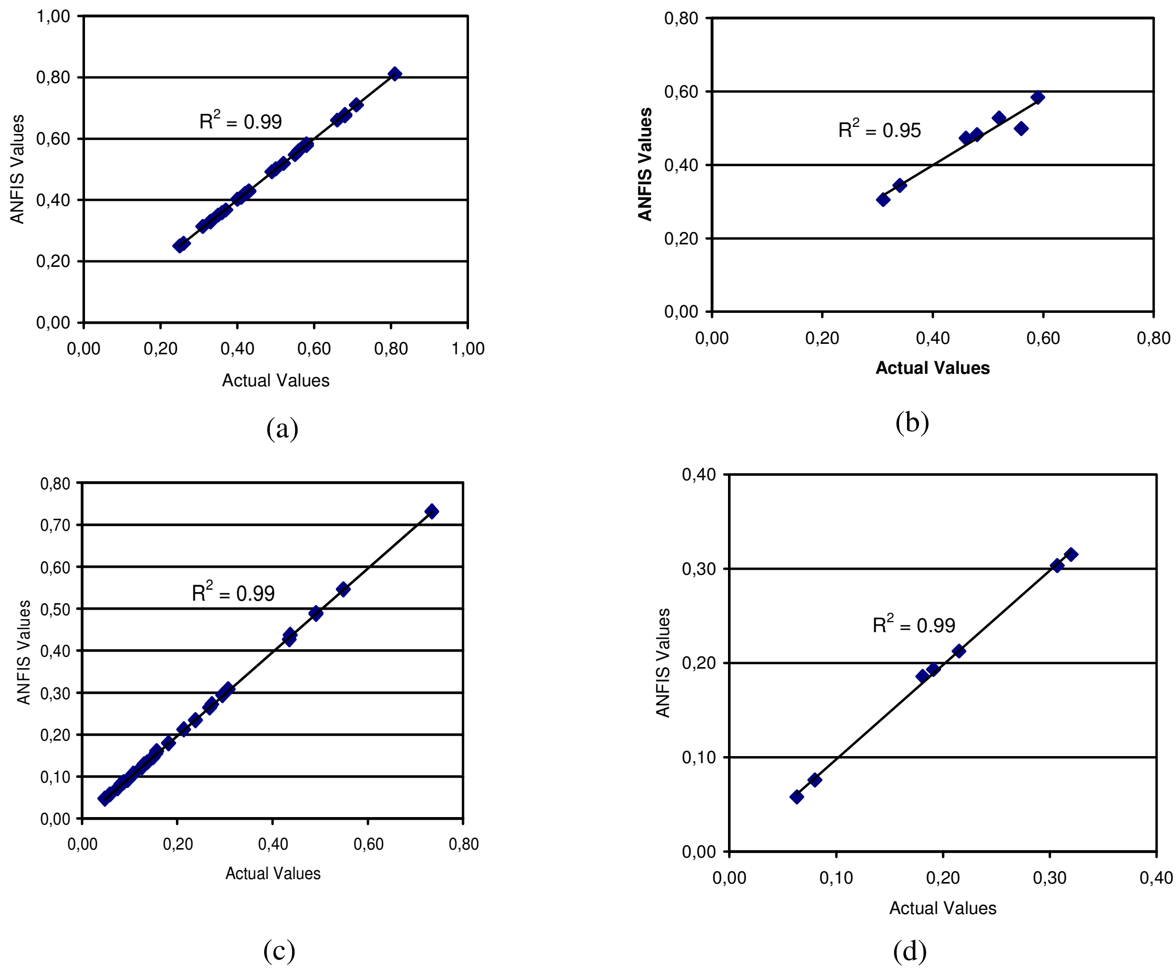

Figure 2. Comparison of the actual and the ANFIS model outputs: a) wind speed training b) wind speed test c) wind power training and d) wind power test for RL2.

Table 2. Statistical data used for the evaluation of ANFIS model performance.

	Surface Roughness Level (RL)	Mean % Error Training	Mean % Error Test	RMSE Training	RMSE Test	R^2 Training	R^2 Test
Wind Speed	RL 0	0.188000	0.923900	0.001405	0.006145	0.999993	0.999857
	RL 1	0.262500	1.011600	0.001504	0.004514	0.999989	0.999889
	RL 2	0.352200	2.760800	0.001954	0.024016	0.999985	0.997454
	RL 3	0.306500	1.884000	0.001601	0.010897	0.999987	0.999263
Wind Power	RL 0	0.538600	1.550700	0.001618	0.004623	0.999974	0.999720
	RL 1	0.627900	2.645200	0.001606	0.004144	0.999970	0.999630
	RL 2	0.696900	2.889600	0.001743	0.003940	0.999964	0.999663
	RL 3	1.039800	2.774500	0.001805	0.006343	0.999957	0.999008

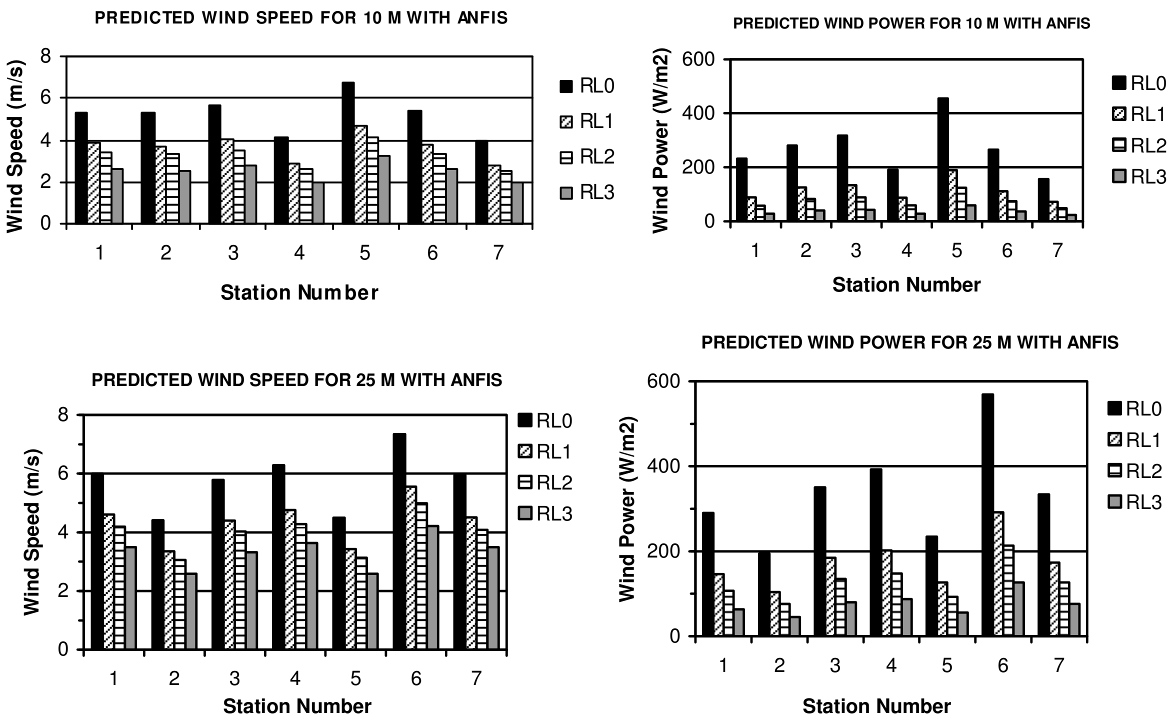

Figure 3. Average wind speed and wind power outputs of the ANFIS model at the stations for each roughness level.

Conclusions

An ANFIS model was developed for use in predicting wind speed and wind power values in the Central Anatolian region of Turkey. The evaluation of the model results indicated that the proposed model is successful in reproducing the actual data in the study region. It was shown that in both training and testing the wind data the model produced reliable outputs with relatively small errors. Therefore, the proposed model can be employed as an effective tool for the prediction of wind speed and wind power values at different locations and heights, providing useful guidelines in the selection of possible wind farm sites.

Symbols

RL	Roughness level.
x, y	Inputs.
A_i, B_i	Fuzzy sets.
f_i	Output within the fuzzy region specified by the fuzzy rule.
p_i,q_i, r_i	Design parameters that are determined during the training process (consequent parameters).
μ_A, (x) and $\mu_{B_{i-2}}(y)$	Membership grade functions.
a_i, b_i, c_i	Bell-shaped membership function parameters (premise parameters).

References

A vision for Turkish energy issues. www.egetek.org; 2002.

Ackermann, T. and Soder, L., “Wind Energy Technology and Current Status: A Review”. Renewable and Sustainable Energy Reviews, 4, 315–374, 2000.

Alexiadis, M.C., Dokopoulos, P.S., Sahsamauoglou, H.S. and Manaousaridis, I.M., “Short-Term Forecasting of Wind Speed and Related Electrical Power”, Solar Energy, 63, 61-68, 1998.

Çam, E., Arcaklioğlu, E., Çavuşoğlu, A. and Akbiyik, B., ”A Classification Mechanism for Determining Average Wind Speed and Power in Several Regions of Turkey Using Artificial Neural Networks”, Renewable Energy 30, 227-239, 2005.

Hanağasıoğlu, M., “Wind Energy in Turkey”, Renewable Energy, 16, 822–827, 1999.

Jang, J.S.R, “ANFIS: Adaptive-network-based Fuzzy Inference System”, IEEE Transactions on Systems, Man and Cybernetics, 23, 665-685, 1993.

Kaygusuz, K. and Sarı, A., “Renewable Energy Potential and Utilization in Turkey”, Energy Conversion and Management, 44, 459–478, 2003.

Öztopal, A, Şahin, A.D, Akgün, N. and Şen, Z., “On the Regional Wind Energy Potential of Turkey”, Energy, 25, 189–200, 2000.

Rahman, S., “Green Power: What Is It and Where Can We Find It?”, IEEE Power & Energy Magazine, 1, 30-37, 2003.

Sfetsos, A., “A Novel Approach for the Forecasting of Mean Hourly Wind Speed Time Series”, Renewable Energy, 27, 163–174, 2002.

Stover, D., “The Forecast for Wind Power”, Popular Science, 247, 65-72, 1995.

Şen, Z. and Şahin, A.D., “Regional Wind Energy Evaluation in Some Parts of Turkey”, Journal of Wind Engineering and Industrial Aerodynamics, 74-76, 345–353, 1998.

Şen, Z., “Areal Assessment of Wind Speed and Topography with Applications in Turkey”, Renewable Energy, 24, 113–129, 2001.

Tolun, S., Menteş, S., Aslan, Z. and Yükselen, M.A., “The Wind Energy Potential of Gökçeada in the Northern Aegean Sea”, Renewable Energy, 6, 679–685, 1995.

Troen, I. and Petersen, E.L., European Wind Atlas, Riso National Laboratory, 1989.

Türkiye Rüzgar Atlası, (Wind Atlas of Turkey), EİE & DMİ, Vol. 218, EİE Press, Ankara, Turkey, 2002.

TÜSİAD, An Overview of Turkey’s Energy Strategy on the Eve of the 21^{st} Century, TÜSİAD Publication, İstanbul, 1999.

Übeyli, E.D. and Güler, İ., “Adaptive Neuro-Fuzzy Inference Systems for Analysis of Internal Carotid Arterial Doppler Signals”, Computers in Biology and Medicine, 35, 687-702, 2005.

www.strategis.ic.gc.ca, Statistical Data, 2002.

www.mathworks.com