WIND SPEED AND ENERGY POTENTIAL ANALYSES

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Abstract

This paper provides a case study on application of wavelet techniques to analyze wind speed and energy (renewable and environmental friendly energy). Solar and wind are main sources of energy that allows farmers to have the potential for transferring kinetic energy captured by the wind mill for pumping water, drying crops, heating systems of green houses, rural electrification's or cooking. Larger wind turbines (over 1 MW) can pump enough water for small–scale irrigation. This study tried to initiate data gathering process for wavelet analyses, different scale effects and their role on wind speed and direction variations. The wind data gathering system is mounted at latitudes: 37º 50″ N; longitude 30º 33″ E and height: 1200 m above mean sea level at a hill near Süleyman Demirel University campus. 10 minutes average values of two levels wind speed and direction (10m and 30m above ground level) have been recorded by a data logger between July 2001 and February 2002. Wind speed values changed between the range of 0 m/s and 54 m/s. Annual mean speed value is 4.5 m/s at 10 m ground level. Prevalent wind

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direction is south west. Artificial Neural Network analyses are also applied to predict wind speed values in winter and spring.

Key Words: Wind energy, wavelet, ANN.

1. Introduction

Wind has been a very important source of energy for utility of electric around the world. Wind energy technology has increasingly developed in last 15 years. In recent years research institutions, national energy organization and private sector have been focused on the new and renewable energy sources in Turkey and Northern Cyprus, ((Tolun et al;1995), (Altunç et al;2002), (Topçu et al ; 2000), (Aslan ; 2000), (Tokgozlu et. al ;1995). Prospects of wind power plants in Libya and a case study have been discussed by El-Osta and Kalifa (2002). From the 200 foot tall windmills in Holland to the wind mills of West Texas, agricultural producers have long relied on renewable energy for their livelihoods. Whether the task was pumping water, dying crops or cooking, farmers have always relied on three thinks: The sun, the wind and the rain. Water pumping may be the most common use of renewable energy in agriculture. Three basic types of water pumps use renewable energy: Mechanical wind mill pumps, Photovoltaic-powered pumps; Wind turbine-powered pumps and Solar powered watt pump. While solar power is a plentiful resource in New Mexico, other alternative power sources are also available. Fischer (1999), discusses a low – cost hybrid system that uses wind power when the sun refuses to shine, the Southwest Wind power Air 303.

Design requirements for medium-sized wind turbines for remote and hybrid power systems have been studied at the University of Massachusetts, (Rogers et al., 2001). The collection and analyses of 15 months of continuously recorded field data from a small remote wind-diesel power system at a coastal farm site are reported by Bowen et. al., (2002). The paper focuses on the available wind data and the performance of the 10kW Bergery wind turbine. Examination of the Spanish electrical sector shows that electric generation utilities currently use a mixture of technologies comprising both conventional energy and renewable energy resources among which the growing use of wind energy should be high lighted (Garcia- Cebrian, 2002). Around the world energy supply is begin liberalized, with electricity and gas exported across national boundaries. New and renewable energy market can protect the environment, (Fells, 2000).

Wind mills have been successful at pumping water by mechanical energy from wells for livestock and homesteads thought the US for years. It is a simple process to have a wind pump switch to pumping water when the battery bank for electrical energy is full. The wind turbine drives the pump at varying speeds, pumping more in high winds than in low winds. Instead of storing generated power in batteries, the system stores any surplus energy during high winds as water in storage tank. When the wind speed more than 4.5m/s it can provide same or more water than solar panels, diesel generators or old-fashioned, mechanical wind mills.

In addition to classical time series, Artificial Neural Network (ANN) is used in forecasting of Hydrological and meteorological series successfully in recent years. ANN, which has ability of learning from data set and working with lack of data, can model nonlinear relationships besides linear relationships successfully. In contrast to statistical approaches it does not need any assumptions such as normality, linearity and stationary on data set, can model a lot of different formed structures and approximate any form of functions in certain accuracy so it is named as general function approximator (Cybenko 1989; Hornik vd.1989; Hornik 1991). Hence ANN becomes an alternative method used in time series analysis. A wide compilation about studies which use ANN in prediction of time series is made by Zhang et al. (1998) and Kaynar et. al. (2001).

This paper presents an overview on wavelet and ANN analyses of wind speed and wind direction in Isparta to implement wind energy and previous analysis.

2. Description of Data and Study Area

2.1. Study Area

Study area, (Isparta; latitude: 37° 50' N, longitude: 30° 33' E, height, 1200 m. above msl.) is in the south western Anatolia. This area is called as the Area of Lakes. This region is under the effect of central and south western Anatolia climatological conditions. It is under the combined effects of Mediterranean and terrestrial climate conditions with hot and dry summers and cold and wet winters. Annually rain fall rate is 600 mm. in Isparta. Complex topography causes orographic and convective rain formation in the study area. Mobile wind velocity measuring system was mounted at the: Süleyman Demirel University Campus. Latitude, Longitude and Elevation, of wind observatory have been given in the Table 2.1.

Table 2.1. Geographic Specifications of Study Area; Süleyman Demirel University Campus.

Station (10m,30m)	Station No	Lantitude (°N)	Longitude (°E)	Height (m)
SDU Campus	0000	37.50	30.33	1200

2.2. Data

Analysis of wind speed, direction, total energy, maximum energy density and power values at two levels (10m and 30m) based on NRG measuring system between 2001 and 2002 have been presented. Hourly averages of wind speed and velocity variations have been observed by using NRG wind velocity-measuring system since July 2001. Ten minutes average values of wind velocity (speed and direction variations) are automatically recorded. Hourly, daily, monthly and seasonal variations of wind velocity characteristics of study area are analyzed by using the Micro-Site packet program.

3. Methodology

3.1. Wind Velocity and Power

The presentation of wind data makes use of the Weibull Distribution Function as a tool to represents the frequency distribution of wind speed. The cumulative distribution function is obtained by integrating the Weibull Distribution and expressed mathematically as follows Tolun et al., (1995):

$$F(u) = \exp[-(u/A)^{k}] \quad (1)$$

Where, F(u) gives the probability of the wind speed exceeding the value u. A(m/s) is the scale parameter, k is the shape parameter, and u is the wind speed. The wind power density over a time interval is given as:

$$E \cong (\rho/2)\,(u_{av})^3 \qquad (2)$$

In this equation, air density (ρ) may be taken as constant (ρ = 1.225 kg/m^3) with an error of less than a few percent, except for mountainous areas and interior stations Tolun et all., (1995). Where, u_{av} is the average wind speed over a time interval T.

At high wind speeds, the wind profile over flat and reasonably homogeneous terrain is well modeled using the logarithmic law. Wind speed data are extrapolated by using the following power law, WMO (1981) and Troen and Peterson (1989):

$$V_r / V_a = (Z_r / Z_a)^p \qquad (3)$$

Where V_r and V_a are the extrapolated and observed wind speeds, Z_a is the anemometer height, Z_r is the extrapolated height and p is the power law components. p is a function of atmospheric stability and , called as wind shear exponent, (Table 2.4).

3.2. Micro-site Packet Program

Micro-site provides you with a range of powerful tools to organize, maintain, and display wind energy data. Much more than just an ordinary spreadsheet program, it is designed specifically to organize wind data according to industry standards, (Micro-Site, 1999). This manual covers full range of tasks given as below:

- Setting up and defining a wind assessment site,
- Maintaining data continuity, even when sensors malfunction,
- Combining sensors into groups for comparative analysis,
- Creating standard summary reports for presenting site performance,
- Estimating turbine power output from a site.

3.3. Multi Layer Perceptron Neural Network

Artificial neural networks are data processing systems devised via imitating brain activity and have performance characteristics like biological neural networks. ANN has a lot of important capabilities such as learning from data, generalization, working with unlimited number of variable. An ANN is typically composed of several layers of many computing elements called nodes. Each node receives an input signal from other nodes or external inputs and then after processing the signals locally through a transfer function, it outputs a transformed signal to other nodes or final result (Zhang et al, 1998).

In MLP, first layer is input layer where external information about problem wanted to be solved is received. The last layer is output layer that data manipulated in network is obtained. The layer exists between input and output layers is called hidden layer. There can be more than one hidden layer in MLP networks. Figure 3.1 shows the architecture of typical MLP network.

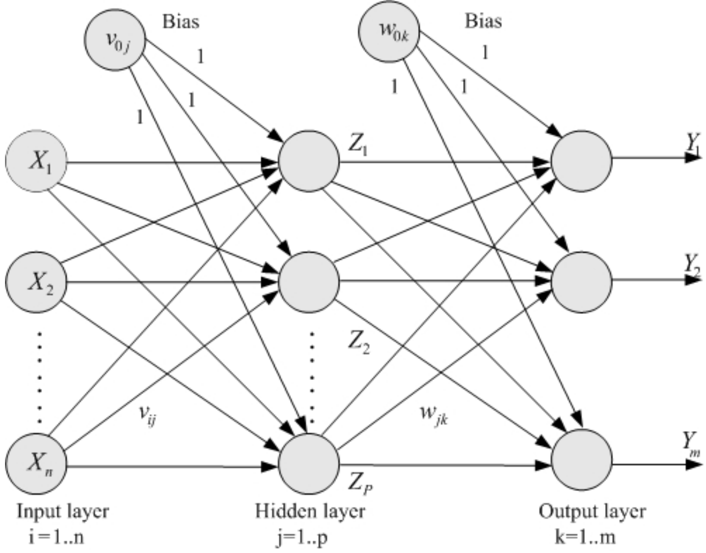

Figure 3.1- Structure of multi layer perceptron neural network

Technically, an ANN's basic job is learning the structure of sample data set, to generalize it. For doing this, network is made to be able to generalize by training with samples of the case (Öztemel 2003, p.30). During the training process, input patterns or examples are presented to the input layer of a network. The activation values of the input nodes are weighted and accumulated at each node in the hidden layer. The weighted sum is transferred by an appropriate transfer function to produce the node's activation value. The output of hidden layer (j) can be calculated as follows:

$$z_j = f\left(\nu_{oj} + \sum_{i=1}^{N} v_{ij}\, x_i\right) \quad (4)$$

$$y_k = f\left(w_{ok} + \sum_{j=1}^{P} w_{jk}\, z_j\right) \quad (5)$$

$$E = (1/2) \sum_{k=1}^{m} (y_k - f_k)^2 \quad (6)$$

The aim of training is to minimize the differences between the ANN output values and the known target values for all training patterns. The most popular algorithm for training is the well-known back propagation which is basically a gradient steepest descent method with a constant step size (Zhang et al., 1999). This algorithm is named as back propagation, because it tries to reduce errors from output to input backwardly. In supervised learning algorithms, a sample data set that consist of input and output values is given to network for training. The given target output values are named as supervisor or teacher in ANN literature. In supervised learning algorithms, weights are adjusted by minimizing error function given in Equation 5 in training level.

4. Analyses

4.1. Statistical Analyses of Wind Velocity and Energy

The wind velocity measurements at Süleyman Demirel University the observatory were analyzed by using Micro-Site Packet Program.

The highest and lowest wind speed values are observed in February and July in respectively. Wind velocity and energy potential characteristic of Süleyman Demirel University observatory. The highest energy density and power values have been recorded in March. The extrapolated wind speed values based on the power law (Equation 3) Weibull parameters are changing in the range of 4.9 and 6.5, (Table 4.4). A total installed capacity of 2 MW is expected to be feasible, to generate energy with the contribution of 2% of the total electric energy. Mean wind speed values have been changed between the range of 0m/s and 54m/s. Annual mean speed value is 4.5m/s at 10 m above mean ground level. Prevalent wind direction is from south west. 5 water pumps are available at 1000m heights at the study area. Total power demand is 400kW for pumping systems. The storage tank will be mounted at 1090m heights above from the pumps. It is expected to supply water for drinking, irrigation of farmlands and other purposes in and near vicinity of the university campus where 32 000 habitants are available. Their drinking water demand is 0,54m^3/day, and for other purposes including farmlands, they consume 0,04m^3/s water. Mean water consumption is 1m^3 /day. Its value has a maximum in summer. The results of paper will be evaluated for this pilot project. This study has a key role on protection of forests, soil and environmental hazardous.

4.2. Wavelet Analyses of Wind Velocity

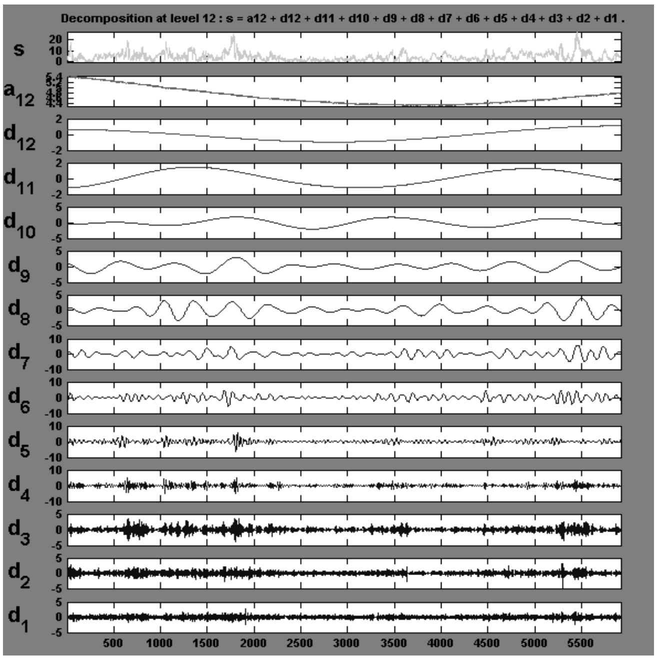

Figure 4.1(a)- Wavelet 1D (Dmeyer, Level 12)- SDU Wind speed variations at 10m above mgl, 10 minutes averages, DJF (Winter, 2001-2002)

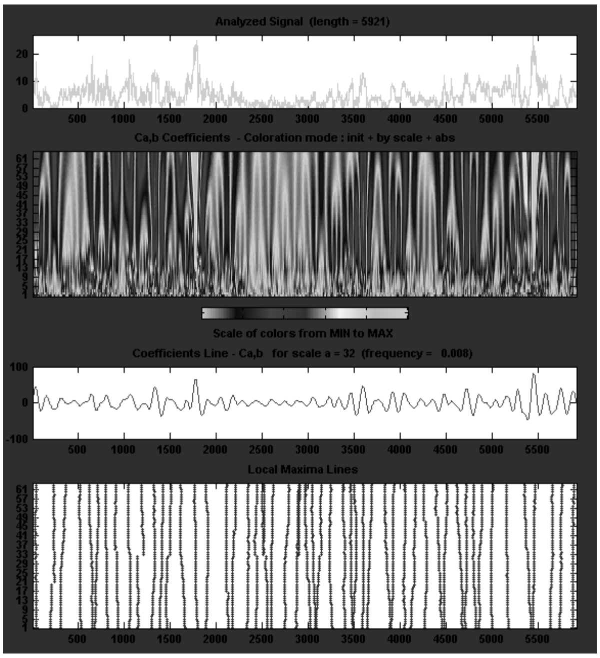

Figure 4.1(b)- Continuous wavelet 1D Mexh, Sampling period: 1, DJF (winter, 2001-2002) , Wind Speed (m/s) at 10m above mgl

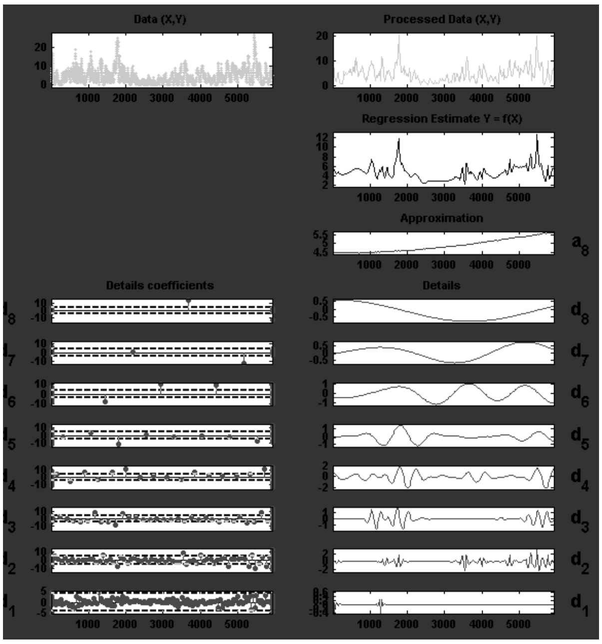

Figure 4.1(c)- Regression estimation, 1D- Fix Design, Dmeyer, Level 8. (DJF, wind speed, 10m)

Figure 4.1 (a) represents temporal variations of wind speed variations at 12 different levels (details) in winter in Isparta. Wind speed values are lower than January and March in February.

In general, large scale fluctuations play an important role on wind speed variations in January and March, (Figure 4.1(b)). MATLAB Wavelet tool helps to build up a linear regression estimation of data. Figure 4.1(c) is an example of this sub tool. Wind speed estimations show an increasing trend of wind speed values at 10m above mean ground level in Isparta SDU-wind observatory in winter.

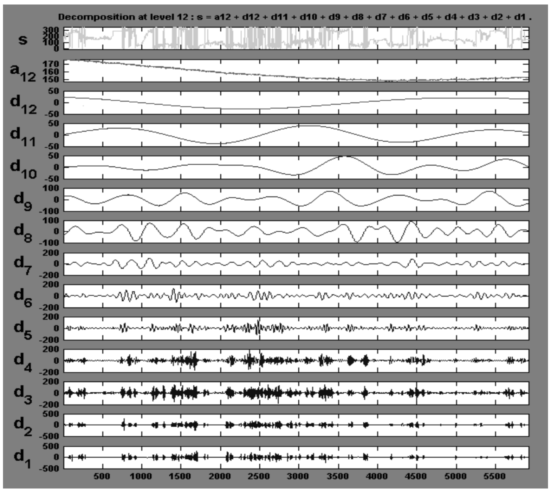

Figure 4.2(a) - Analysis of wind direction (degrees), SDU (winter,

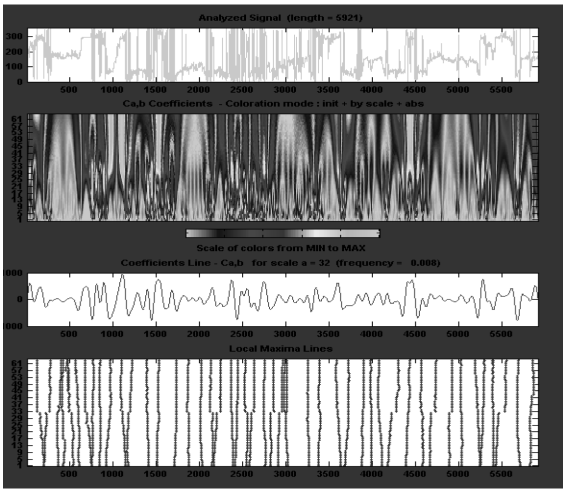

Figure 4.2(b) - Continuous Wavelet 1D, Wind direction (DJF, winter 2001-2002

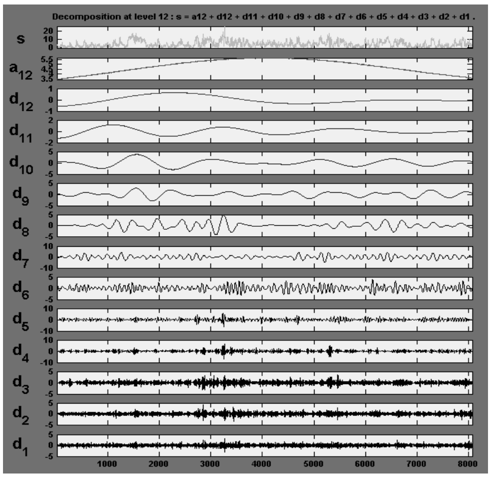

Figure 4.3(a)- Wavelet 1D analyses of Wind Speed Values (m/s) in Isparta, Dmeyer, Level 12, (SDU

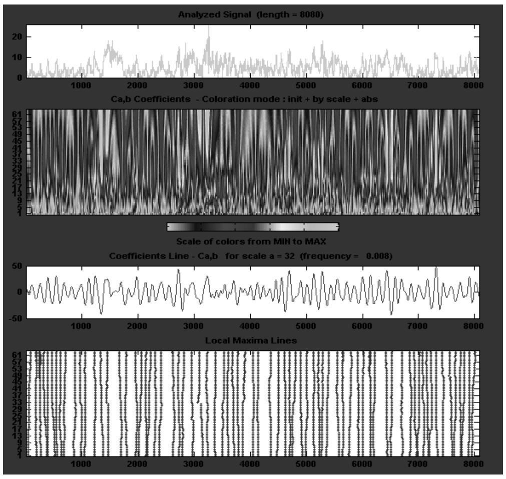

Figure 4.3(b) - Continuous Wavelet Analysis of Wind Speed Values (m/s), (1-D, Mexh., Level 1), SDÜ, Spring - MA, 2002)

During all winter term wind direction show a great variability, (Figure 4.2(a)). Other details of wind direction at different levels (details) are given at the same figure. In the last part of period effects of small scale fluctuations on wind direction are less than large scale effects. Figure 4.2(b) show the role of small and large scale evens on wind direction variation. The frequency of the effects of large scale evens on wind direction approximately changes between 15 days (300min) and one month (600min).

In spring small scale effects are more effective on wind speed variations, (Figure 4.3. (a)). Frequency of large scale effects on wind speed variations in spring is more than winter term and their effects have been observed combined with small scale effects for all period, (Figure 4.3(b)).

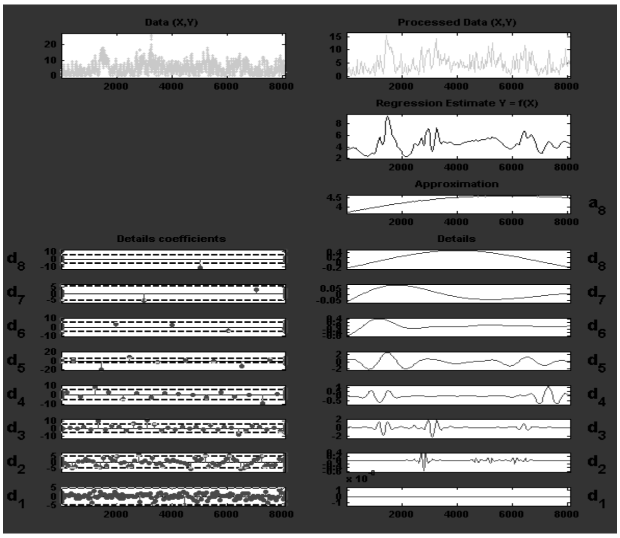

Figure 4.3(c) - Regression Estimation of Wind Speed Values, (m/s, 10m amgl), (1D-Fixed Design, MA, Spring, 2002)

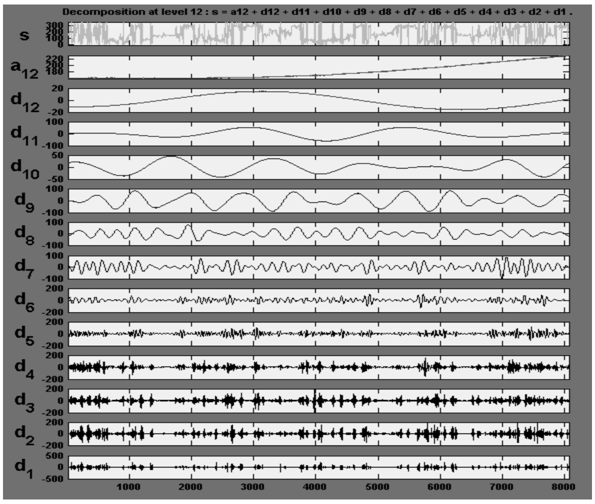

Figure 4.4(a)- Wind Direction Analysis at SDU, Wavelet 1D, Dmeyer, Level 12, 10m amgl, Spring (MA, 2002)

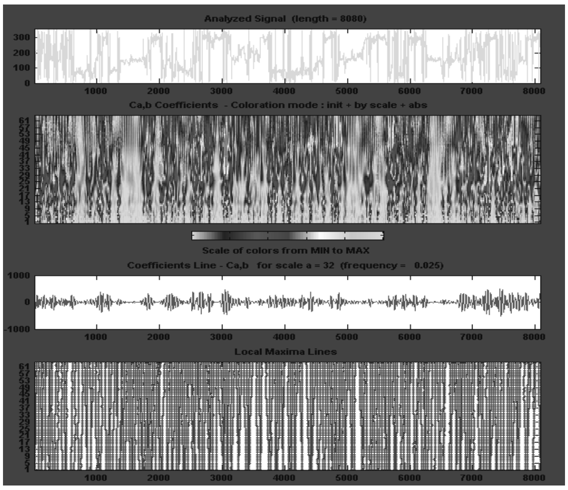

Figure 4.4(b) - Continuous Wavelet 1D Analysis of Wind Direction (degrees), Mexh, Level 1, Spring

Figures 4.4 (a) and (b) show Wavelet 1D and Continuous Wavelet 1D analyses of wind direction variations in Isparta. In the second parts of March and April, large scale evens play an important role on wind direction variations.

4.3. ANN Analyses of Wind Speed

Data used in this study is hourly and ten minutes averages and their time series that show wind speed between 21.02.2002 and 25.04.2002. The last ten days observation of data set (the last 240 data for hourly, the last 1440 data for ten minutes time series) used to test predictions. %80 of the rest of data is used training and %20 for validation in MLP models. Data set is normalized to range [-1, 1] to prevent saturation of hidden nodes before feeding into the neural network and ANFIS models. MATLAB 'premnmx' function is used to normalize data.

In this study, software is developed using Matlab program for creating artificial neural network. All created MLP models within the study have three layers architecture. By means of changing the number of neurons in input layer from 1 to 12 and the number of neurons used in hidden layer from 1 to 10, 120 different MLP neural network models are obtained. Linear transfer function is used in the output layer node, whereas tangent-sigmoid transfer function is preferred in the hidden layer nodes. Levenberg-Marquardt back propagation algorithm is used to train all MLP models. Network training parameters, epoch number and goal error rate, which stop training, are chosen 1000 and 0.001 respectively. Besides, to achieve a good accuracy and avoid over fitting, validation vectors are used to stop training early, if the network performance on the validation vectors fails to improve. Feeding network with training data, training process is implemented and the artificial neural network model having minimum squared error (MSE) for testing data is chosen from 120 models. MLP model having 7 input neurons and 5 hidden neurons for hourly time series and 9 input neurons and 2 hidden neurons for ten minutes time series are described as the most appropriate models, (Figures 4.5 – 4.8).

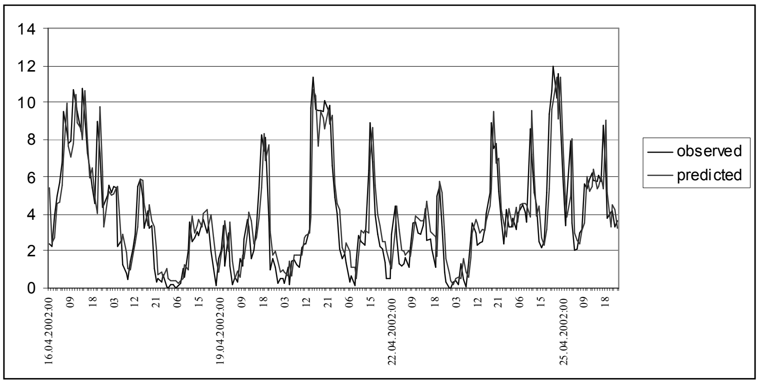

Figure 4.5 - Observed and predicted wind speed (m/s) values for hourly time series test data

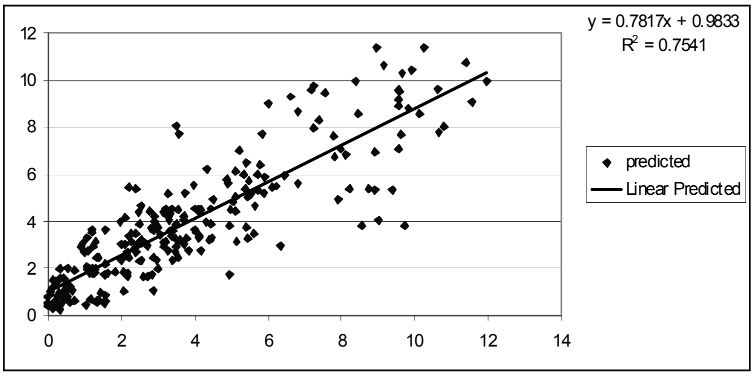

Figure 4.6 - Regression of predicted-observed wind speed (m/s) values for hourly time series test data

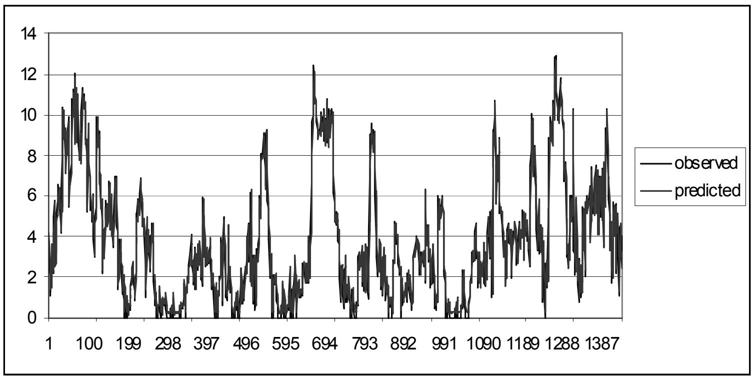

Figure 4.7- Observed and predicted wind speed (m/s) values for ten minutes time series test data

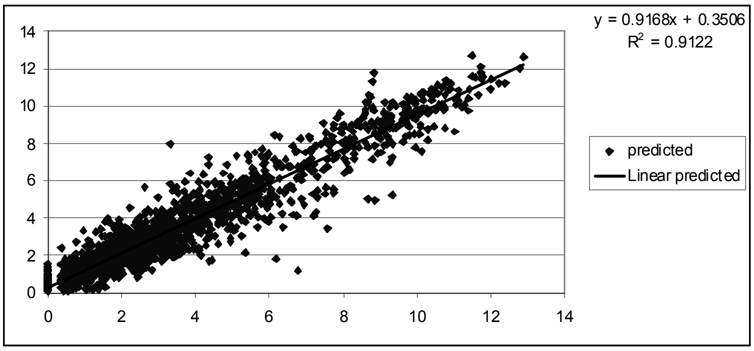

Figure 4.8 - Regression of predicted-observed wind speed (m/s) values for ten minutes time

5. Results and Conclusions

Wavelet analyses of wind speed and wind direction variations in SDU (Isparta) spring and winter 2001 - 2002 explain the role of small and large scale evens. Positive NAO (North Atlantic Oscillations) accompany by increasing trend of wind speed values, (Giden et al, 2010, Tokgozlu and Aslan, 2009). Because of the limited data sources, it is not certain that, whether if there is a significant relation between wind direction and NAO variations. ANN analysis shows a strong relation between observed and estimated wind speed variations. This study is related with some national energy plans on wind energy converting systems (WECSs). Expected energy output was performed for different sizes. It is recommended one large size wind turbine would facilitate the construction of water pumping system in SDU, Isparta.

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