TIME SERIES PREDICTION OF WIND SPEED

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Abstract
In this paper a time series prediction of wind speed with artificial neural networks is presented. For this purpose the mean hourly wind speed records for the area of Kourris dam, located at the south of Cyprus, are used. Wind data for ten consecutive years (1991-2000) are available for this area. The network was trained to predict the mean monthly hourly wind speed of a year (e.g. 1994) by using the values of wind speed for the same month, same hour for the three previous years (e.g. 1991-1993), consecutively. The data for the wind speed up to the year 1999 have been used for the training of the network whereas those for the years 1997-1999 (input) and 2000 (output) were used for the validation of the network. It should be noted that the data for the year 2000 were completely unknown to the network. The wind speed for the validation data set was predicted with a correlation coefficient of 0.82 which is satisfactory for wind speed which is very unstable. Therefore the method proved to be very promising both for predicting missing values and for forecasting.

1. Introduction
Wind speed prediction is very important for the long term estimation of the performance of wind turbines. The availability of wind speed data is also very important in the case where suitable locations are selected for the placement of wind turbines. Often there are missing data in wind speed databases due to various reasons. It is therefore very important to be able to predict wind speed (forecasting) and to fill missing data values from databases.

The increased use of energy and the depletion of the fossil fuel reserves combined with the increase of the environmental pollution have encouraged the search for clean and pollution-free sources of energy. One of these is wind energy. This is a clean, inexhaustible and a “free” source of energy that has served the mankind for many centuries by propelling ships, driving wind turbines to grind grains and for pumping water. Despite the high cost of wind power this may become a major source of energy in the years to come. This is so because the severe pollution of the planet originating from the burning of the fossil fuels and the nuclear energy risks cannot continue forever.

The present world capacity of wind parks is about 15,000 MW (Sayigh, 2001). Despite the success of Cyprus in solar water heating no other renewable energy applications are investigated on the island. The wind potential of Cyprus is limited but there are certain locations of the island where small wind parks can be installed. One of this is the area near the Kourris dam. In this area the very first wind park will be located by the Electricity Authority of Cyprus. The park will be relatively small and will be constructed on a pilot basis, mainly to evaluate the potential of Cyprus in this form of renewable energy.

The predicted variations of meteorological parameters such as wind speed, relative humidity, water vapour pressure, solar radiation, air temperature, etc. are needed in the renewable industry for design, performance analysis, and running cost estimation of these systems.

For proper and efficient utilisation of wind power, it is important to know the statistical characteristics, persistence, availability, diurnal variation, and prediction of wind speed. The wind characteristics are needed for site selection, performance prediction and planning of wind turbines. Of these characteristics, the prediction of mean monthly and daily wind speed is very important.

Mohamed *et al*. (1998) have used an artificial neural network (ANN) to predict the wind speed one hour ahead with very satisfactory results. More and Deo (2003) used neural networks to forecast daily, weekly and monthly wind speed at two coastal locations in India. They found that the ANN technique is more accurate than the traditional statistical time series analysis. In another work a multilayered artificial neural network has been used to predict the mean monthly wind speed in a south east region of Cyprus (Kalogirou *et al.*, 1999). Data for the period 1986-1996 were used to train the neural network, whereas data for the year 1997 were used for validation. Both learning and prediction were performed with adequate accuracy. Two network architectures of the similar type have been tried. One with eleven neurons in the input layer and one with five. The second one proved to be more accurate in predicting the mean wind speed. The maximum percentage difference for the validation set was confined to less than 1.8% on an annual basis, which is considered adequate.

Neural networks have also been used before by the authors for the prediction of precipitation (Kalogirou *et al.*, 1998). For the interested reader a review of applications of neural networks in renewable energy systems is given in (Kalogirou, 2001).

In the present work ANNs are used to predict the mean monthly hourly wind speed of an area near Kourris dam using similar values of wind speed of the previous years. The mean monthly hourly wind speed is a representative figure of the wind potential of a site. Based on this figure one can decide whether a particular site is has a good wind potential for wind energy applications.

2. Data Collection

The region is located at the southern part of Cyprus as shown in Fig. 1. A meteorological station is in operation in the region for a number of years. The observed data of wind speed in this station cover ten consecutive years (1991-2000). All data are recorded and analysed by the Meteorological Services Department of the Ministry of Agriculture, Natural Resources and Environment. A sample of these data is shown in Table 1.

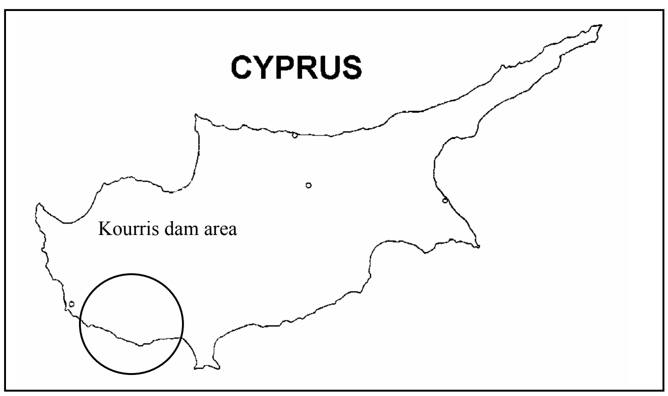

Figure 1 Map of Cyprus showing the area where the site under investigation is located.

3. Methodology

The available data were manipulated in order to be used for the neural network training and testing. The database used was divided into two sets: A training data set having all wind speed records for each hour of a month for the years from 1991 to 1999 and a verification data set for all the hours of each month for the year 2000. The training data set has been used for the training and testing of the artificial neural network, while the verification data set has been used for validation of the network. The network was trained to predict the mean monthly hourly wind speed of a year (e.g. 1994) by using the values of wind speed, for the same month and same hour, for the three previous years (e.g. 1991-1993), then the data for the years 1992-1994 were used as input and those for the year 1995 as output and so on. This procedure is used consecutively for the preparation of the required databases. The data for the years 1997-1999 (input) and 2000 (output) were used for the validation of the network. In this way the two databases were constructed with the training one to comprise 1728 patterns and the testing database to comprise 288 patterns representing all 24 hourly values for each month for the year 2000. It should be noted that the data for the year 2000 were completely unknown to the network.

Table 1 Sample of weather data available

Month	Hour	Years									
		1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
1	1	4.7	4.4	4.9	4.7	4.6	4.6	4.8	4.4	5.0	5.4
1	2	4.6	4.5	5.0	4.6	5.0	5.0	4.7	4.3	4.8	5.0
1	3	4.8	4.9	4.9	4.7	5.2	4.9	5.0	4.4	4.6	5.0
1	4	4.8	4.8	5.1	4.9	5.2	4.6	5.2	4.3	4.9	4.8
1	5	4.9	4.6	4.8	5.0	5.1	4.6	5.0	4.6	4.8	4.7
1	6	4.9	4.9	5.0	4.7	5.0	4.7	5.0	4.6	5.2	4.8
1	7	4.9	4.7	5.0	4.7	5.0	4.6	4.7	4.8	5.0	4.9
1	8	4.7	4.8	5.4	4.8	4.6	4.4	4.9	4.8	4.7	4.7
1	9	3.7	3.9	4.3	3.6	3.6	3.4	4.4	4.5	3.7	3.7
1	10	3.0	3.1	2.9	3.6	2.6	2.8	2.8	3.3	2.9	3.5
1	11	3.1	3.3	3.3	3.8	3.2	3.4	3.1	3.4	3.4	4.0
1	12	3.6	3.5	3.6	4.0	4.0	3.8	3.7	4.0	3.9	4.8
1	13	3.9	4.0	4.1	3.9	4.2	4.0	4.0	4.6	4.1	4.8
1	14	4.1	4.0	4.2	3.9	4.4	4.2	4.1	4.7	4.2	5.1
1	15	3.9	4.2	4.3	4.0	4.4	4.2	4.4	4.8	4.1	4.8
1	16	3.5	4.0	4.0	3.4	4.1	3.6	4.1	4.1	3.5	4.4
1	17	2.9	3.0	3.2	2.7	3.6	2.8	3.4	3.7	2.8	3.6
1	18	2.5	2.5	2.6	2.7	2.9	3.1	2.6	2.6	2.3	3.5
1	19	3.2	3.1	3.0	3.1	3.0	3.6	3.2	2.5	2.8	3.8
1	20	3.8	3.6	4.0	3.1	3.3	3.9	3.8	2.7	3.6	4.0
1	21	4.4	3.7	4.3	3.7	4.2	4.0	4.2	3.2	3.9	4.6
1	22	4.7	4.1	4.6	3.9	4.5	3.9	4.2	3.7	4.3	4.6
1	23	4.9	4.2	4.7	3.9	4.7	4.3	4.4	3.9	4.8	4.8
1	24	4.8	4.3	5.1	4.1	5.0	4.4	4.7	4.3	4.9	5.2
2	1	4.6	4.4	4.5	4.3	5.5	4.7	4.6	4.1	5.1	4.9
2	2	4.9	4.3	4.4	4.5	5.6	5.1	4.9	3.9	5.2	5.0
2	3	…	…	…	…	…	…	…	…	…	…

Different network structures, sizes and learning parameters have been tried. The architecture that was ultimately selected is shown in Fig. 2. It is composed of five slabs, three of which are hidden. It is a feedforward architecture, which has different activation functions in each slab, as shown in Fig. 2. Different activation functions were applied to the hidden layer slabs in order to be able to detect different features in a pattern processed through the network. This type of architecture has been used successfully in a number of engineering applications of neural networks (Kalogirou, 2000, 2001). The activation function used for each slab is also shown in this figure.

The five neuron input layer comprise the input data. These are the month, hour and mean monthly hourly wind speed for three years. The output of the network is a single neuron representing the mean monthly hourly wind speed for the next year. The learning procedure in the neural network was implemented by using the backpropagation algorithm. Also, the learning rate was set to a constant value of 0.1 and the momentum factor to 0.1. The weights were initialised to a value of 0.3. From a total of 1728 patterns, 80 percent were used for training the network (1383 patterns) and the remaining 345 patterns (20%) were randomly selected to be used as test patterns. An increased number of hidden neurons (22 in each slab) were used in order to enable the network to learn the wind patterns correctly.

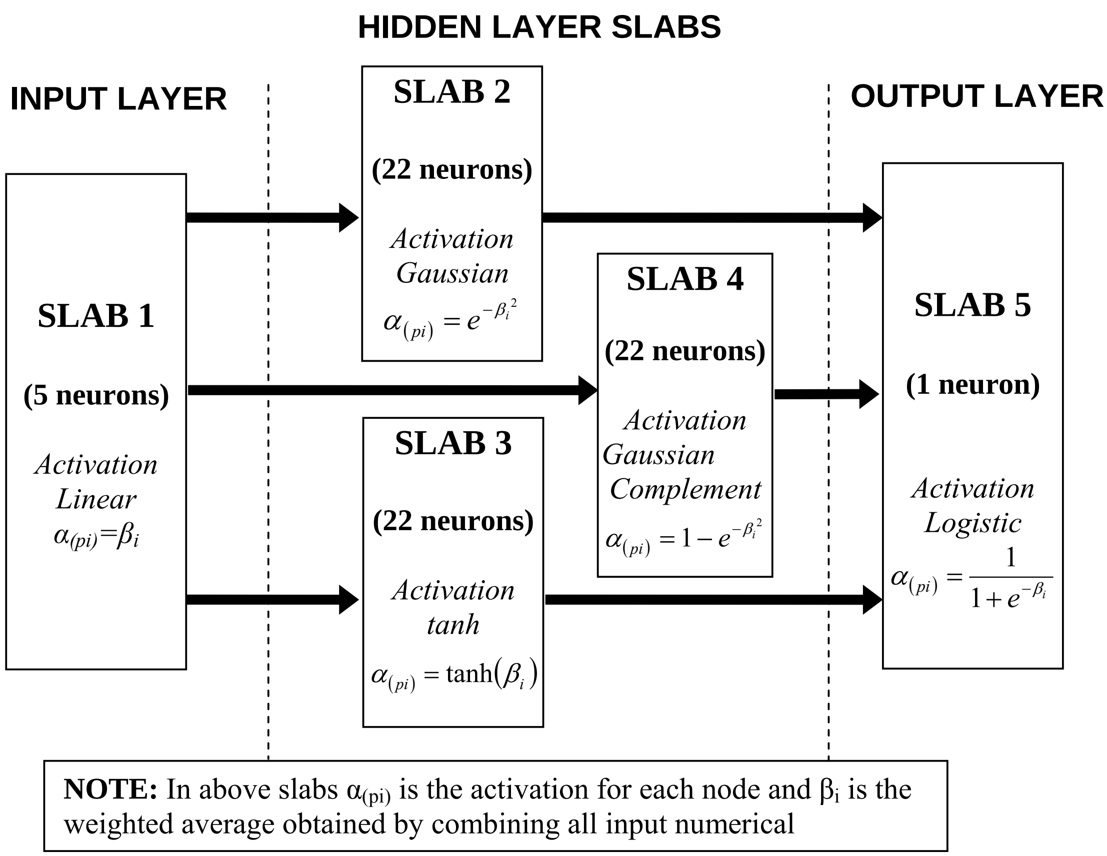

Figure 2 The selected neural network architecture.

4. Results and Discussion

The training patterns were learned with an adequate accuracy. The correlation coefficient obtained from the learning phase is equal to 0.8517. For an independent assessment of the network the results of the verification year 2000 are presented. The correlation coefficient obtained this time is 0.8165, which is considered satisfactory. The results for the year 2000 are shown in Figs. 3 and 4; the first for the months January to June and the second for the months July to December. The maximum error of the wind speed has been found to be 1.25 m/s. The observed and estimated wind speed patterns appear to display a quite satisfactory match. In particular, the seasonality of wind speed is well simulated. The actual average annual wind speed is equal to 4.097 m/s whereas the network estimated value is equal to 4.092 m/s.

It should be noted that the training of the neural network required about 10 minutes on a Pentium II, 400MHz computer. The subsequent predictions for the validation cases required less than a second on the same machine; so a quick estimation time is obtained without sacrificing accuracy.

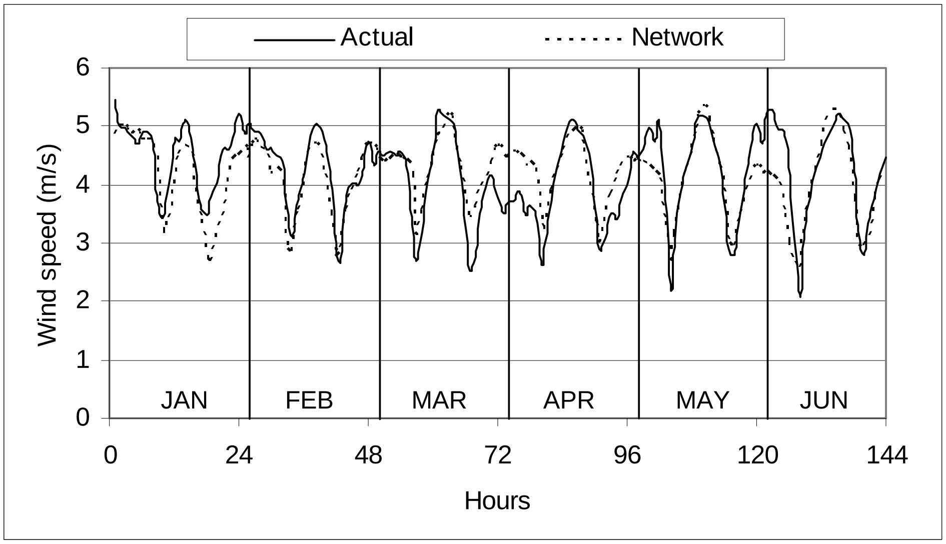

Figure 3 Actual against network estimated wind speed for the months January to June.

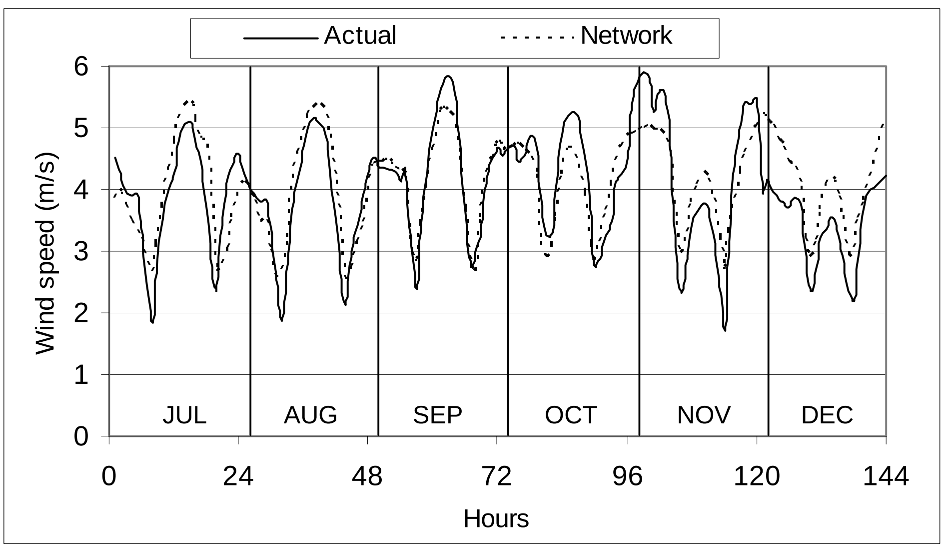

Figure 4 Actual against network estimated wind speed for the months July to December.

5. Conclusions

In this paper a time series prediction of wind speed with artificial neural networks is presented. For this purpose the mean monthly hourly wind speed records for the area of Kourris dam, located at the south of Cyprus, are used. The network was trained to predict the mean monthly hourly wind speed of a year by using the values of wind speed for the same month and same hour for the three previous years, consecutively. The training of the network was fast and accurate. The correlation coefficient obtained from the learning phase is equal to 0.8517. The data for one complete year (2000) were used for the validation of the network. It should be noted that these data were completely unknown to the network. The wind speed for the validation data set was predicted with a correlation coefficient of 0.82 which is satisfactory for wind speed which is very unstable. Therefore the method proved to be very promising both for predicting missing values and for forecasting.

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