Pergamon

Renewable Energy, Vol. 13, No. 3, pp. 345–354, 1998

Printed in Great Britain
0960–1481/98 $19.00+0.00

PII: S0960–1481(98)00001–9

A NEURAL NETWORKS APPROACH FOR WIND SPEED PREDICTION

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(*Received* 10 *April* 1997; *accepted* 20 *October* 1997)

Abstract—This paper introduces neural networks technique for wind speed prediction and compares its performance with an autoregressive model. First, we studied the statistical characteristics of mean monthly and daily wind speed in Jeddah, Saudi Arabia. The autocorrelation coefficients are computed and the correlogram is found compatible with the real diurnal variation of mean wind speed. The stochastic time series analysis is found to be suitable for the description of autoregressive model that involves a time lag of one month for the mean monthly prediction and one day for the mean daily wind speed prediction. The results on a testing data indicate that the neural network approach outperforms the AR model as indicated by the prediction graph and by the root mean square errors.

1. INTRODUCTION

The increasing global population and fast depleting reserves of fossil fuel and increasing environmental pollution have encouraged the search for clean and pollution free sources of energy. The power of wind is a clean, inexhaustible, and a free source of energy that has served human-kind for many centuries by propelling ships and driving wind turbines to grind grains and pump water [1]. Due to the availability of cheap and plentiful petroleum, high cost and uncertainty of wind as a source of energy placed it at an economic disadvantage. However, after the 1973 oil embargo, people realized that the world's oil supplies would not last forever and therefore alternative energy sources, other than conventional, have to be developed.

In spite of the high cost of wind power over those for coal and nuclear, wind power may become a major source of energy in the time to come. Broadly speaking, an hybrid system consisting of wind and solar (photo voltaic) generators in combination with a battery storage option can be used for the supply of small electrical loads at remote locations [2]. The remote applications may include electric supply to telecommunication stations, alpine

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huts or data logging stations for environmental parameters, irrigation and water pumping, agribusiness operations as well as building small desalination plants for drinking water [3]. The Kingdom of Saudi Arabia has a vast open land and hence offers good opportunities for harnessing the power of wind for remote locations which are not connected with the power grid.

For proper and efficient utilization of wind power, the knowledge of statistical characteristics, persistence, availability, diurnal variation, and prediction of wind speed is very important. These wind characteristics are needed for site selection, performance prediction, and planning of windmills. Of these characteristics, the prediction of mean monthly and daily wind speed is important for short term future wind power planning. The predicted variations in meteorological parameters such as wind speed, relative humidity, water vapor pressure etc. are needed in the renewable energy industry for design, performance analysis, and running-cost estimation of these systems [4]. In an earlier study, Njau developed an electronic system for air temperature and wind speed prediction and found good agreement between the predicted and observed values of both the temperature and wind speed [5]. The same author used a semi empirical type of correlation for the prediction of hourly, daily, and monthly mean values of wind speed for Dares Salaam, Tanzania [6]. Rehman and Halawani used stochastic time series analysis for the prediction of hourly wind speed for nine Saudi Arabian cities and found a relatively good agreement between predicted and observed values [7].

The utilization of neural networks is described by predicting the monthly and daily mean wind speed values for one city (Jeddah) located at the red-sea coast of Saudi Arabia. The predictions of neural networks are compared with those of autoregressive models. Both of these techniques are described in the following sections. The observed data covers a period of 12 years between 1970 to 1982. Figure 1 shows the mean monthly values of wind speed for this period and Fig. 2 presents the mean daily values for the year 1970.

2. ARTIFICIAL NEURAL NETWORKS

The current interest in artificial neural networks (ANNs) is largely due to their ability to mimic natural intelligence in its learning from experience [8]. They learn from examples by

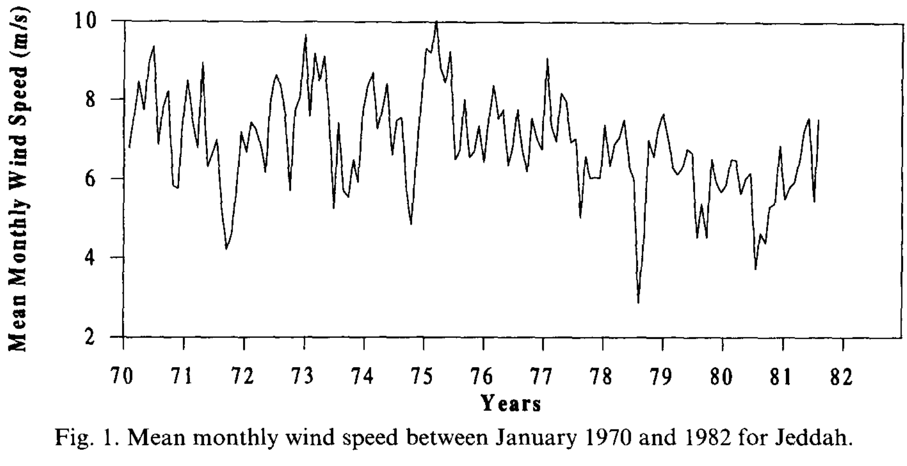

Fig. 1. Mean monthly wind speed between January 1970 and 1982 for Jeddah.

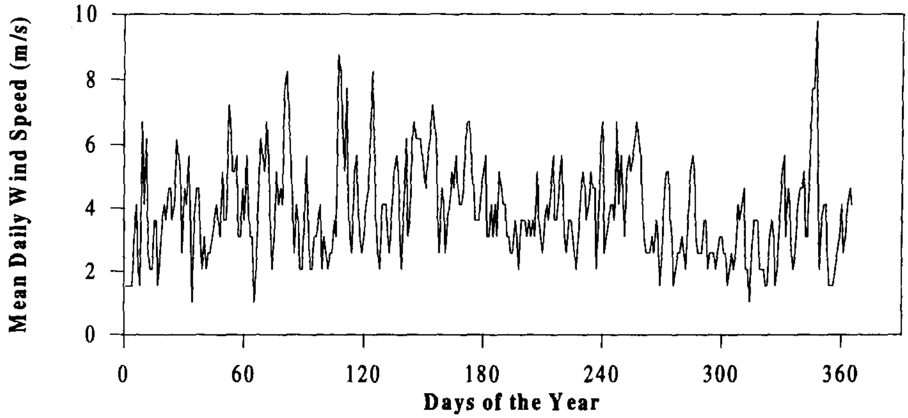

Fig. 2. Mean daily wind speed values for the year 1970.

constructing an input-output mapping without explicit derivation of the model equation. ANNs have been used in a broad range of applications including: pattern classification [9, 10], function approximation, optimization, prediction and automatic control [11] and many others. Here ANNs are used for wind speed prediction.

An artificial neural network consists of many interconnected identical simple processing units called neurons. Each connection to a neuron has an adjustable weight factor associated with it. Every neuron in the network sums its weighted inputs to produce an internal activity level v_i,

$$v_i = \sum_{j=1}^{n} w_{ij} x_{ij} - w_{io} \tag{1}$$

where w_{ij} is the weight of the connection from input j to neuron i, x_{ij} is input signal number j to neuron i, and w_{io} is the threshold associated with unit i. The threshold is treated as a normal weight with the input clamped at -1. The internal activity is passed through a nonlinear function φ to produce the output of the neuron y_i,

$$y_i = \varphi(v_i) \tag{2}$$

The weights of the connections are adjusted during the training process to achieve the desired input/output relation of the network. Figure 3 shows a single neuron with typical nonlinear functions.

Artificial neural networks come in many different paradigms, some require topologies with total interconnection among neurons and others require arrangement in layers. A multilayer feedforward network has its neurons organized into layers with no feedback or lateral connections. Layers of neurons other than the output layer are called hidden layers. The input signal propagates through the network in a forward direction, on a layer-by-layer basis. Figure 4 shows a three-layer feedforward network.

The back-propagation algorithm [12] is a supervized iterative training method for multilayer feedforward nets with sigmoidal nonlinear threshold units. It uses training data consisting of p input-output pairs of vectors that characterizes the problem. Using a generalized Least-Mean-Square algorithm the backpropagation algorithm minimizes the

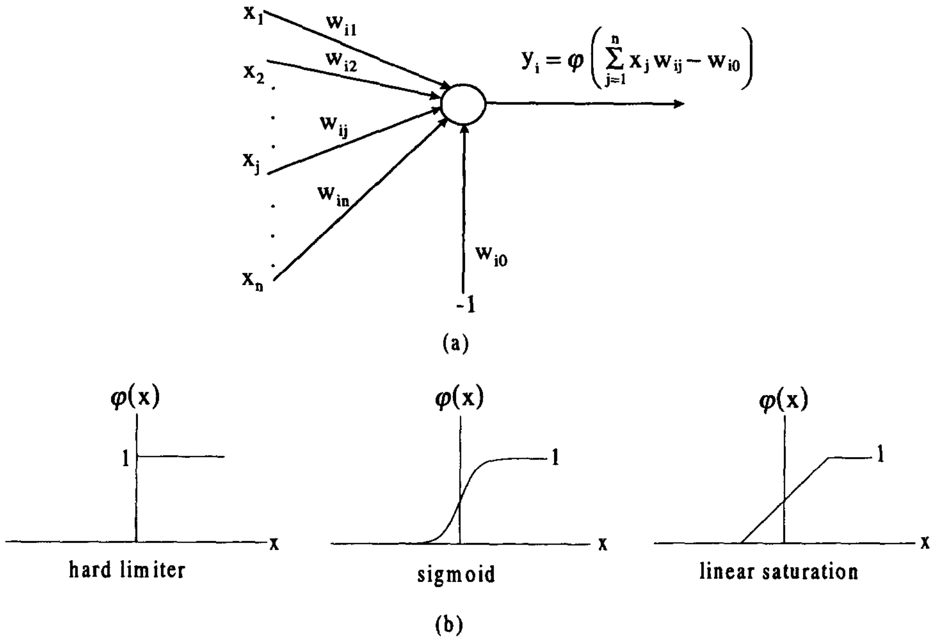

Fig. 3. (a) A single neuron, (b) Typical non-linear functions.

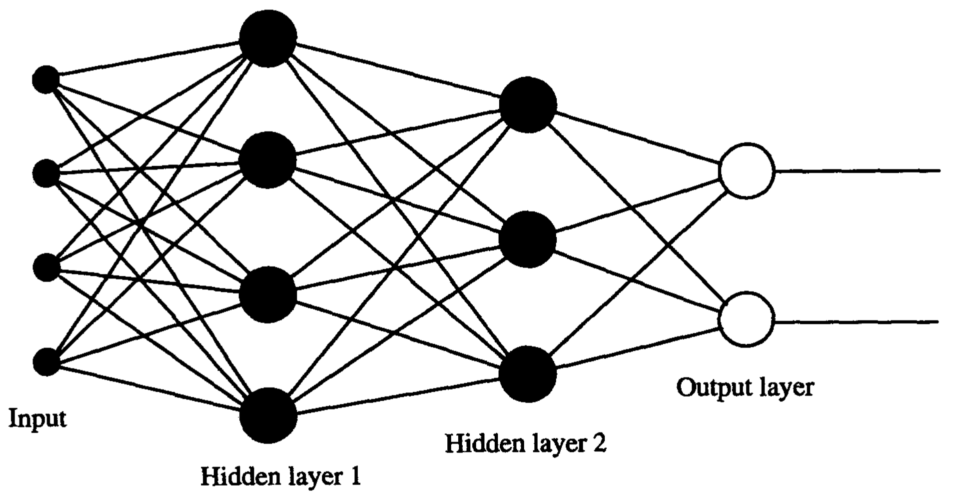

Fig. 4. A three-layer feedforward neural network.

mean square difference between the real network output and the desired output [13]. The error function that the backpropagation algorithm minimizes is the average of the square difference between the output of each neuron in the output layer and the desired output. The error function can be expressed as:

$$E = \frac{1}{2P}\sum_{p}\sum_{k}(d_{pk}-o_{pk})^2 \tag{3}$$

where p is the index of the P training pair of vectors, k is the index of elements in the output vector, d_{pk} is the kth element of the pth desired pattern vector, and o_{pk} is the kth element of the output vector when pattern p is presented as input to the network.

Minimizing the cost function represented in eqn (3) results in an updating rule to adjust the weights of the connections between neurons. The weight adjustment of the connection between neuron i in layer m and neuron j in layer $m+1$ can be expressed as:

$$\Delta w_{ji} = \eta\delta_j o_i \tag{4}$$

where i is the index of units in layer m, η is the learning rate, o_i is the output of unit i in the mth layer, and δ_j is the delta error term back-propagated from the jth unit in layer $m+1$ defined by:

$$\delta_j = [d_j - o_j]o_j[1-o_j], \quad \text{if neuron } j \text{ is in the output layer}$$

$$\delta_j = y_j[1-y_j]\sum_k \delta_k w_{kj}, \quad \text{if neuron } j \text{ is in a hidden layer}$$

where k is index of neurons in the layer $(m+2)$, ahead of the layer of neuron j. Choosing a small learning rate η leads to slow rate of convergence, and too large η leads to oscillation. A simple method for increasing the rate of learning without oscillation is to include a momentum term as:

$$\Delta w_{ji}(n+1) = \eta\delta_j o_i + \alpha\Delta w_{ji}(n) \tag{5}$$

where n is the iteration number, and α is a positive constant which determines the effect of past weight changes on the current direction of movement in weight space. Detailed description of the multilayer feedforward neural networks and the backpropagation algorithm may be found in [13].

3. AUTOREGRESSIVE MODELING

Generally speaking, time series analysis provides facilities for investigating and modeling the statistical structure of series of observations collected at equally spaced intervals of time. The models, so developed, can be used to forecast the series. In particular, the stochastic time series analysis is an important and useful tool for the study of the statistical structure of wind speed data [14]. In fact, the time series analysis is intended to investigate: (i) trends; (ii) seasonal patterns associated with fixed integer seasonal periods; (iii) cycles or waves of stable amplitude and period; (iv) quasi-cycles i.e. waves of fluctuating amplitude and period; and (v) irregular statistical fluctuations and swings about overall mean or trend. The general expression for pure autoregressive (i.e. zero moving averages) model can be written as:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + a_t \tag{6}$$

where $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive parameters and $x_t, x_{t-1}, x_{t-2}, \ldots, x_{t-p}$ are measured values at $t, t-1, t-2, \ldots, t-p$, respectively. In eqn (6), a_t is an uncorrelated error found to be normally distributed with mean zero. In this study we assumed a noise free system. The autoregressive model is used here to predict the mean daily and monthly values of wind speed which are then compared with those obtained from multilayer feed-forward neural networks, described in section 2.

The autocorrelation function characterizes the pattern of wind persistence. The sample autocorrelation coefficients are obtained from,

$$r_k = \frac{\sum_{t=1}^{n-k} (x_t - \bar{x})(x_{k+t} - \bar{x})}{\sum_{t=1}^{n} (x_t - \bar{x})^2} \tag{7}$$

where r_k is the sample autocorrelation coefficient, k is the time lag, $\bar{x}$ is the mean wind speed, and n is the total number of training data. The mean wind speed $\bar{x}$ is calculated from,

$$\bar{x} = \frac{1}{n} \sum_{t=1}^{n} x_t \tag{8}$$

The autocorrelation function usually gives an indication about the order of the model to best fit the data.

4. RESULTS

4.1. *Mean monthly wind speed prediction*

After normalization and subtracting the mean, we divided the available mean monthly wind speed data (144 months) into two parts; one for training (120 months); and the other for testing (24 months). The testing data was not used in defining the coefficients of the AR process nor for adjusting the weights of the neural network.

The correlogram obtained by plotting the autocorrelation values r_k against time lag in months is shown in Fig. 5. This figure shows a seasonal effect on the data, and the correlogram would not help in determining the order of the AR process. We studied several

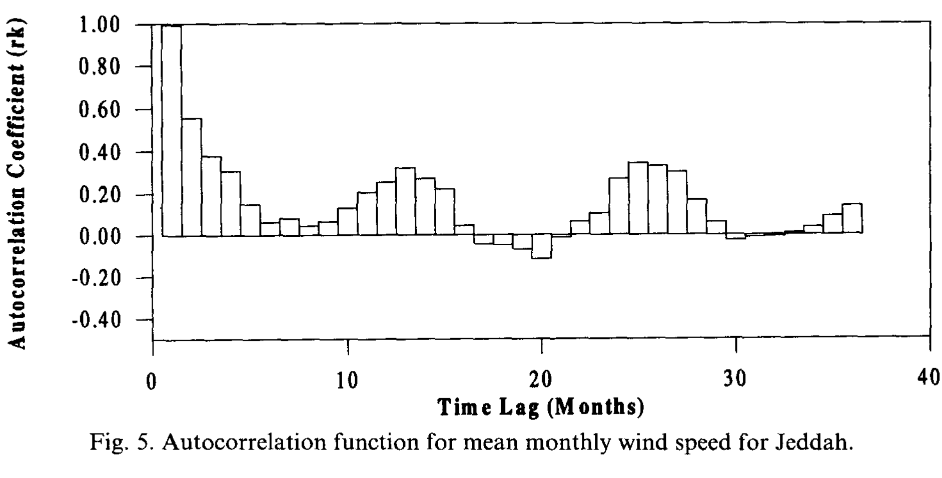

Fig. 5. Autocorrelation function for mean monthly wind speed for Jeddah.

AR processes with progressively higher order p. For each value of p we calculated the Root-Mean-Square-Error (RMSE) defined by,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_{ti})^2} \tag{9}$$

where x_t is the predicted value as in eqn (8). Figure 6 shows the relationship between the RMSE and the order of the AR process p. This figure indicates that there is no significant improvement by increasing the order of the AR process from one value to the other. Therefore, we chose an AR model with one coefficient only and consequently, used only one past value as an input to the neural network to predict the current value. Using the least mean square error method, the single autoregressive coefficient is found to be (-0.532) with standard deviation (0.079). The performance of the AR model on the testing data (data that has not been used to obtain the model coefficient) after re-scaling and the addition of the mean is shown in Fig. 7. The RMSE on the testing data is (2.88) for mean monthly wind prediction.

For the neural network model we used the same training and testing data as that for the AR model. Using one input and one output, we trained several networks with different number of hidden neurons. Among these, the best network, based on the RMSE over the training data was one with 6 hidden units. The performance of this network after re-scaling on the testing data is shown in Fig. 7 with RMSE value of (1.87). These results indicate the superiority of the neural networks system over the AR model, based on the RMSE values for both cases.

4.2. *Mean daily wind speed prediction*

In this case we divided the available mean daily wind speed data (4802 days) into two parts; one for training (730 days); and the other for testing (4072 days). The correlogram for the mean daily wind speed is shown in Fig. 8. Again, following the same procedure as in the previous case, we chose an AR model with one coefficient only. The single coefficient

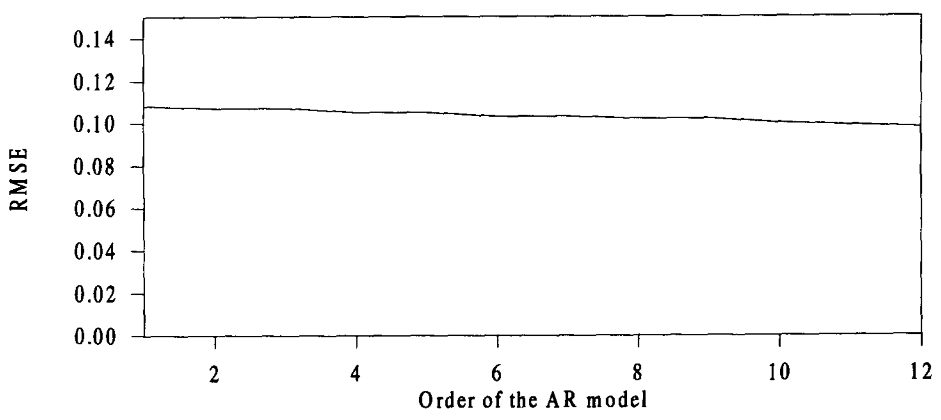

Fig. 6. The relationship between the order of the AR model and the Root-Mean-Square-Error (RMSE) on the testing data.

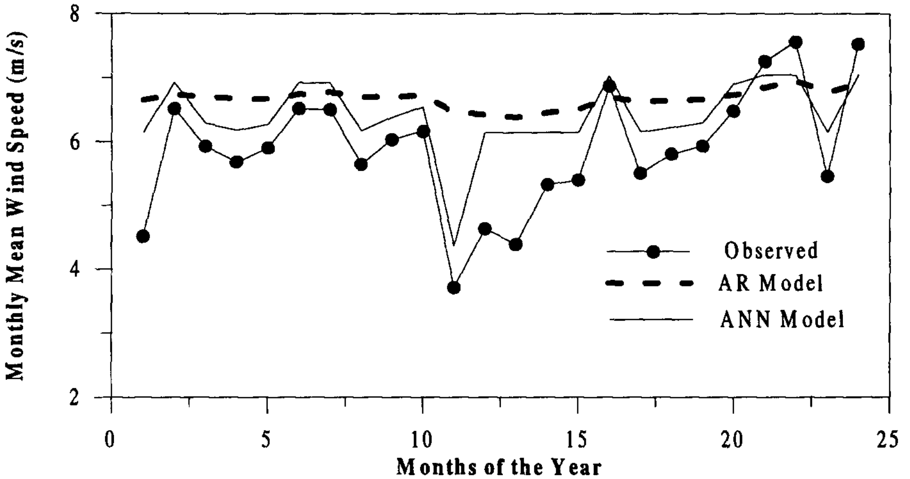

Fig. 7. Performance of AR model and ANN for predicting wind speed during the period from January 1980 to December 1981 for Jeddah city, Saudi Arabia.

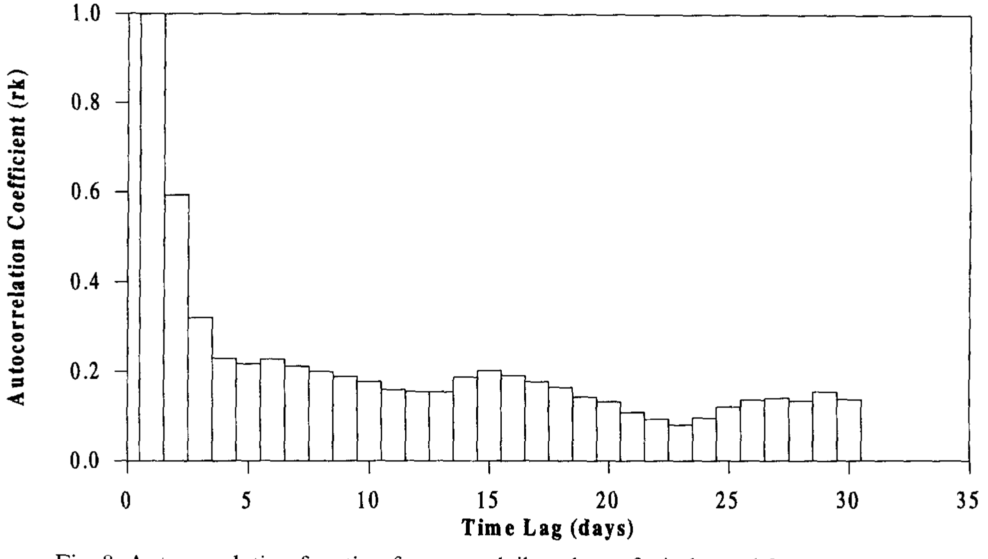

Fig. 8. Autocorrelation function for mean daily values of wind speed for Jeddah city.

is found to be (−0.6002) with standard deviation (0.0296). The performance of the AR model is shown in Fig. 9 on the testing data with RMSE value of (1.37).

For the neural network model we used the same training and testing data as that for the AR model. Using one input and one output, we trained several networks with different number of hidden neurons. Among these, the best network, based on the RMSE over the training data was one with 24 hidden units. The performance of this network on the testing data is shown in Fig. 9 with RMSE value of (1.24). These results also indicate the superiority

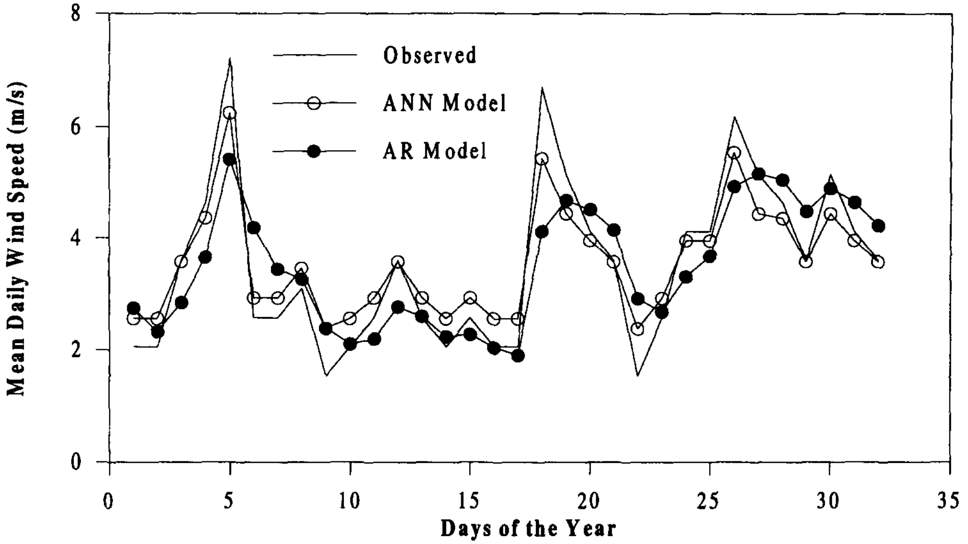

Fig. 9. Performance of ANN and AR models for predicting mean daily wind speed during the month of January 1972 for Jeddah city.

of neural networks system over the AR model on the mean daily wind speed based on the RMSE values for both systems.

The performance of both systems was further compared on a multi-step prediction (predicting more than one day in advance), where the output of the system is fed again as input. The performance of both systems is shown in Fig. 10, which indicates that, overall the neural network system performs better than the AR model.

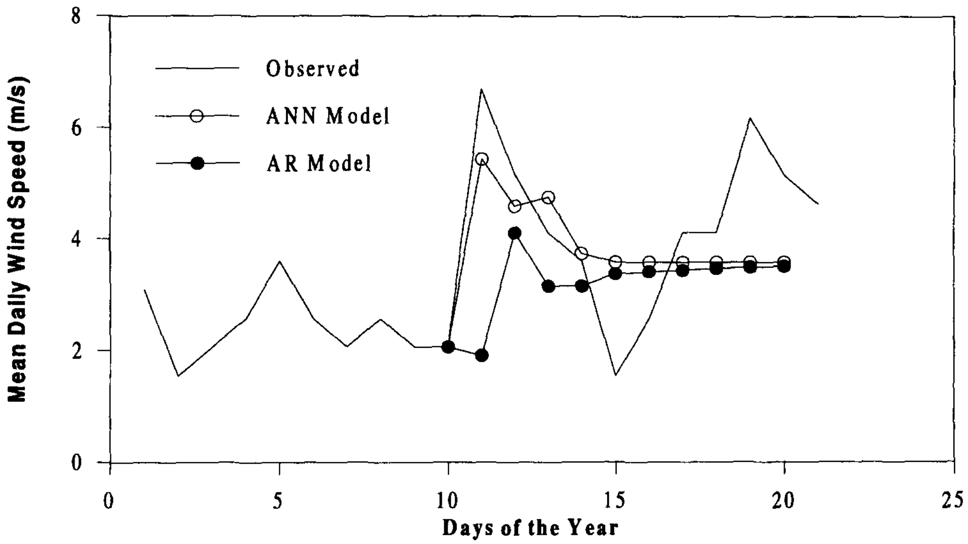

Fig. 10. Performance of ANN and AR models for multistep prediction of mean wind speed (predicting 10 days in advance in this case) for Jeddah city.

Finally, we compared the computation complexity of both systems. Neural networks training in this case consumed (60.2) MFLOPS (Mega Floating Point Operations) while finding the coefficient of the AR model consumed (0.54) MFLOPS. However, the training is usually an off-line process.

5. CONCLUSION

This paper introduces the neural networks technique for wind speed prediction. It compares favorably against the autoregressive model of statistical time series analysis for daily and monthly mean speed values. The computational complexity of the AR model was better than that of the neural networks. However with the advancing computers the computation time of both systems was negligible.

Acknowledgements—The authors wish to acknowledge the support of the Research Institute of the King Fahd University of Petroleum and Minerals, Dhahran-31261, Saudi Arabia.

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