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Modeling of Wind Speed for Palestine Using Artificial Neural Network

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Abstract: This study presents a wind speed prediction using Feedback forward artificial neural networks for two sites in Palestine which are Ramallah and Nablus. MATLAB is used to develop and train the proposed network using weather records for Palestine. However, three statistical values are used to evaluate the proposed networks. These statistical values are mean absolute percentage error, MAPE, mean bias error, MBE and root mean square error, RMSE. Based on results, the proposed network predicts an accurate daily wind speed values. The MAPE, RMSE and MBE values for the predicted daily wind speed values for Ramallah city are 8%, 0.5305 (12.15%) and -0.0192 (-0.441%). Meanwhile, the MAPE, RMSE and MBE values for predicted daily wind speed values for Nablus city are 9.25%, 0.8407 (14.94%) and 0.09 (1.6%), respectively. Such proposed approach helps in weather forecasting and estimating the output power of a wind turbine.

Key words: Wind speed, ANN, palestine, modeling

INTRODUCTION

Wind generation system is one of the most popular uses of the indirect solar energy and its installation is rapidly growing because it is considered as a clean and environmentally-friendly source of energy. The technology employed in wind energy systems is quite well-developed with improvements and modifications made regularly, particularly in energy conversion processes. Large-scale wind farms are connected to the electric power transmission network meanwhile, smaller facilities are used to provide electricity to isolated locations. Wind energy, as an alternative to fossil fuels, is plentiful, renewable, widely distributed, clean and produces no greenhouse gas emissions during operation. However, the construction of wind farms is not universally welcomed because of their visual impact but any effects on the environment are generally among the least problematic of any power source. The intermittency of wind seldom creates problems when using wind power to supply a low proportion of total demand but as the proportion rises, increased costs, a need to upgrade the grid and a lowered ability to supplant conventional production may occur. Power management techniques such as exporting and importing power to neighboring areas or reducing demand when wind production is low, can mitigate these problems (Patel, 1999; Boyle, 2006).

Wind speed prediction is important for weather forecasting and estimating the output power of wind turbines. A part of researches which have been done in this field is presented by Mohandes *et al*. (1998), Sfetsos (2000), Barbounis *et al*. (2006), Barbounis and Theochairs (2007), Bilgili *et al*. (2007), Cadenas and Rivera (2007), Flores *et al*. (2005) and Aksoy *et al*. (2004). A neural network approach is formulated for the wind speed prediction and compares its performance with an autoregressive model, after observing the statistical of mean monthly and daily wind speed in Jeddah, Saudi Arabia is presented by Mohandes *et al*. (1998). While a comparison of various time series forecasting approaches on mean hourly wind speed data had been proposed by Sfetsos (2000), Barbounis *et al*. (2006) and Barbounis and Theochairs (2007) proposed a recurrent ANN for long-term wind speed and power forecasting. Bilgili *et al*. (2007) used an ANN for wind speed prediction of a target station using reference stations' data. In addition a Comparison of two techniques for wind speed forecasting in the South Coast of the state of Oaxaca, Mexico was presented by Cadenas and Rivera (2007). A control algorithm based on neural network has been proposed by Flores *et al*. (2005). This algorithm has been used for wind speed and active generation power. However, by Aksoy *et al*. (2004), a new wind speed data generation scheme based on wavelet transformation is introduced and compared to the existing

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wind speed generation methods namely normal and Weibull distributed independent random numbers.

The main objective of this study is to present a novel ANN models for predicting daily wind speed for Palestine. This work was done based on a long term metrological data for two sites in Palestine. These data were provided by Palestine Technical University-Kadoorie, Tulkarm, Palestine.

WIND SPEED PREDICTION USING ANN

Artificial neural networks (ANNs) are information processing systems that are non-algorithmic, non-digital and intensely parallel. They learn the relationship between the input and output variables by studying previously recorded data. An ANN resembles a biological neural system, composed of layers of parallel elemental units called neurons. The neurons are connected by a large number of weighted links, over which signals or information can pass. A neuron receives inputs over its incoming connections, combines the inputs, generally performs a non-linear operation and outputs the final results. MATLAB was used to train and develop the ANNs for clearness index prediction. The neural network adopted was a feed forward, multilayer perception (FFMLP) network, among the most commonly used neural networks that learn from examples. However, Fig. 1 shows the feed-forward back propagation (FF) network diagram for wind speed prediction. FF network is a full-connected, three layer, feed-forward, perceptron neural network. Fully connected means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer. However, feed forward means that the values only move from input to hidden to output layers; no values are fed back to earlier layers.

The transfer function adopted for the neurons was a logistic sigmoid function:

$$f(z_i)=\frac{1}{1+e^{-z_i}} \tag{1}$$

$$zi=\sum_j^4 =1W_{ij}X_j+\beta_i \tag{2}$$

where, zi is the weighted sum of the inputs, X_j is the incoming signal from the jth neuron (at the input layer), W_{ij} the weight on the connection directed from neuron j to neuron I (at the hidden layer) and β_i the bias of neuron i.

Neural networks learn to solve a problem rather than being programmed to do so. Learning is achieved through training. In other words, training is the procedure by which the networks learn and learning is the end result. The most common methodology was used, supervised training. Measured daily clearness index data were given and the network learned by comparing the measured data with the estimated output. The difference (i.e., an error) is propagated backward (using a back propagation training algorithm) from the output layer, via the hidden layer, to the input layer and the weights on the interconnections between the neurons are updated as the error is back propagated. A multilayer network can mathematically approximate any continuous multivariate function to any

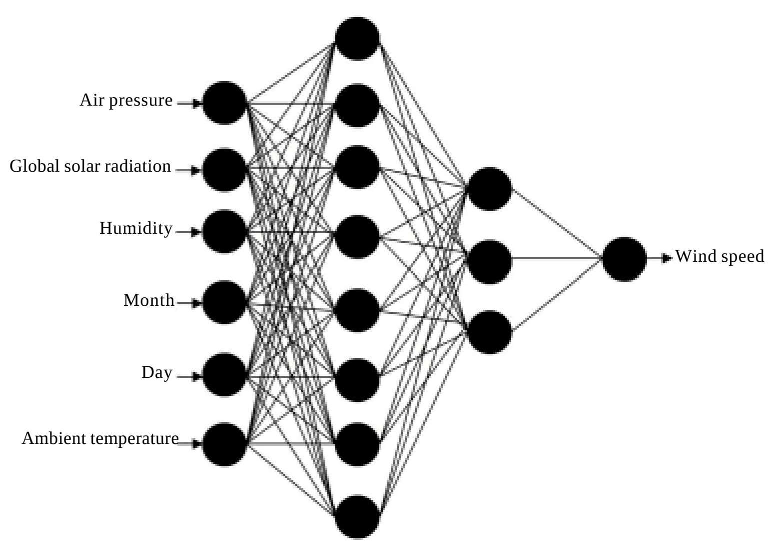

Fig. 1: FFNN for wind speed prediction

degree of accuracy, provided that a sufficient number of hidden neurons are available. Thus, instead of learning and generalizing the basic structure of the data, the network may learn irrelevant details of individual cases (Mehrotra *et al*., 1996; Cihan *et al*., 2000).

MATLAB is used to developed and train the proposed network model. The developed model has 6 inputs and one output. The inputs are global solar radiation, humidity, air pressure, ambient temperature, day and month. Meanwhile the output is daily wind speed.

ANN evaluation criteria: To evaluate the proposed neural network three error statistics are used. These statistics are Mean Absolute Percentage Error (MAPE) Mean Bias Error (MBE) and Root Mean Square Error (RMSE). MAPE is a measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage and is defined by the formula:

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\frac{I-I_p}{I} \tag{3}$$

where, I is the actual value and Ip is the forecast value. The difference between I and I_p is divided by the actual value I again. The absolute value of this calculation is summed for every fitted or forecast point in time and divided again by the number of fitted points n. This makes it a percentage error so one can compare the error of fitted time series that differ in level.

In addition, Most ANN models being evaluated quantitatively and ascertain whether there is any underlying trend in the performance of the ANN models in different climates using MBE and RMSE. MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on the long term performance of the models. A positive MBE value indicates the amount of overestimation in the predicted global solar radiation and vice versa. On the other hand, RMSE provides information on the short term performance and is a measure of the variation of predicted values around the measured data. It indicates the scattering of data around the linear lines. Moreover, RMES shows the efficiency of the developed network in predicting a future individual values, large positive RMES means big deviation in the predicted value form the real one. However, MBE and RMSE are given as follows:

$$\text{MBE}=\frac{1}{n}\sum_{i=1}^{n}(I_{Pi}-I_i) \tag{4}$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_{Pi}-I_i)^2} \tag{5}$$

where, I_{pi} is the predicted value, I_i is the measured value and n is the number of observations

RESULTS AND DISCUSSION

The used weather data contain 2000 daily records for each Nablus city (Latitude = 32.14, longitude = 35.16) and Ramallah city (latitude = 31.9, longitude = 35.2) West Bank, Palestine for the period (2004-2009). 1634 (mid of 2004 to 2008) records were used to train the developed network, while 366 records (year 2009) were used to test the network.

Ramallah city: Figure 2 shows regression plots for ANN wind speed model for Ramallah city. These plots include validation, training and testing of the developed ANN model. The Litter R above each plot indicates the correlation between the target and the output variables. In addition, the x-lable of each plot represents the target values which are daily wind speed values during year 2009. On the other hand, y-lable shows the relation between the target values which have been provided and the output values which represented by the predicted values. However, the overall correlation between the target values and the predicted values is 94.38% which is acceptable. Figure 3a and b show the predicted daily wind speed values compared with the measured values. From the Fig. 3, the prediction is accurate along the year with very minor underestimations at the second half of the year. However, based on the proposed evaluation criteria the MAPE, RMSE and MBE values for the predicted daily wind speed values for Ramallah city are 8%, 0.5305 (12.15%) and -0.0192 (-0.441%), respectively. These results prove the accuracy of the developed model. Moreover, the RMSE value shows that the developed model is able to predict a future values in an acceptable accuracy. The MBE value shows that the developed model has an underestimation in predicting daily wind speed for Ramallah by .0192 m sec^{-1} which means 0.441%.

Nablus city: As for Nablus city, Fig. 4 shows the performance of the developed ANN model for daily wind speed for Nablus. The developed model shows better correlation between the target and the outputs compared with the developed ANN model for Ramallah. The targets and the outputs of Nablus's ANN model were correlated by 97.34%. However, Fig. 5a and b show the predicted values of daily wind speed in Nablus compared with the measured values. Minor overestimations in predicting wind speed values at the beginning of the year, while an accurate prediction for wind speed values along the year was noticed. The statistical values which used in

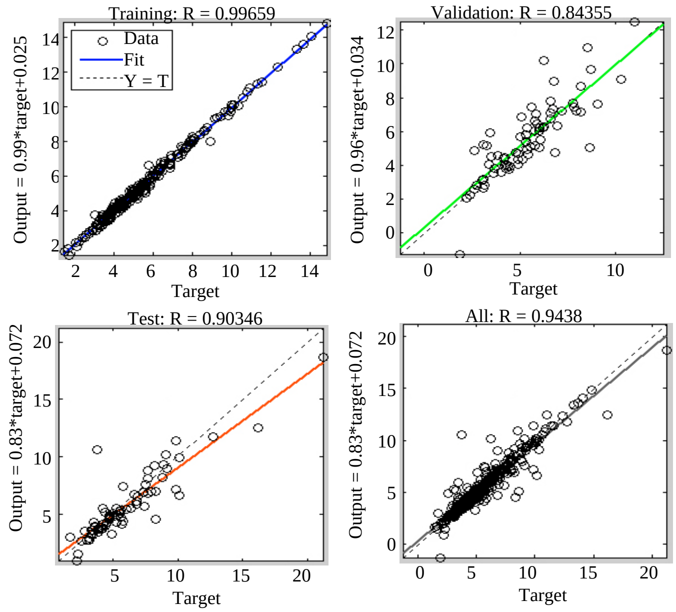

Fig. 2: Validation, training and testing of the developed ANN model for predicting wind speed for Ramallah

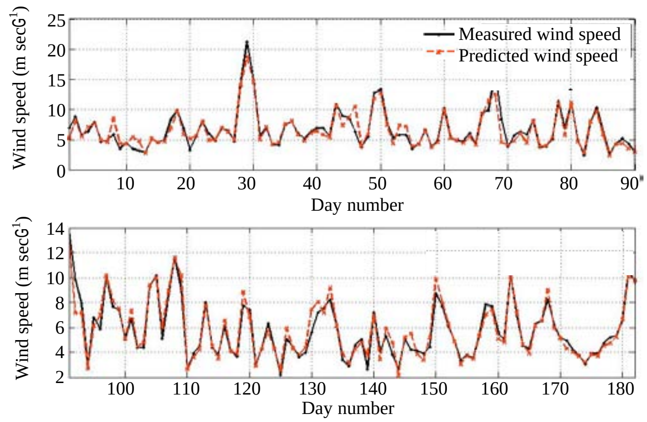

Fig. 3a: Daily wind speed prediction results for Ramallah

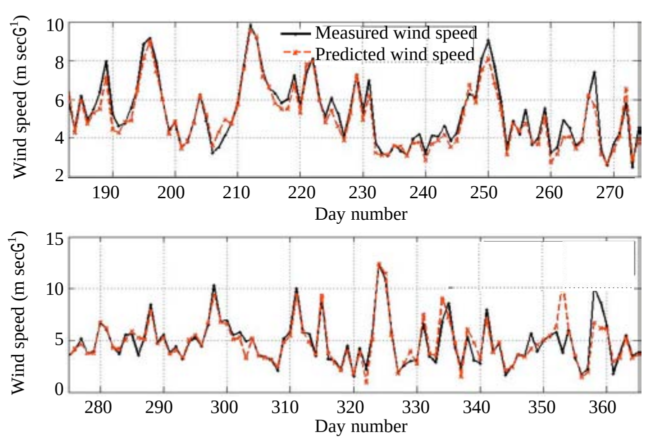

Fig. 3b: Daily wind speed prediction results for Ramallah

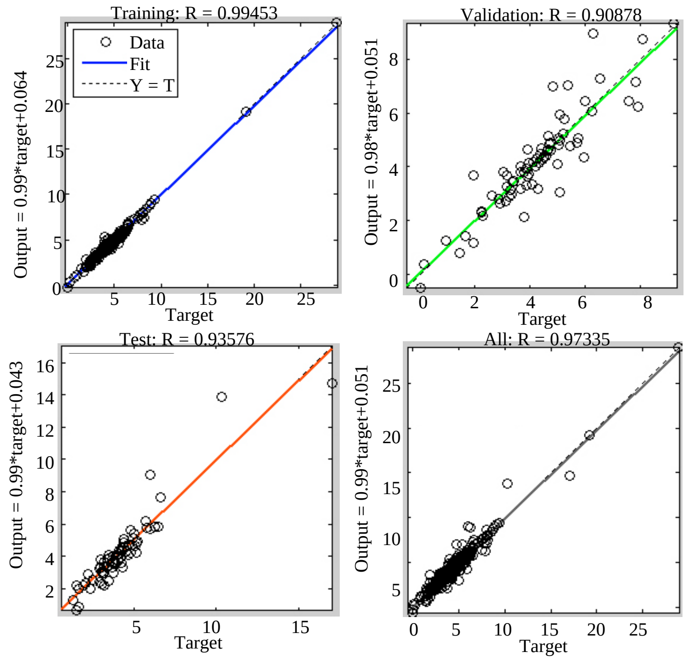

Fig. 4: Validation, training and testing of the developed ANN model for predicting wind speed for Nablus

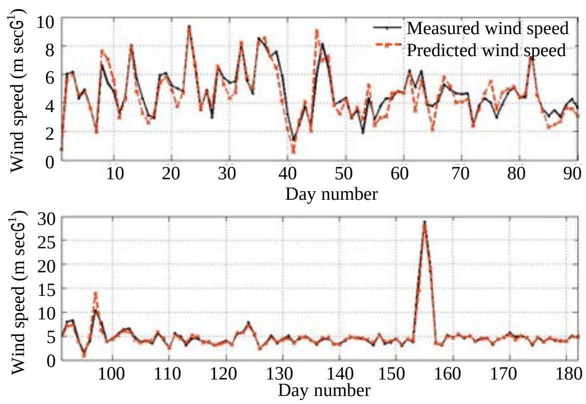

Fig. 5a: Daily wind speed prediction results for Nablus

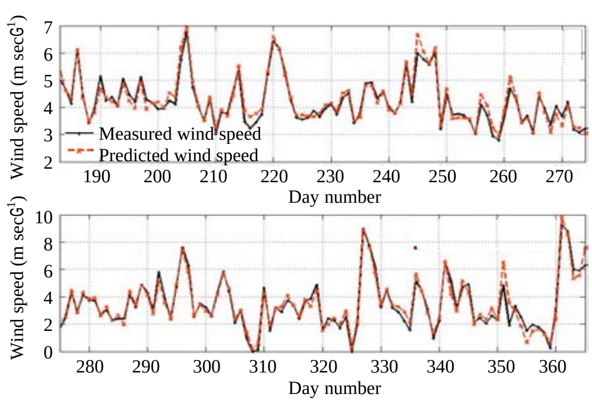

Fig. 5b: Daily wind speed prediction results for Nablus

evaluating the developed models show that the developed model for Nablus has an MAPE, RMSE and MBE values for the predicted daily wind speed values for Nablus city 9.25%, 0.8407 (14.94%) and 0.09 (1.6%), respectively. Based on this the developed ANN model for Ramallah exceeds developed ANN model for Nablus since it is MAPE and RMSE is lower than. On the other hand, the developed ANN model for Nablus shows an overestimation in prediction daily wind speed values by 0.09 m sec^{-1} which means 1.6% on the contrary of the developed ANN model for Ramallah which shows an underestimation in predicting daily wind speed values.

CONCLUSION

Predictions for daily wind speed for Palestine using feedback forward neural networks were done. ANN models using MATLAB were developed for two cities in Palestine which are Ramallah and Nablus. However, MAPE, RMSE and MBE values for the predicted daily wind speed values for Ramallah city were 8%, 0.5305 (12.15%) and -0.0192 (-0.441%). While, MAPE, RMSE and MBE values for the predicted daily wind speed values for Nablus city were 9.25%, 0.8407 (14.94%) and 0.09 (1.6%), respectively. Such predictions could be used in estimating wind turbines output power in Palestine.

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