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An Analysis of Wind Speed Prediction Using Artificial Neural Networks: A Case Study in Manjil, Iran

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Abstract *In this study, air temperature, relative humidity, and vapor pressure data collected from Manjil station between 1993–2004, were used for wind speed predictions in a future time domain using artificial neural networks. The following combinations of data are considered for this study: (i) month of the year, monthly mean daily air temperature, and relative humidity as inputs, and monthly mean daily wind speed as output; (ii) month of the year, monthly mean daily air temperature, relative humidity, and vapor pressure as inputs, and monthly mean daily wind speed as output. The generalized regression neural networks, multilayer perceptron, and radial basis function neural networks were used in this study. The measured data between 1993 and 2003 is applied for training and the data for 2004 is used for testing. The data for testing were not applied for training the neural networks. Obtained results show that neural networks are well capable of estimating wind speed from simple meteorological data. These results indicate that using vapor pressure along with the month of the year, monthly mean daily air temperature, and relative humidity based on a multilayer perceptron network has better performance than the other cases with the mean absolute percentage error of 7.03% (2004).*

Keywords generalized regression neural networks, multi-layer perceptron neural networks, prediction, radial basis function neural networks, wind speed

1. Introduction

The power of wind is a clean, endless, and free source of energy, which has helped mankind for centuries to move the ships and run the turbines in order to mill the grains and pump water. Because an ample supply of petroleum was cheap and accessible (pre-1970s), the high cost and uncertainty of wind placed it at an economic disadvantage. However, after the 1973 oil embargo, it became clear that the oil supplies would not remain forever and so other kinds of energy sources must be developed (Mohandes et al., 2004).

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Manjil, which is located between N 36°14′18″–N 36°41′42″ and E 49°23′6″–E 49°31′48″ (about 80 km south of the Caspian Sea) in Gilan province, is considered to be a windy city of Iran. The wind speed average of Manjil is about 6 m/s (which was measured at a height about 10 m above the ground) in winter and the wind conditions are great, especially in the summer. The strong north wind blowing from May to September, whose average wind speed is 14 m/s (at 10 m height), can be explained by the local climate and geographical conditions (Hagenkort, 2005; Mostafaeipour and Abarghooei, 2008). It is estimated that the wind energy potential is about 12 GW in Iran (IORE, 2006).

Predicting the wind speed is very important in order to use the wind power sufficiently. It is required for selecting the site, to predict the optimum size of the wind machine that is used for a special site (Mohandes et al., 1998).

Several studies are presented for predicting the wind speed. In a study by Njau (1994a), an electronic system to predict air temperature and wind speed was developed. He found a good agreement between the predicted and actual values of wind speed and temperature.

Njau (1994b) also has considered a semi-empirical correlation to predict the hourly, daily, and monthly average values of wind speed in Dares Salaam, Tanzania. Rehman and Halawani (1994) used stochastic time series analysis to predict the hourly wind speed of nine cities of Saudi Arabia and found a good agreement between the predicted and actual values. Also, Mohandes et al. (2004) developed support vector machines models to predict wind speed and compared their performance with multi-layer perceptron (MLP) neural networks. Cadenas and Rivera (2007) compared autoregressive integrated moving average and artificial neural networks (ANN) techniques to predict the wind speed in the south coast of Oaxaca, Mexico. However, many researchers have presented their papers in this regard based on different techniques (Cellura and Cirrincione, 2008). In this study, three types of ANNs are applied to predict wind speed in Manjil station using measured air temperature, relative humidity, and vapor pressure.

2. Neural Networks

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large number of interconnected neurons. Each neuron is capable of performing only simple computation (Pham et al., 2006a). Consequently, the architecture of an artificial neuron is simpler than a biological neuron. ANNs are constructed in a layer that connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. Learning in ANNs is achieved through particular training algorithms that are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of a biological system (Yilmaz and Ozer, 2009).

However, as an assembly of neurons, a neural network can learn to perform complex tasks including pattern recognition, system identification, trend prediction, and process control (Pham et al., 2006a).

2.1. Generalized Regression Neural Network (GRNN)

The GRNN can solve any function approximation problem. The GRNN proposed by Specht (1991) does not require an iterative training procedure. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero. The GRNN is used for the estimation of continuous variables, as in standard regression techniques. It is related to the radial basis function network, and is based on a standard statistical technique called kernel regression. By definition, the regression of a dependent variable y on an independent x estimates the most probable value for y, given x and a training set. The regression method will produce the estimated value of y, which minimizes the mean-squared error (MSE). The principal advantages of the GRNN are fast learning and convergence to the optimal regression surface as the number of samples becomes very large. The GRNN is particularly advantageous with sparse data in a real-time environment, because the regression surface is instantly defined everywhere.

The schematic diagram of GRNN architecture is presented in Figure 1. As it can be seen from Figure 1, the GRNN is organized using an input layer, a pattern layer, a summation layer, and an output layer. The relation between input and output can be expressed as:

$$y = \frac{\sum_{j=1}^{m} w_j \varphi_j(X)}{\sum_{j=1}^{m} \varphi_j(X)} \equiv \frac{\alpha}{\beta}, \tag{1}$$

where $X = [x_1, x_2, \ldots, x_n]^T$ is a n-dimensional input vector, w_j is the weight between the jth pattern layer node and summation layer node, and φ is the Gaussian function. Layer 1, the input layer, accepts the input signals into the GRNN. The nodes at layer 1 represent linguistic variables (namely the driving frequency f and the phase difference φ in the TWUSM drive system (Celikoglu, 2006). Layer 2, the pattern layer, possessed a nonlinear transformation applied on the data from the input space to the pattern space. The most popular choice for the function φ is a multivariate Gaussian function with an

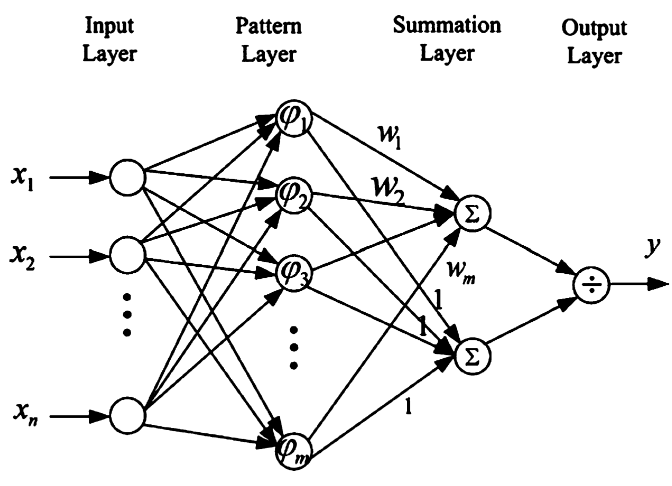

Figure 1. Schematic diagram of GRNN.