2Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 2 (6) May 2013: 141- 147

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com

CASE STUDY

The Application of a Hybrid Artificial Neural Network and Genetic Algorithm (ANN-GA) to Mapping of Wind Speed Profile for Electrical Energy applications: A Case study for South Coasts of Iran

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ABSTRACT
Since wind speed greatly influences the issues such as the scheduling of a power system, and the dynamic control of the wind turbine, wind speed prediction is critical for wind energy conversion systems.
In this study, a Hybrid Artificial Neural Network and Genetic Algorithm (MLP-GA) is applied to predict monthly average wind speed, based on meteorological variables. Month of the year, monthly mean air temperature, mean relative humidity, vapor pressure and wind speed data between 1994 and 2005 provided by Iranian Meteorological Organization for south coasts of Iran, were used in this study. In order to consider the effect of each meteorological variable on wind speed prediction, two following combinations of input variables are considered:
(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 measured data between 1994 and 2003 were used as training and the remained data (i.e. 2004 and 2005) used as testing. Obtained results indicate that using vapor pressure along with the month of the year, monthly mean daily air temperature, and relative humidity has better performance than another case with the mean absolute percentage error of 10.86% and correlation of coefficient of 93.95% on testing data sets.
Keywords: *Genetic Algorithm; Artificial Neural Networks; Hybrid Networks; Meteorology; Prediction; South Coasts of Iran.*

Received 10.04.2013 Accepted 08.05.2013

INTRODUCTION

Nowadays, wind energy is one of the most attractive sources of energy. The prediction of wind energy is easily obtained using estimated wind speed. So, wind speed measurements are the most important parameters for the wind energy applications [1].
For low priced and effective development and utilization of wind energy a comprehensive knowledge about the statistical characteristics, persistence, availability, diurnal variation and prediction of wind speed in time and special domain is of great importance [1].
Studying the behavior of wind speed at the intended site requires long-term data in a nearby location along with empirical, semi-empirical, physical, neural networks, etc techniques [2].
Wind estimation is difficult due to the complex structure of parameters which affect wind strongly such as topographical properties of the earth, the rotation of the world, temperature and pressure differences (Bilgili et al., 2007). Using ANN has proved its efficiency as a prediction tool to predict factors through other input variables which have no any specified relationship [3]. Several studies are presented for predicting the wind speed. [4] 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. [2] developed SVM (support vector machines) models to predict wind speed and compared their performance with MLP (multi-layer perceptron) neural networks. [5] compared autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN) techniques to predict the wind speed in the south coast of Oaxaca, Mexico. [6] used Fuzzy modeling techniques and artificial neural networks to estimate annual energy output of a wind turbine in Netherlands. [7] applied a hybrid time series approach for wind speed prediction in Hexi Corridor of China. [8] used

artificial neural network–Markov chain model for very short-term wind speed prediction. [9] presented stochastic models for wind speed forecasting in Italy.
In this study, Monthly mean air temperature, mean relative humidity, and vapor pressure data are used to predict wind speed using a hybrid Neural Network and Genetic Algorithm (ANN-GA) technique.

HYBRID ARTIFICIAL NEURAL NETWORKS- GENETIC ALGORITHM (ANN-GA) METHOD

Genetic Algorithm

The theoretical basis of GAs lies in the concept of schema (plural schemata) [10]. Schemata represent solution templates where each location can be defined or left unspecified. The larger the number of uninstantiated locations is, the greater the number of potential solutions that a schema represents. Schemata leading to higher fitness individuals are propagated through the generations and their number is increased as an effect of the selection process. The ability to process several possible solutions through a single schema is believed to determine the search power of GAs and is given the name implicit parallelism [11, 12]. High fitness schemata whose uninstantiated locations occupy a short and compact portion of the encoding are considered to be the building blocks [11] of the optimization process. GAs are designed to multiply and differently recombine these building blocks in order to grow the final optimal solution (building blocks hypothesis) [11]. The schemata theorem [10] allows the estimation in a probabilistic way of the number of criteria schema instances that are transmitted to the following generations.
GA starts with a randomly generated population of chromosomes and applies genetic operators to create new and fitter populations. The most common genetic operators are the selection, crossover and mutation operators. The selection operator chooses chromosomes from the current population for reproduction. Usually, a biased selection produce is adopted which favor the fitter chromosomes. Crossover is the main search operator in GAs, creating offsprings by randomly mixing sections of the parental genome. The number of sections exchanged varies widely with the GA implementation. The most common crossover procedures are one-point crossover, two point crossover and uniform crossover[11]. In canonical GAs (i.e. Holland's original algorithm), a crossover probability is set for each couple. Couples not selected for recombination will generate two offsprings identical to the parents. A small fraction of the offsprings is randomly selected to undergo genetic mutation. The mutation operator randomly picks a location from a bit-string and flips its contents. The importance of this operator in GAs is however secondary, and the main aim of mutation is the preservation of the genetic diversity of the population. Together, these operators simulate a guided random search method which can eventually yield the optimum set of weights to minimize the error function. Further details about GA and other intelligent optimization techniques can be found in [13, 14]

Artificial Neural Networks

One of the most important branches in artificial intelligence which is very applicable in solving engineering problems is artificial neural networks. Neural networks are computational models of the biological brain [15]. Any how, the architecture of an artificial neural network is simpler than a biological brain [16].
The multilayered feedforward neural network has an input layer to receive inputs from sensors or other sources, an output layer to communicate with the outside world and one or more hidden layers for data processing to transform the inputs into outputs. The architecture of a feedforward neural network with one hidden layer is shown in Figure1.

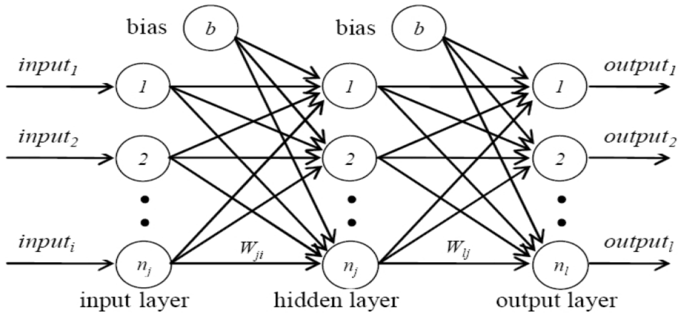

Figure1. Feed forward neural network with one hidden layer

Each layer is made up of processing elements called neurons. Every neuron has a number of inputs, each of which must store a connection weight to indicate the strength of the connection. Connections are initially made with random weights.

The neuron sums the weighted inputs and computes a single output using an activation function. A number of different activation functions can be used. Each neuron in a layer is fully connected to every neuron in the subsequent layer forming a fully connected feedforward neural network. In a feedforward neural network, information flows from the input layer to the output layer without any feedback. There is one bias neuron for each hidden layer and the output layer, as illustrated in Figure 1, and they are connected to each neuron in their respective layer. These connections are treated as weights. During the training process these weights are adjusted to achieve optimal accuracy and coverage [15, 17].

In this work GA is used to optimize the weights assigned to the connections between the neurons within the neural network where each chromosome represents a neural network with a particular set of weights.

PROBLEM DEFINITION AND RESULTS

A hybrid ANN-GA is used to predict wind speed using meteorological variables for five ground stations, located in the south coasts of Iran (i.e. Kish, Siri, Jask, Bandarabass and Aboumosa). Table 1 presents information for the considered stations in this study.

Table1.Information for considered cities

Location	Longitude (°E)	Latitude (°N)	Elevation (m)
Aboumosa	54.83	25.83	6.6
Bandarabass	56.37	27.22	9.8
Jask	57.77	25.63	5.2
Kish	53.98	26.50	30
Siri	54.48	25.88	4.4

In order to consider the effect of each meteorological variable on wind speed prediction, measured air temperature, relative humidity, vapor pressure and wind speed data between 1994 and 2005 provided by Iranian Meteorological Organization for the stations, were used in the following combinations:

(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 measured data between 1994 and 2003 were used as training and the remained data (i.e. 2004 and 2005) used as testing. Figures 1 and 2 show the average values of air temperature, relative humidity, vapor pressure, and wind speed on training period (i.e. 1994-2003) and testing period (i.e. 2004 and 2005) for considered stations, respectively.

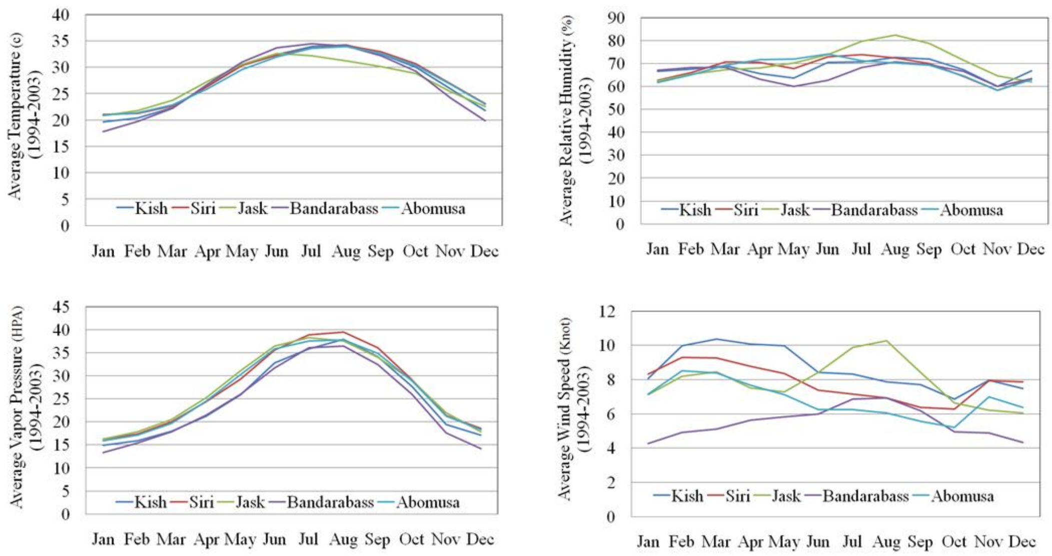

Figure 2. Average values of air temperature, relative humidity, vapor pressure, and wind speed on training period (i.e. 1994-2003) for considered stations.

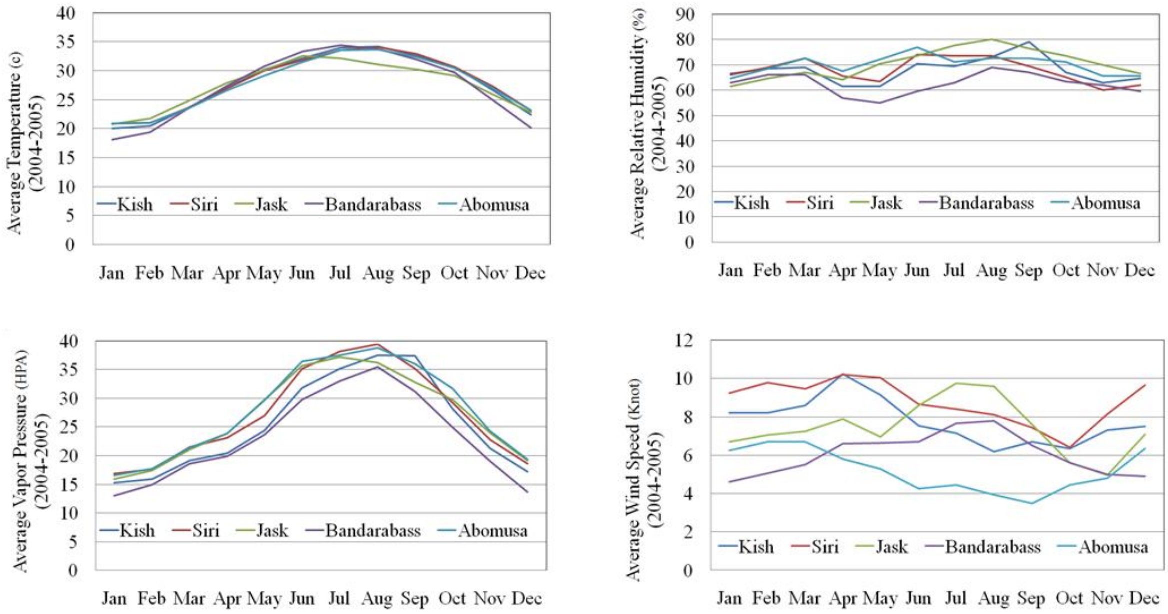

Figure 3. Average values of air temperature, relative humidity, vapor pressure, and wind speed on testing period (i.e. 2004 and 2005) for considered stations.

RESULTS AND DISCUSSION

In this section, optimal network configuration are found using an ANN-GA algorithm implemented in MATLAB 2010 (Math Works, Natick, MA). In order to determine the optimal network architecture for each combination of variables, various network architectures were designed; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. Eventually, logistic sigmoid transfer function (logsig) for both hidden layers, and linear transfer function (purelin) for output layer were found to be the best configuration for both combinations. Table 2 shows the performance of best trained networks in this study.

Table2. Training and testing errors of each combination.

Combination	Training		Testing	
	MAPE (%)	R^2 (%)	MAPE (%)	R^2 (%)
I	12.71	93.53	14.01	91.97
II	10.79	93.98	10.86	93.95

As it can be seen in this table, the optimum network for first combination and second combination has Mean Absolute Percentage Errors (MAPE) of 10.86% and 14.10% and correlation coefficient (R^2) of 91.97% and 93.95% on testing period, respectively.
Figure 4 to 8 show the comparison between predicted wind speed values based on best ANN-GA model (i.e. combination II) and measured values on testing data (2004 and 2005) for all considered stations.

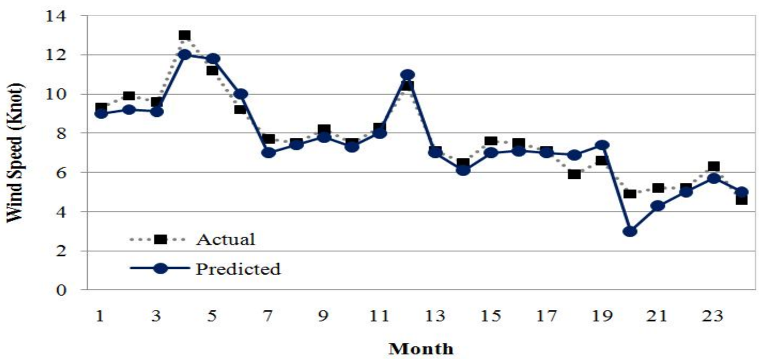

Figure 4. Comparison between predicted wind speed values based on best ANN-GA model (i.e. combination II) and measured values on testing data (2004 and 2005) for Kish station.

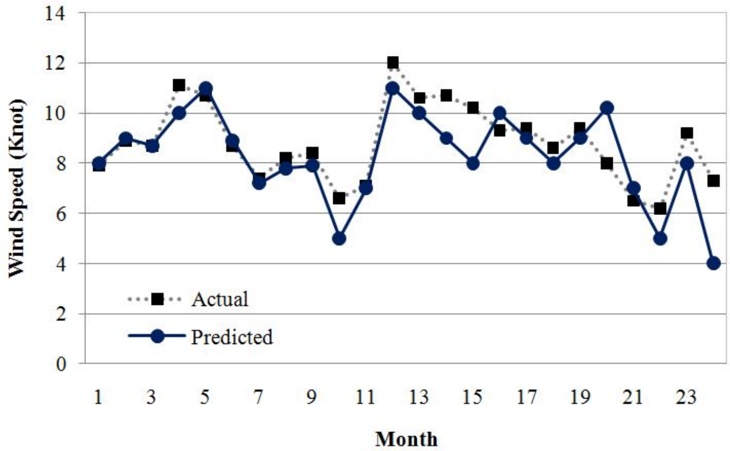

Figure 5. Comparison between predicted wind speed values based on best ANN-GA model (i.e. combination II) and measured values on testing data (2004 and 2005) for Siri station.

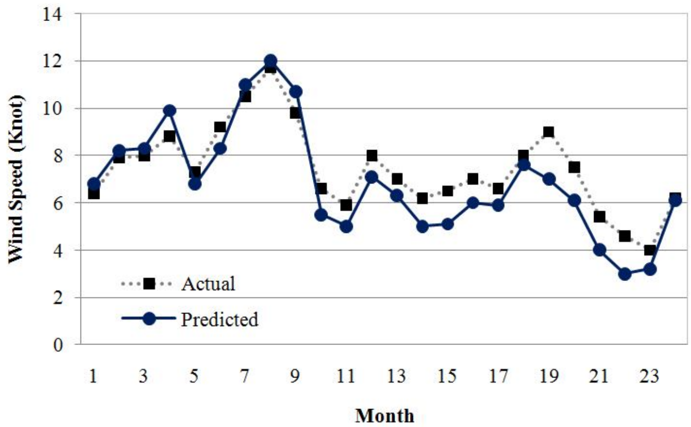

Figure 6. Comparison between predicted wind speed values based on best ANN-GA model (i.e. combination II) and measured values on testing data (2004 and 2005) for Jask station.

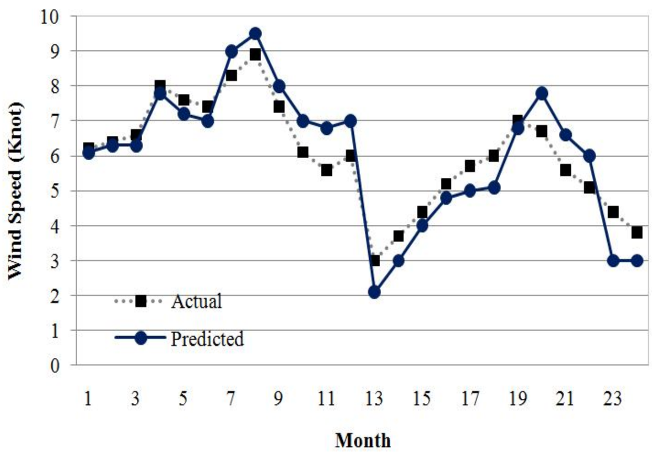

Figure 7. Comparison between predicted wind speed values based on best ANN-GA model (i.e. combination II) and measured values on testing data (2004 and 2005) for Bandarabass station.

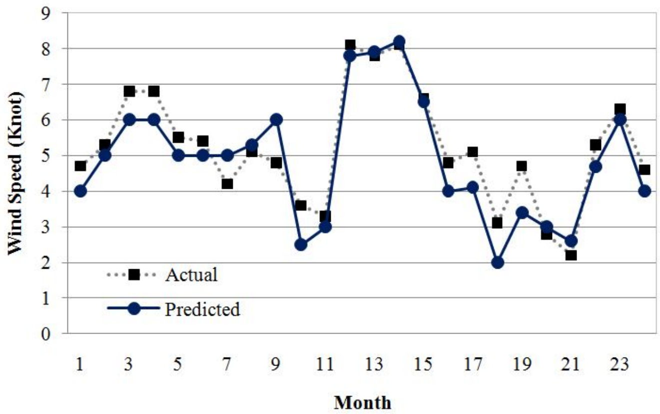

Figure 8. Comparison between predicted wind speed values based on best ANN-GA model (i.e. combination II) and measured values on testing data (2004 and 2005) for Aboumosa station.

CONCLUSION

Numerous research efforts have been devoted to improving the accuracy of wind speed forecasting through the optimization of parameters and further analysis of factors that have a significant impact on the final output in these models. In this paper, a new hybrid method based on weights adjustment of neural networks was proposed to forecast the monthly average wind speed values for a period of time. Genetic Algorithm (GA) was used as an optimization method in this study.

Monthly wind speed was forecasted according to measured values of air temperature, relative humidity, vapor pressure. This is of great importance because above parameters are commonly accessible. Data for eight stations, from 1994 to 2003 were used for training ANNs networks and data for 24 months (i.e. 2004 and 2005) were used for testing the operation of the ANNs networks. For one case, month of the year, monthly mean daily air temperature and relative humidity are considered as inputs and daily wind as output. In second case, month of year, monthly mean daily air temperature, relative humidity and vapor pressure are considered as inputs and monthly wind speed as output. These cases were used for the prediction of the monthly wind speed. Obtained results indicate that using vapor pressure along with the month of the year, monthly mean daily air temperature, and relative humidity has the mean absolute percentage error of 10.86% and correlation of coefficient of 93.95% on testing data sets and has better performance than another case.

ACKNOWLEDGMENTS

The authors are grateful for the financial support provided for the present work by Dezful Branch, Islamic Azad University, Dezful, Iran.

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How to Cite this Article
Hassan B., H. Haroonabadi, R. Zadehali.(2013).The Application of a Hybrid Artificial Neural Network and Genetic Algorithm (ANN-GA) to Mapping of Wind Speed Profile for Electrical Energy applications: A Case study for South Coasts of Iran. *Bull. Env. Pharmacol. Life Sci.,* Vol 2 (6) May 2013: 141-147