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ORIGINAL ARTICLE

A New approach for wind Speed Modeling

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ABSTRACT
In this study a new framework is presented to forecast wind speed based on meteorological parameters using Artificial Intelligence. A Hybrid Multi Layered Perceptron Neural Network and Genetic Algorithm (MLP-GA) is applied to predict monthly average wind speed based on number of month, monthly mean air temperature, relative humidity, and vapor pressure. Siahpoosh wind farm is considered as a case study in the present work.
Keywords: Multi Layered Perceptron Neural Network (MLP); Genetic Algorithm (GA); Wind Speed Prediction. Siahpoosh Wind Farm.

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INTRODUCTION

Different kinds of methods are proposed by researchers to forecast wind speed (See [1-) Wind speed forecasting methods are classified into different categories: Physical models, Spatial Correlation models, Conventional Statistical models, and Artificial Intelligence models. In the last decade, Artificial Intelligent models are widely used to forecast wind speed [1]. Rehman and Halawani 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]. Cadenas and Rivera compared autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN) techniques to predict the wind speed in the south coast of Oaxaca, Mexico [3]. Jafarian and Ranjbar used Fuzzy modeling techniques and artificial neural networks to estimate annual energy output of a wind turbine in Netherlands [4]. Guo et al., applied a hybrid time series approach for wind speed prediction in Hexi Corridor of China [5]. Pourmousavi and Ardehali used artificial neural network–Markov chain model for very short-term wind speed prediction [6]. Bivona et al., presented stochastic models for wind speed forecasting in Italy [7].

Barati et al., presented a wind speed model using multilayer perceptron neural networks for South Coasts of Iran [8]. In a different work same authors used Genetic Algorithm (GA) to train an MLP network to predict wind power for same location [9]. In both works, they used month of the year, monthly mean daily air temperature, relative humidity and vapor pressure data as input and monthly mean daily wind speed as the output of the network. The measured data between 1994 and 2003 were used as training and the remained data (i.e. 2004 and 2005) used as testing dataset. Sancho et al., suggested a method of exploiting the diversity in input data using banks of artificial neural networks for accurate short-term wind speed prediction, which yields better results compared to those obtained from a system using single neural networks [10]. Riahy and Abedi presented a new linear prediction method for short-term wind speed forecasting. They used a linear prediction method in conjunction with filtering of the wind speed waveform to forecast wind speed based on the observation that filtering out less effective frequency components from a wind speed spectrum can increase the correlation between real and predicted winds [11]. Mohandes et al., introduced a support vector machines (SVM) algorithm for wind speed prediction and compared its performance with multilayer perceptron (MLP) neural networks. The results indicated that SVM compares favourably with the MLP model based on root mean square error testing between actual mean daily wind speed data from Madina city, Saudi Arabia and predicted data [1]. Mohammad et al., proposed a new strategy in wind speed prediction based on fuzzy logic and artificial neural networks. They trained their new strategy on real wind data measured in Rostamabad in northern Iran from 2002 to 2005 [12]. The experimental results demonstrated that the proposed method not only provided

significantly less rule base but also increased the estimated wind speed accuracy when compared to traditional fuzzy and neural methods. Barbounis and Theocharis proposed a locally feedback dynamic fuzzy neural network (LF-DFNN) model using spatial wind speed information from remote measurement stations at wind farms to estimate multi-step ahead wind speed from 15 min to 3 h ahead. Furthermore, they trained the LF-DFNN models using an optimal online learning scheme, the decoupled recursive prediction error algorithm (DRPE). It was shown that DRPE outperformed three gradient descent algorithms: the back propagation through time, real-time recurrent learning, and recursive back-propagation algorithms, in training of recurrent LF-DFNN forecast models [13].
This study hybridizes two types of Artificial Intelligent techniques (i.e. Multi Layered Perceptron Neural Networks (MLP) and Genetic Algorithm (GA)) to forecast wind speed. Manjil station is considered as a case in the present work.

HYBRID MLP-GA

Genetic Algorithms (GAs)

Genetic Algorithms (GAs) use operators inspired by natural genetic variation and natural selection to evolve a population of candidate solutions. 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 [14]. In canonical GAs, 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 are 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 can be found in [13-17].

Multi Layered Perceptron Neural Networks (MLPs)

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. Any how, the architecture of an artificial neural network is simpler than a biological brain [18].
The multi layered 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. 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 [19- 21].

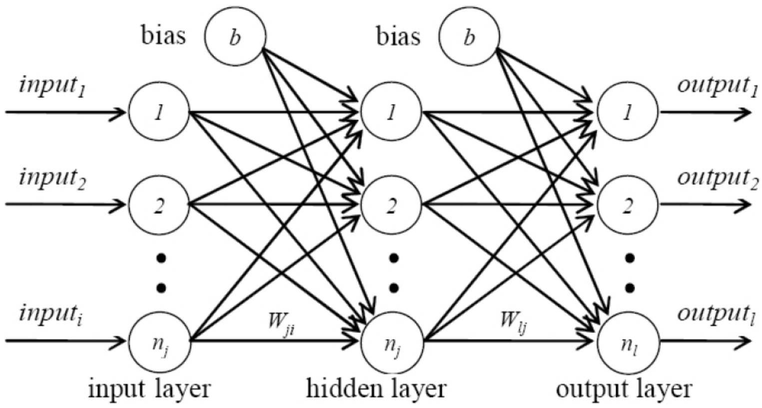

Figure 1. Feedforward neural network with one hidden layer.

Optimization of neural networks

The training of a neural network involves the minimization of an error function. 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. The aim of the GA is to find the genes producing the smallest value of the error function. The MLP network training procedure using GA thus comprises the following steps:

1- Generate an initial population of chromosomes.

2- Apply the training data set to determine the value of the error function associated with each chromosome.

3- Based on the error value obtained in step 2, apply genetic operators (i.e. selection, crossover, mutation, and etc) to create new and fitter population.

4- Stop if the value of the error function has fallen below a predetermined threshold or after completing a set number of generations.

5. Else, return to step 2.

Data description

The observed data between 1997 and 2009 collected by Siahpoosh wind farm located in Manjil station were used in this study (partly for training the neural networks (1997- 2003) and partly for testing (2004- 2009). All data (input/output) were normalized in range [0.1, 0.9]. Figures 1 to 3 show the Wind statistics and the Weibull distribution of the wind farm.

RESULTS AND DISCUSSION

In this section, NeuroSolutions Software by NeuroDimensions Inc., was adopted to optimize Multi Layered Perceptron Neural Networks using Genetic Algorithm.

The performance of GA was satisfactory using the following user-specified parameters:

Population Size: 50

Selection: Roulette

Crossover: One Point with Crossover Probability: 0.9

Mutation: Uniform with Mutation Probability: 0.01

Maximum Generation: 100

In order to determine the optimal network structure, various network architectures were designed and the number of neuron and hidden layer were changed. A network with **4-12-1** architecture was found to perform reasonably good predictions.

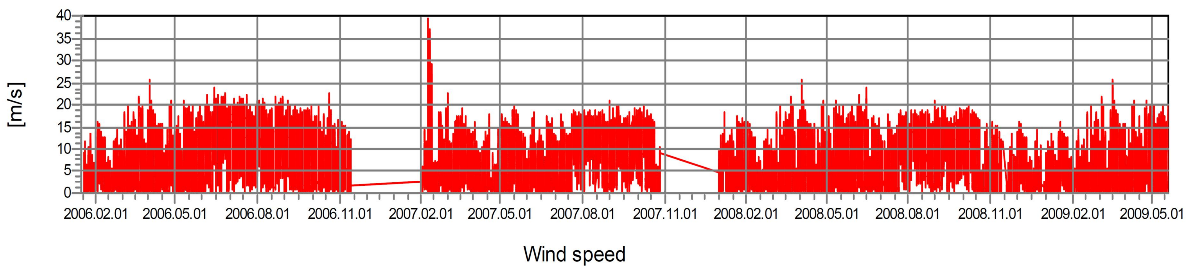

Figure 1. daily wind speed data for Siahpoosh wind farm.

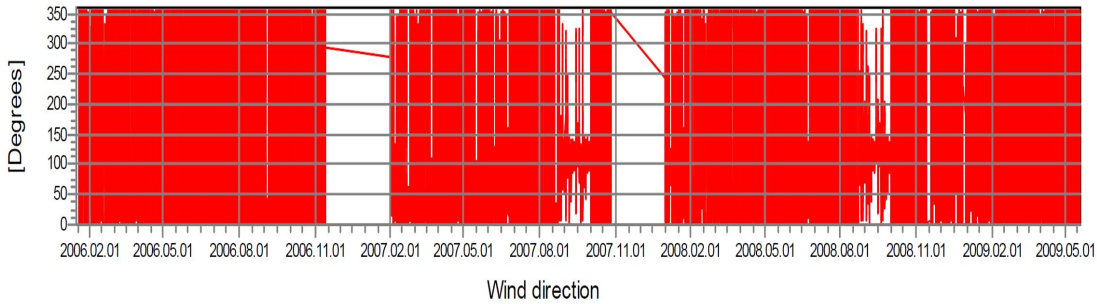

Figure 2. daily wind direction data for Siahpoosh wind farm.

Correlation coefficient (r), mean squared error (MSE), normalized mean squared error (NMSE), mean absolute error (MAE), minimum absolute error (MINAE) and maximum absolute error (MAXAE) were used as statistical indices to accomplish the performance of the models. Table 1 shows the architecture, training and testing errors for MLP-GA model. As it can be seen in this Table, the correlation coefficient (r) is about 90.93%. Figure 2 shows the comparison between measured and predicted wind speed values on testing period for MLP-GA model.

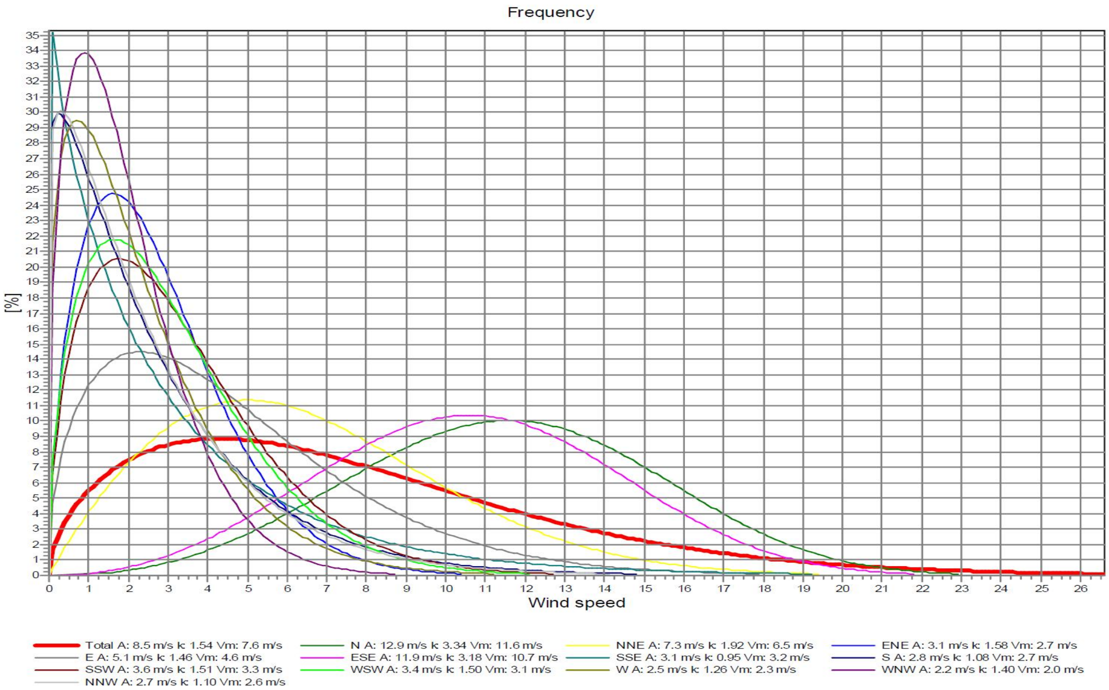

Figure 3. Weibull distribution analysis for Siahpoosh wind farm.

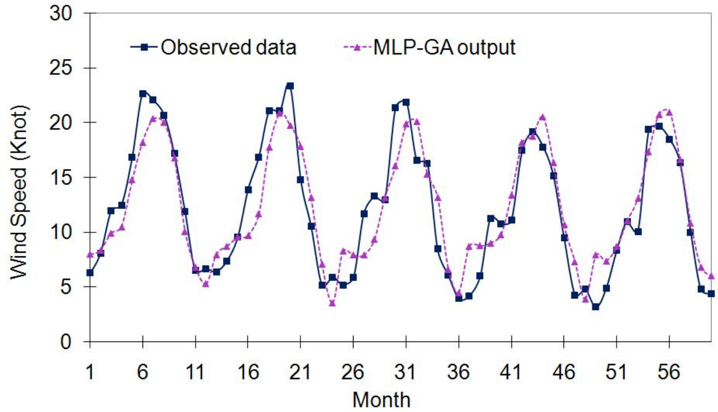

Figure.4. Comparison between observed and predicted values of wind speed on testing period for MLP-GA model.

Table2. Performance of MLP-GA model on train and test data sets.		
statistical indice	Train	Test
MSE	0.006540833	9.93245069
NMSE	-	0.27333121
MAE	-	2.24191911
Min Abs Error	-	0.01151728
Max Abs Error	-	9.54760032
r	-	**0.89009319**

CONCLUSION

GA algorithm was successfully used to train a MLP network in order to predict wind speed based on simple meteorological variables. Collected data by Manjil station, located in Gilan province, was used to demonstrate the developed method. The results showed that the predicted wind speed values were in good agreement with observed data. Future work is focused on comparing the methods presented here with the other available tools. Predicting of wind speed can also be investigated with neural networks trained with other intelligent optimization techniques like Bees Algorithm (BA), Gravitational Search Algorithm (GSA), Cuckoo Search (CS) algorithm, Imperialist Competitive Algorithm (ICA) and etc. The results of the different methods can be compared with available methods.

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