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Comparison of different neural network training algorithms for wind velocity forecasting

MortezaKhalajiAssadi [1, a*], ShervinSafaei [2, b]

[1]Mechanical Engineering Department, UNIVERSITI TEKNOLOGI PETRONAS(UTP), Malaysia

[2]Faculty of Environmental and Energy Sciences, Science and Research Branch, Islamic Azad University, Tehran, Iran

[a]morteza.assadi@petronas.com.my, [b]shervinsafaie@gmail.com,

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Abstract

In this paper the wind speed is predicted by the use of data provided from the Mehrabad meteorological station located in Tehran, Iran, Collected between 2003 and 2008. A comprehensive analogy study is presented on Comparison of various Back Propagation neural networks methods in wind velocity forecasting. Four types of activation functions, namely, BFGS quasi-Newton, Bayesian regularized, Levenberg -Marquardt, and conjugate gradient algorithm, were studied. The data was investigated by correlation coefficient and characterizing the amount of dependency between the wind speed and other input data. The meteorological parameters (pressure, direction, temperature and humidity) were used as input data, while the wind velocity is used as the output of the network. The results demonstrate that for the similar wind dataset, Bayesian Regularized algorithm can accurately predict compared with other method. In addition, choosing the type of activation function is dependent on the amount of input data, which should be acceptably large.

1. Introduction

Energy is an essential element in the social and economic development of each country. Nowadays, the amount of fossil fuels availability is decreasing in the world wide. Fossil fuel consumption causes many negative effects in the environment such as climate change due to the large amount of Carbon Dioxide emission into the atmosphere. Therefore, renewable energy sources are globally welcomed due to their low environmental pollution. The benefits of renewable energy are sustainability, being available everywhere and without any pollution. In particular, wind energy is gaining considerable popularity worldwide[1].Power generation rate of wind turbines varies according to several factors, such as wind velocity and direction, and also meteorological parameters, such as temperature, pressure, density and humidity. Therefore, it is extremely essential to be able to predict wind velocity for the next few hours. Because of the continuous speed fluctuations, it seems imperative to find the effecting parameters and the relative factors. Artificial neural network (ANN) is one of the approaches used in academia to estimate hourly approximate values of wind power generators [2].Nowadays, forecasting methods and modeling procedures are geared toward using more parameters by the use of neural networks. The neural network models trained with time series have the ability to model arbitrarily linear and nonlinear functions. ANN is a Methodology used to map input vector(s) to the corresponding output vector randomly without pre supposing any fixed relationship between them. ANN can learn from past data, recognize hidden patterns or relationships in past observations and use them to predict future values [3].We believe various network structures, learning rates, and inputs result in different prediction precision. By contrast, in literature usually only BP models are used for wind speed prediction, and consequently the final conclusions regarding the function of ANN model in wind speed forecasting may be seriously misleading. A thorough investigation is required on the selection of kind of neural network and parameters of model regarding multiple evaluation criteria and multiple datasets from different sites. To bridge the research gap, this paper aims to analyze and draw an analogy between the performances of four typical ANN techniques, namely, BFGS quasi-Newton(BFG),Bayesian regularized(BR), Levenberg –Marquardt(LM), and conjugate gradient algorithm(CGB) Neural Networks, in 1-h-ahead wind speed forecasting.

This paper is organized as follows: Section 2 describes the analysis of wind speed in Mehrabad station, together with a brief description of the data used in this study. Section 3 introduces our method of wind velocity. Simulation results are presented and discussed in Section 4. Finally, Section 5 highlights the findings and concludes the paper.

2. Analysis of Wind Inputs

The Mehrabad meteorological station located in the west of Tehran Great City, - Iran, precisely located at the latitude of 35°41″ and longitude of 51° 19″. In this paper, meteorological data is chosen within a period of three hours provided.All The data have been collected for a period from the year 2003 to 2008.Fig.1show the hourly wind speed time series in the Mehrabad station.The selected data and variables including humidity, wind direction, ambient air temperature and atmospheric pressure are used as inputs to the neural network. A correlation coefficient has been used to find out the relationship between the input meteorological data and the wind velocity. Also it is used to select the methods that parameters are input to the neural network [4].

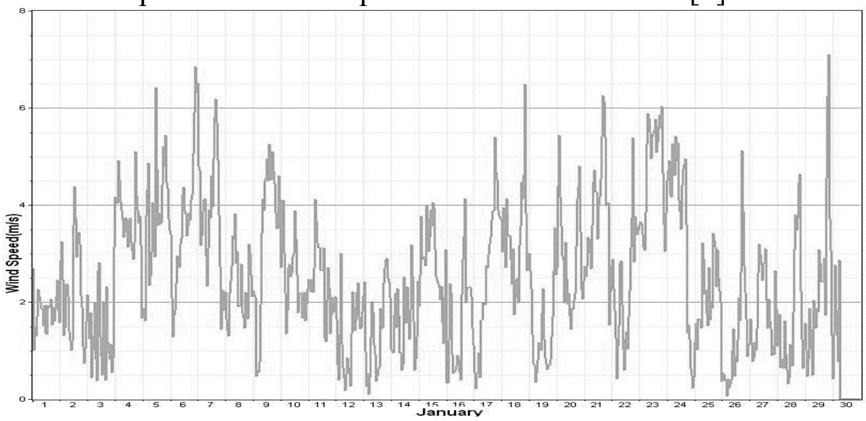

Fig.1. Hourly wind speed time series of the Mehrabad station

In this study, various criteria have been used to determine the accuracy of prediction, such as, the Mean Squared Error (MSE) and the Mean Absolute Percentage Error (MAPE). MAPE is a common index, which shows the difference between predicted values of a model and its observed cases. In this paper, Eq.1 has been used to determine the MAPE. [4]

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} abs(\frac{o_i - t_i}{o_i}) \times 100 \quad (1)$$

where o_i is actual value and t_i is the predicted value.

3.Artificial Neural Network

Correct forecast of wind velocity is crucial for installing wind turbines. Artificial neural networks are a network system which based on simulation of human learning behavior. A neural network usually consists of an input layer, a number of hidden layers and an output layer. [5].the data enters the network from the input layer to the output layer through the hidden layer. Typical multilayered neural network and an artificial neuron are illustrated in Fig 2[6].

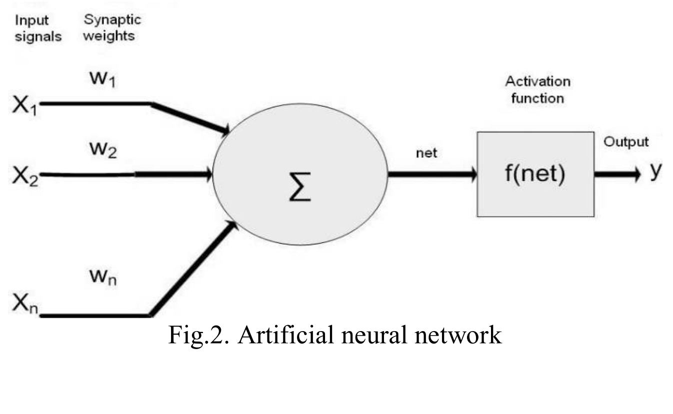

Fig.2. Artificial neural network

The neuron output signal y is given by the following relationship, as shown in Eq.2:

$$y = f\left(\sum (x_1 w_1 + x_2 w_2 + x_3 w_3 + \ldots) + \beta\right) \quad (2)$$

where y is the output from neuron; x_1; x_2; x_3,... are the input values; w_1; w_2; w_3,... are the connection weights; β is the bias value; f is the transfer function. Two commonly used neuron activation functions for the neuron are sigmoidal and tansig functions. Both functions are continuously differentiable everywhere and typically has the following mathematical form:

Sigmoidal: $$f(x) = \frac{1}{1+\exp(-ax)}, a > 0 \quad (3)$$

Tansig: $$f(x) = a\tan(bx), a \,\&\, b > 0 \quad (4)$$

3.1. The Back Propagation Class of Neural Networks

The back propagation method is a technique used in training multilayer neural networks in a supervised manner. The back propagation method, also known as the error back propagation algorithm, is based on the error-correction learning rule [7]. It consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activity pattern is applied to the input nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the networks are all fixed. During the backward pass, the synaptic weights are all adjusted in accordance with an error-correction rule.[8]

4. Model Inputs and Parameters

ANN architecture used in this study for Mehrabad meteorological station is shown in Fig. 3. The input data, which are the temperature, pressure, wind direction and humidity, have been illustrated in the Fig.3 The wind velocity is as a target function. The mentioned parameters were input into the software as individual inputs, whenever their error was not acceptable. In the next step, two inputs, for instance temperature and humidity, were given to the software, where their error was not acceptable either. Therefore, the result of individually and commonly choosing every parameter indicated that all parameters should be input into the MATLAB software simultaneously.

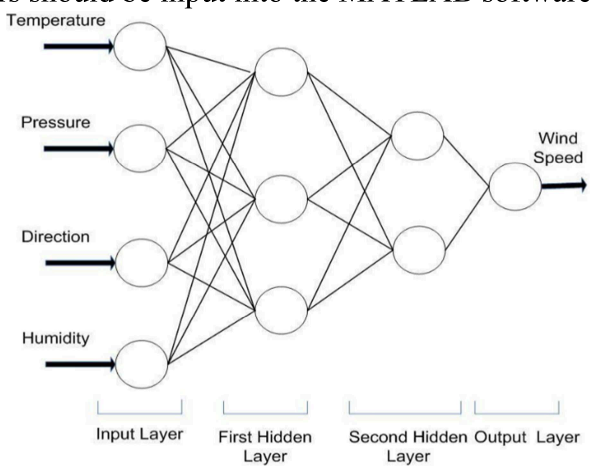

Fig.3. Structure of neural network

5. Results and Discussion

The data of five year is divided into several windows where half of them (non-consecutive ones) are used for training and the other half is used for testing the ANN. All inputs and outputs are normalized before training. In this study the number of the selected is chosen by trial and error and also with respect to our previous experiences. In addition the number of input neurons depends on the number of effective factors in wind velocity prediction. Different layers of a 3 layer neural network are used in all stages considering the application of methods and the selection of neurons. Therefore, in building the ANN models for forecasting wind speed, factors such as the model inputs and learning rates, should be properly determined since this decision directly affects the forecast accuracy. In this study it is used a BP neural network to determine the trend in the daily wind speed series. Each training input data came with a desired output. The four BP methods that we used are the BFGS quasi-Newton (BFG), Bayesian Regularized(BR), Levenberg –Marquardt(LM)and conjugate gradient algorithm(CGB).By extensive calculation, the results confirmed that different learning rates or spread constants, as well as different number of inputs, can result into value in terms of MAPE. Fig 4, 5, 6 and 7 show the wind velocity prediction with method which cited them.

From these figures, artificial neural networks clearly seem to get trained with various inputs or at different learning rates exhibit varying levels of accuracy in forecasting the wind speed. For Mehrabad site, the MAPE values are listed in Table 1. It can also be noticed that the sorts of ANN models may affect the predicting accuracy. In the literature, the vastly-used type of ANN model for wind speed forecasting is BP, and it types have been less studied. This presents an important challenge on which methods are better to use in practice. Moreover, amongst all tested models, one result is gained. For example, in fig .4 Wind velocity forecast has been conducted by using the training function BFG which has the error of 28% for a 2-month time period (July and March) in 2007.

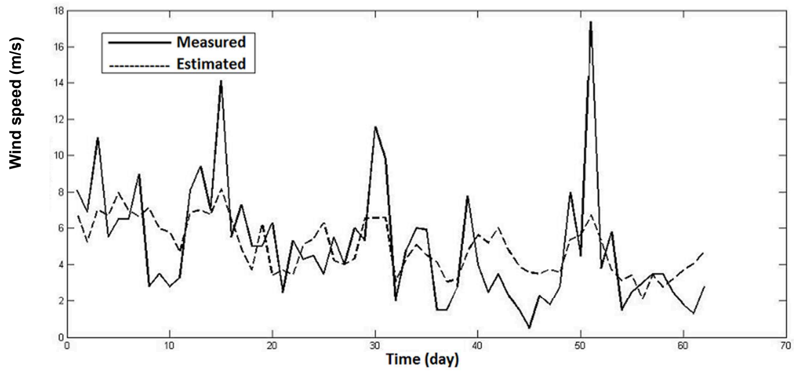

Fig. 4. Comparison between prediction of (BFG with tansig) and actual results for Mehrabad station

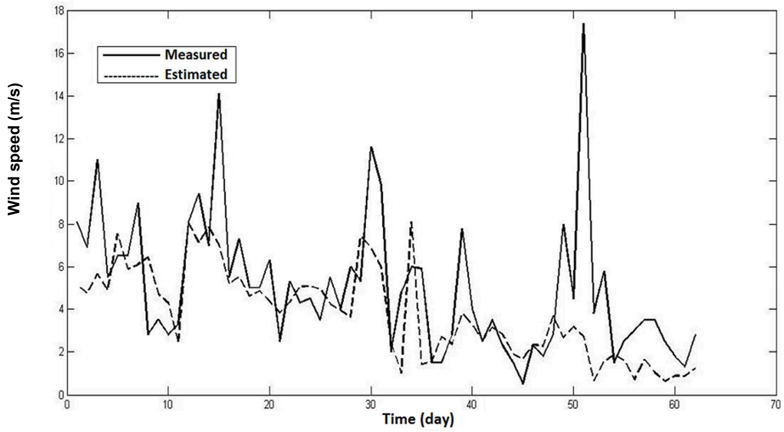

Fig.5.Comparison between prediction of (LM with tansig) and actual results for Mehrabad station

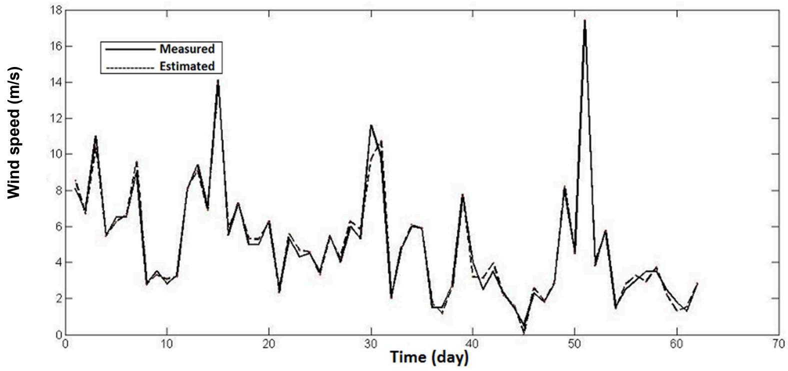

Fig.6. Comparison between prediction of (BR with tansig) and actual results for Mehrabad station

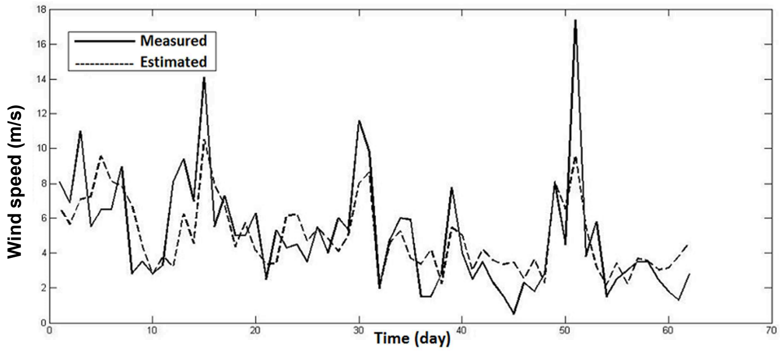

Fig.4. Comparison between prediction of (CGB with tansig) and actual results for Mehrabad station

Table.1 Different Back Propagation neural networks methods in terms of MAPE for Mehrabad site.

Training Algorithm	Transfer function		MAPE %
	Hidden Layer	Output Layer	
BR	Tansig	Linear	5
BFG	Tansig	Linear	28
LM	Tansig	Linear	26.8
CGB	Tansig	Linear	25.2

For each one of ANN models (BR, CGB, BFG and LM), the effects of alternative inputs and learning rates were examined in terms of multiple performance metrics. It was understood that, different inputs and learning rates, as well as model structures, directly affect the forecast accuracy. It can also be observed that the BR models may incredibly affect the forecasting precision, according to the result.

6. Conclusion

The goal of the present research is to analyze of four algorithms based on Back Propagation neural network. The main focus was on emphasizing the diversity of various forecasting methods available and also on providing a comparison of present mechanisms to determine the best available. Results show that the neural networks model trained using Bayesian Regularization provide that the best results. The best mean error level of our approach was 5%, which is within acceptable range. We conclude that our approach can be utilized to forecast wind velocity in a target station considering the input data for required times steps. Finally, it is advisable to observe that the developed models can be used to forecast wind speed velocity.

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