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Short-term wind speed forecasting using feed-forward back-propagation neural network

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Abstract

This paper deals with a neural network approach for Short term wind speed forecasting. Now a day, short-term wind speed forecasts have become gradually more important for the power system management or energy trading due to the large penetration of wind power technology and development of wind energy markets. In this new era, short-term wind speed forecasting is necessary for producers and consumers to become stable in the electricity market as in the electricity grid at any moment balance must be maintained between electricity consumption and generation. In this paper, a multi-layered feed-forward artificial neural network, trained by the resilient back propagation (Rprop) learning algorithm has been used for hourly forecasting of wind speed in the region of Canada.

Keywords: Wind Speed Forecasting, ANN, Feed forward Back propagation, Resilient back propagation learning algorithm

1. Introduction

The energy is a vital input for the socio-economic development of any country. With the development of agricultural and industrial progress and increasing demand for energy it has become necessary to use renewable sources of energy like wind energy as an important source of electricity. Wind is caused by large-scale movements of air generated principally by differences in the temperature within the atmosphere due to differential solar heating (Manwell *et al*, 2009). The wind energy is free, so all wind-generated electrical energy is accepted as it comes, i.e. as wind is available. However, its availability is not known in advance. Because of the increasing access of wind resources in power systems, efforts have been made to forecast the wind activities and the corresponding electrical energy production (Ferreira, 1992). Short-term wind speed forecasting is an extremely important field of research for the energy sector, as the system operators must handle an important amount of fluctuating power from the increasing installed wind power capacity. The time scales concerning short-term prediction are in the order of some days and from minutes to hours (Costa *et al*, 2008, Khotanzad *et al*, 1998). Earlier reported approaches to forecast of wind speed were mainly based on Numeric Weather Predictions and Time series models.

Artificial Neural Network (ANN) techniques are relatively easy to implement and shows better performance in short-term wind forecasting, being less time consuming than conventional time series techniques. Three-layered feed-forward neural networks are specially suited for forecasting implementing nonlinearities using sigmoid functions for the hidden layer and linear functions for the output layer. The feed-forward back-propagation (FF-BP) neural model using a logistic activation function, a linear output function with the resilient back-propagation learning algorithm proved a good design for the short term forecasting of wind speed.

This paper presents a flexible application of using an ANN approach to forecast short-term wind speed of weather station at Canada. Section 2 shows the availability of forecasting methods around the world. Section 3 describing the ANN Model used specifically for the data with the system architecture. In Section 4 there is a source of Data collection and the criteria used to select the input variables. Section 5 presents training of the feed-forward back-propagation neural network as measured by the mean square error of values (Fig. 3). Section 6 demonstrates the simulation and results (Fig. 4, Fig. 5 and Fig 6). Finally, Section 7 summarizes the conclusions.

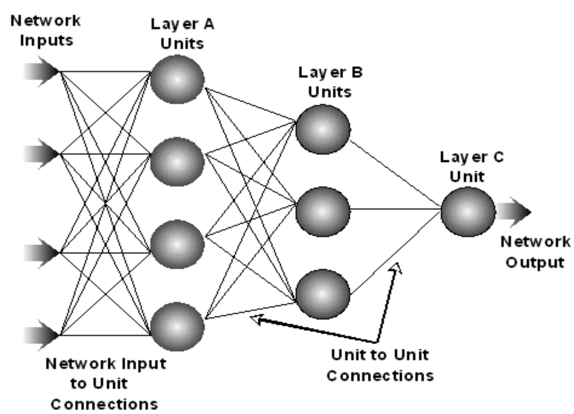
2. Available Forecasting Methods

Wind speed forecasting plays a very important role especially in areas of wind generation. Various forecasting techniques based on Numeric Weather Prediction (NWP) methods, Artificial Neural Networks (ANNs) methods and Hybrid methods have been used in wind forecasting.

3. ANN Model Used

Artificial Neural Networks (ANNs) is an information processing paradigm that consist of networks of many simple processors (units) operating in parallel, each possibly having a small amount of local memory. A *multilayer perceptron* neural network, with feedforward architecture with three layers of units is used due to its status and capacity to solve large amount of problems. The algorithm used for the training is the well known *back-propagation* method (Haykin, 2003). Fig. 1 depicts the feed-forward neural network which is used. This neural network shows the first layer (layer A) and the second layer (layer B), which are called hidden layers. This network has one unit in the third layer (layer C), which is called the output layer. Each network-input-to-unit and unit-to-unit connection (the lines in Figure 1) is modified by a weight. In addition, each unit has an extra input that is assumed to have a constant value of one. The weight that modifies this extra input is called the bias. All data propagate along the connections in the direction from the network inputs to the network outputs, hence the term *feed-forward* (Negnevitsky, 2002).

Figure 1. A three-layer feed-forward neural network



In this work neural networks with several architectures were trained and validated using the cross-validation method. This method consists of performing the optimization of the weights, i.e., finding the set of weights that minimizes the mean square errors (MSE) between the obtained outputs and the desired ones, with a training set of patterns and in every epoch comparing the value for the MSE obtained with a different set. The second set is usually known as the validation set and the training is stopped when the MSE in the validation set starts to increase. Each network is trained with the back-propagation algorithm with different iterations or epochs in a batch situation. The influence of the number of epochs and the number of neurons in the hidden layer into the neural net performance is observed. The smallest MSE validation is obtained with the neural network of 24 neurons hidden layer and trained during 100 epochs. As a consequence the structure adopted for the neural network has an entrance layer with 24 inputs, two hidden layers with 12 and 6 neurons respectively and an output layer with 1 neuron. Short term wind speed forecasting with FF-BP involves following steps:

- Data Assembling & Pre-processing
- Data Conversion & Normalization
- Statistical Analysis
- Design of Neural Network object
- Training of Network
- Simulation of network response to new inputs
- Validation
- Testing

4. Processing of Data

All of the hourly average data were collected from the web site of weather station Goderich which is located at the Ontario province, Canada (Giebel *et al*, 2003) and processed for loading into the neural modeling application MATLAB Neural Network Toolbox (Release 2007a), running on a personal computer using the Windows 7 operating system with 3 GB RAM. Data were normalized, patterns were generated and statistical analysis was performed for good correlation among the input data values (Larson *et al*, 2004). A large part of the data is fed into the training network and the remaining part into the testing network.

4.1 1nput Variables and Selection: The most important tasks in building an ANN time series forecasting model is the selection of the input Variables. Although for the models, there is no systematic approach suggested which could be followed, certain statistical parameters can be used to determine the relevant inputs. In this paper, statistical analysis is carried out to find the amount of dependency between each of the meteorological values and to get rid of the redundant values that might be present in the data set by applying "*Spearman rank correlation*" method. The purpose of obtaining the correlation is to measure and interpret the strength of a linear or nonlinear relationship between two continuous variables. Both correlation coefficients take on values between -1 and +1, ranging from being negatively correlated (-1) to uncorrelated (0) to positively correlated (+1). The sign of the correlation coefficient (i.e., positive or negative) defines the direction of the relationship. The absolute value indicates the strength of the correlation. The list of different input variables are prsented in theTable 1 and the results of Correlation are prsented in theTable 2. A correlogram study was also performed for cross correlation between Temperature and wind speed as shown in Fig. 2.

Table 1. List of different input variables

S.No.	Input Variables	Units
1.	Temperature	Deg.C
2.	Dew Point Temperature	Deg.C
3.	Relative Humidity	%
4.	Wind Direction	10's Deg
5.	Wind Speed	Km/h
6.	Station Pressure	Kpa

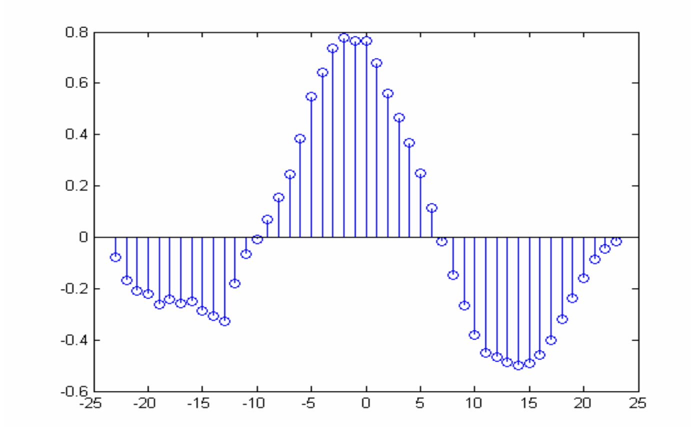


Figure 2. Temperature Vs wind speed

4.2 Data Preprocessing and Post processing: The capacity to learn from examples is one of the main characteristics of the neuronal networks; consequently the network finds a relation between the values of wind presented on its inputs and the outputs. This learning technique is known as supervised learning. All neural networks take numeric input and produce numeric output (Negnevitsky *et al*, 2006). The transfer function of a unit is typically chosen so that it can accept input in any range, and produces output in a strictly limited range. Although the input can be in any range, there is a dispersion effect so that the unit is only sensitive to inputs within a fairly limited range. In this method one of the most common transfer function, the logistic function is used.

Table 2. Results of correlation

Correlation	Wind Speed	Temperature	Humidity	Dew Point Temperature	Wind Dir	Wind Chill	Station Pressure
Wind Speed	1						
Temperature	0.8	1					
Humidity	-0.8	-0.8	1				
Dew Point Temp.	0.8	0.9	-0.4	1			
Wind Direction	0.4	0.2	0	0.1	1		
Wind Chill	0.7	0.9	-0.6	0.8	0.8	1	
Station Pressure	-0.7	-0.8	0.5	-0.7	0.1	-0.8	1

5. Training Algorithm

The Back propagation which is the best-known training algorithm was used (Jursa *et al*, 2008). During the training of neural network, the algorithm progresses very slowly along a steep, narrow, valley, bouncing from one side across to the other. Using very small steps may direct the training in the correct direction, but that also require a large number of iterations (Romero *et al*, 2007). The algorithm therefore progressed iteratively, through a number of epochs. On each epoch, the training cases are submitted to the network, and target and actual outputs compared and the error calculated. This error, together with the error surface gradient, is used to adjust the weights, and then the process repeats. The initial network configuration is random and training stops when a given number of epochs reach an acceptable level. The network model configuration set epoch number to 100, the resilient back-propagation learning algorithm set to a learning parameter of 0.01 and a logistic neural activation function. All variables were standardized by normalization of means and standard deviations. Training was governed by minimizing the mean square error between observed and predicted. Figure 3 illustrates the mean square error during training.

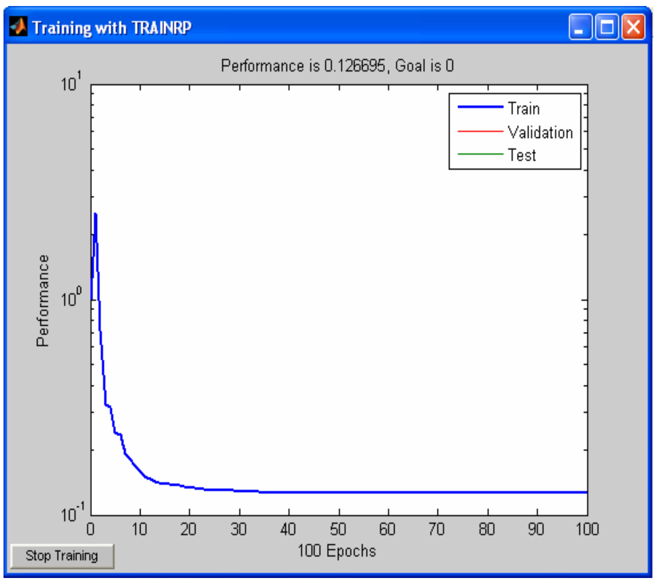


Figure 3. Performance curve using Training function of 100 Epochs

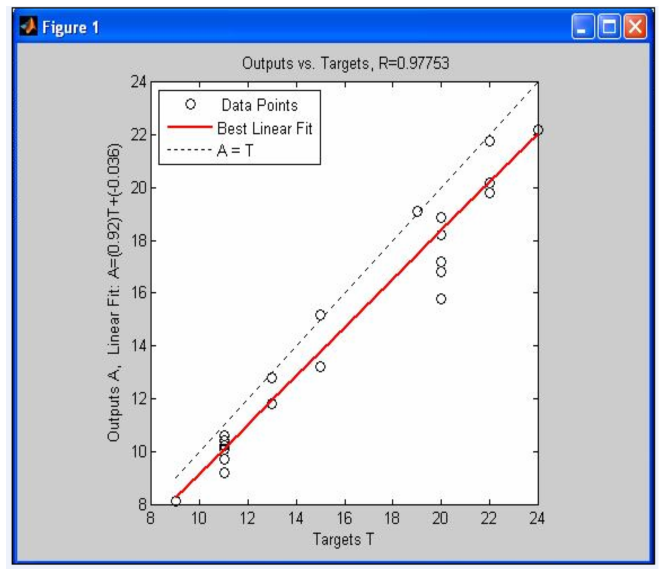


Figure 4. Linear regression of the Actual (A) and Target (T) wind speed using feed-forward back-propagation Neural network

6. Simulation and Results

The data set is comprised of first, second, third, fourth and fifth day (24 hour per day) of the January month (year 2009), as the input and target output or predicted variable. One fourth of the total data was selected for training, one fourth for validation and the remaining one half for testing. Network performance was estimated by linear regression between the actual and target wind speed after Post-processing (Fig. 4). For an independent assessment of the network the results of the verification month of January (year 2009) are presented. The required data for this year are prepared and filtered. The results are shown graphically in Fig. 5. For more accurate evaluation of the ANN performance, the following absolute percentage error (e) is used and defined as:

$$e = \frac{\text{Actual wind speed- forecasted wind speed}}{\text{Actual Wind speed}} \times 100 \qquad (1)$$

The maximum percentage error for January 4, 2009 is 5.24 %. However, an average of this absolute error over a period of time may be used for an overall evaluation and comparison with other neural network models. The optimum network architecture with minimum Mean Absolute Percentage Error (MAPE) of 3.81% also plotted in Fig. 6.

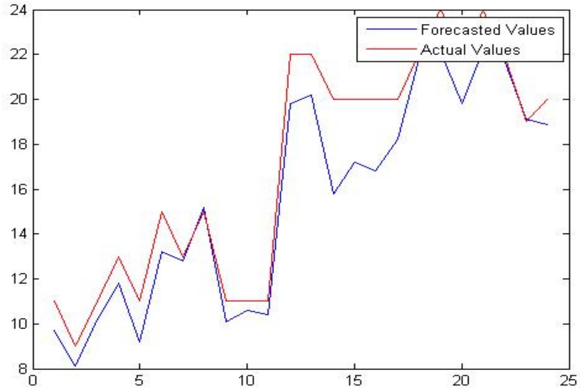


Figure 5. Forecasted (24 hours) wind speed compared to actual values

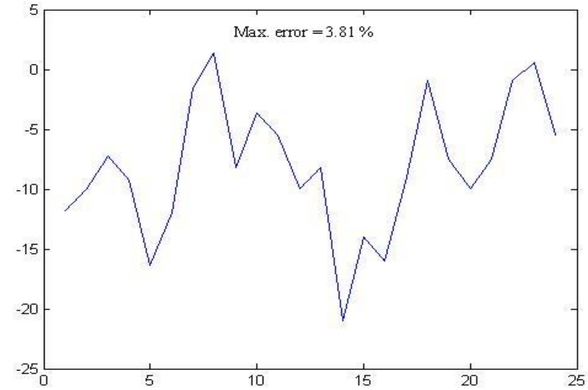


Figure 6. Error in wind speed forecasting for 24 hours

7. Conclusions

The study of the wind speed forecast is of great importance for the operators of the energy power grids because the production and utilization of the wind energy. The deviation of the wind throughout the day it is necessary to have an idea of the production of energy from wind turbines, mainly in grids with great installed capacity of this type of renewable power plants as expected. The application of a feed-forward back-propagation artificial neural network to the wind speed data of Canada indicated its practicality to forecasting of wind speed and other variables. The feed-forward back-propagation neural model using a logistic activation function, a linear output function with the resilient back-propagation learning algorithm proved a good design for the short term forecasting of wind speed. This method does not intend to replace the meteorological models, but to be applied without the need of meteorology data. For the management of the production reserve that will have to be available to cover the variations of production due to variation of the speed of the wind, in future works it will be necessary to refine the set of patterns for trainings, adding to it, other data that might be considered useful for the forecast of the wind, namely Air temperature, Dew Point Temperature, Relative Humidity, Wind Direction and Station Pressure.

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