Performance Analysis of Artificial and Wavelet Neural Networks for Short Term Wind Speed Prediction

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Abstract

In recent years, the importance of integrating the production of wind energy into electrical energy networks has been increasing rapidly. The biggest challenge to integrate wind energy into the power grid wind power is variability and discontinuity. To deal with this situation, the best approach is to predict future values of wind power production. Wind speed estimation methods with high accuracy are an effective tool that can be used to minimize these problems. This paper presents a short-term wind speed prediction using artificial neural network (ANN) and wavelet neural network (WNN) and compares the performance of these networks. Data are collected from a weather station located in Ondokuz Mayis University in ten minute resolution for a period of one year. Wind speed predictions are presented within a period of 24-hours for 10 minute ahead. Although ANN and WNN use the same topology, the performance of the proposed prediction system based on WNN has higher than that of ANN. The root mean square error (RMSE) and the mean squared error (MSE) values have been selected as performance criteria.

1. Introduction

Wind energy is one of the fastest growing renewable electricity and electricity generation from wind increases by a factor of 13 worldwide. Many countries are increasing their installed capacity of renewable wind generation [1]. But the wind is random and fluctuant, when wind power penetration over a certain value, there will be a serious influence on power quality and the operation of power systems [2]. Therefore, to estimate wind speed / wind energy more accurately is one of the hot topic at the moment. For example, in the case of a competitive energy market, for many reasons the right wind forecast has always been attractive. Firstly, depending on the imbalance of market price, the price of energy market is incentive. Secondly, a good production estimate for before an hour or a day can help to improve the functioning markets [3, 4].

The developments of wind power prediction methods have important technical and economic advantages. For example, methods used to calculate the probability of energy costs, estimate of the error associated with wind generators. Error estimated costs, wind power sales to reach 10% of total revenue [5]. Probability of wind energy in the very short term and short term forecasts; the uncertainty of estimates based on the best information appears to be a general method for bidding strategy [6].

Classification of the wind estimates methods based on time scale does not create certainty. The short term and very short term forecasts, including ten-minute-ahead, one-hour-ahead, and one-day-ahead predictions, have been taken into account respectively. This prediction module will be developed with statistical models and Artificial Intelligence (AI) technologies respectively to capture the relations between input variables and the output valuable, such as future total wind farm power.

2. Literature Review

The last decade, more attention to very short term wind estimation have been focused on the non-linear models [8]. Hoppmann et al [9] developed a system for short term wind speed prediction on the basis of continuous wind measurements at distinct locations of a high-speed railway line. Every 20 minutes, the average and standard deviation of wind speed of the last 10 minutes is calculated in this method.

Reference [10], Potter et al described an adaptive neuro-fuzzy inference system (ANFIS) to estimating very short term wind speed prediction. The persistence model was developed using the same data to provide comparison. The ANFIS shows a large reduction in mean absolute percentage error for the same data.

Riahy et al [11] recommended a new technic, based on linear prediction for very short term wind speed estimation. The method utilizes the linear prediction method in conjunction with filtering of the wind speed waveform. Real wind speed data based on experimental results is applied for verification. The results show significant performance of the proposed method.

Reference [12] proposed a new integrated method utilizing Wavelet-based networks and Particle Swarm Optimization (PSO) forecasting very short term wind speed prediction, where the PSO algorithm is applied for training a Wavelet networks. The proposed approach is compared to multilayer perceptron networks with Back Propagation training algorithm. Results show that the new approach improved forecasting accuracy.

In this study, we are interested in the artificial neural network (ANN) and the wavelet neural network (WNN) for wind speed forecasting. This paper presents two types of short-term wind speed forecasting models. The aim of this paper is to compare the forecasting performance for wind speed by using the actual meteorological data.

3. Artificial Neural Network (ANN)

The main principle of artificial neural networks puts forth that an input set is received then transformed into an output set. To succeed that the network needs to be trained to generate the convenient outputs for the presented inputs. The sample data which shall be presented to the network are at first transformed into a vector. This vector is offered to the network and network generates the required output vector for this particular vector. In every single iteration weight connections of network are regulated to generate the proper output.

Single layer feed forward network is the simplest form of feed forward networks. The single layer feed forward network consisting of only one layer of nodes at which computation is performed, frequently with only one node in this layer. This model also called as perceptron model. . A basic architecture of a perceptron model is shown in Fig. 1.

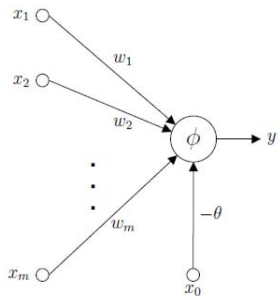

Fig. 1. Perceptron with *m* inputs

Typically multilayer feed forward network consist of a set of inputs as an input layer, one or more hidden layers and one output layer. The input signals are distributed in a forward direction on a layer-by-layer. The hidden neurons enable the network to learn complex nonlinear tasks. The multilayer feed forward network model is a generalization of single layer perceptron model and it is used for many applications. A basic architecture of a multilayer networks with two hidden layers is shown in Fig. 2.

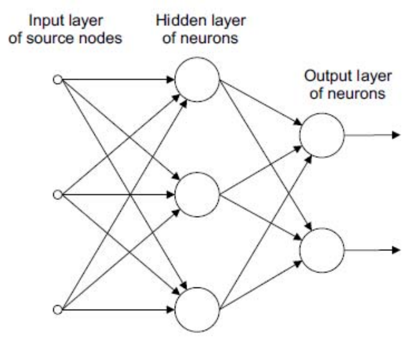

Fig. 2. Multilayer Feed Forward Neural Network

4. Wavelet Neural Network (WNN)

Wavelet neural networks combine the theory of wavelets and neural networks into one. A wavelet neural network generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family. One application of wavelet neural networks is that of function estimation. Given a series of observed values of a function, a wavelet network can be trained to learn the composition of that function, and hence calculate an expected value for a given input.

The structure of a wavelet neural network is very similar to that of a (1 + 1/2) layer neural network. That is, a feed-forward neural network, taking one or more inputs, with one hidden layer and whose output layer consists of one or more linear combiners or summers (see Fig. 3). The hidden layer consists of neurons, whose activation functions are drawn from a wavelet basis. These wavelet neurons are usually referred to as wavelons.

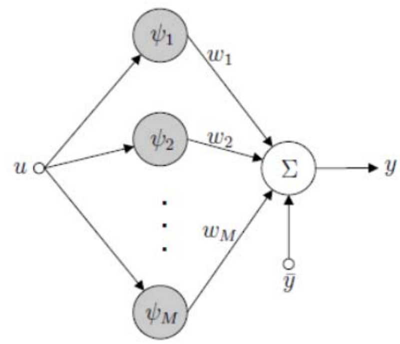

Fig. 3. A Wavelet Neural Network

There are two main approaches to creating wavelet neural networks. In the first the wavelet and the neural network processing are performed separately. The input signal is first decomposed using some wavelet basis by the neurons in the hidden layer. The wavelet coefficients are then output to one or more summers whose input weights are modified in accordance with some learning algorithm. The second type combines the two theories. In this case the translation and dilation of the wavelets along with the summer weights are modified in accordance with some learning algorithm.

In general, when the first approach is used, only dyadic dilations and translations of the mother wavelet form the wavelet basis. This type of wavelet neural network is usually referred to as a wavenet. We will refer to the second type as a wavelet network [7].

5. Case Study

In this study, a neural network method is developed to retrieve wind speed at 40 metres height. The used neural networks are the multilayer networks. The artificial neural network is a fully connected, forward feeding, multilayered perception that consists of one input layer, one hidden layer and one output layer. Levenberg-Marquardt is used for training data in the present study. The input layer has three neurons that correspond to the temperature, humidity and air pressure given. The first hidden layer has 10 neurons with hyperbolic tangent transfer functions and finally the output layer has one neuron with linear transfer function. The Artificial Neural Network's results as shown at Fig.4. The wavelet neural network has also the same topology but the first hidden layer has 10 wavelons with the Mexican Hat type activation functions. Results of 10 minute ahead, wind speed predictions are presented within a period of 24-hours. The Wavelet Neural Network's results as shown at Fig.5. The root mean square error (RMSE) and the mean squared error (MSE) values of each method as shown at Table 1.

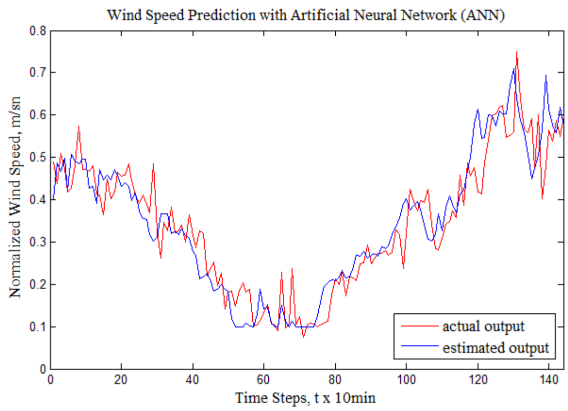

Fig. 4. Wind Speed Prediction with Artificial Neural Network

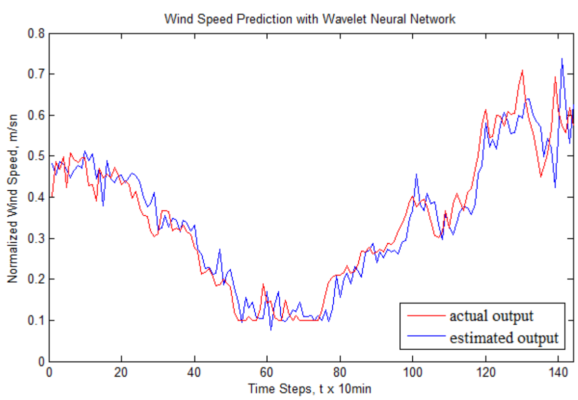

Fig. 5. Wind Speed Prediction with Artificial Neural Network

Table 1. Performance Criterion

	RMSE	MSE
Artificial Neural Network (ANN)	0.0627	0.0039
Wavelet Neural Network (WNN)	0.0527	0.0027

5. Abbreviations

ANN is Artificial Neural Network,
WNN is Wavelet Neural Network,
AI is Artificial Intelligence,
ANFIS is Adaptive Neuro-Fuzzy Inference System,
PSO is Particle Swarm Optimization,
RMSE is The Square Root Of The Average Error,
MSE is the mean squared error.

6. Conclusions

This paper presents the outcome of an attempt made to predict the wind speed based on measured values of temperature, relative humidity and air pressure. In this study, two different neural network estimation methods is applied to predict very short term wind speed prediction. A data set with 10 minutes resolution is used to evaluate proposed method. Considering criterions, the results show that the root mean square error (RMSE) and the mean squared error (MSE) values of Wavelet Neural Network more successful than Artificial Neural Network. For future work, an attempt will be made for predicting wind speed used WNN with different wavelet activation functions and to compare the performance of that networks with in their selves and other artificial intelligence methods.

7. References

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