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New Intelligent Technique for Estimating the Parameters of Wind Energy Conversion System

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Abstract: In this study artificial neural network based power estimation has been proposed for the prediction of Wind Energy Conversion Systems (WECS). A simple feed forward network has been used for predicting the wind power generation. In this study, wind speed and a variable (count) are taken as inputs and electric power generated is considered as output. The gradient descent method is adopted for the updating the weights of the neural network. The ANN method has been tested on real time system data. The simulation results of the proposed method have been compared with Back propagation algorithm. It has been observed from the results that the proposed method provides better performance than the existing method.

Key words: Wind energy prediction, ANN, back propagation method, electric power, neural network, India

INTRODUCTION

The wind power is a significant alternate source of energy in these times of energy crisis. The wind energy is free so all wind-generated electric energy is acceptable should be accounted for. However, its availability is not known in advance. Because of the increasing penetration of wind resources in power systems, efforts have been made to predict the wind behavior and the corresponding electric energy production (Ferreira, 1992). Prediction of wind energy is necessary as wind is an intermittent source of energy (Wang *et al*., 2004). Prediction of wind energy (Mabel and Fernandez, 2008) is an important tool for utilities to ensure grid stability and a favorable trading performance in the electricity market.

India has an installed capacity of 10833.72 MW of wind electric power generation capacity as on September, 2009 (Centre for Wind Energy Technology; Indian Wind Turbine Manufactures Association). In terms of wind power installed capacity, India is ranked 5th in the World after USA, Germany, Spain, China. Today India is a major player in the global wind energy market.

In literature, several methods like physical and statistical methods have been reported to predict wind energy. The physical method needs a lot of physical considerations to reach the best prediction precision. The statistical method aims at finding the relationship of the on-line measured power data. For a statistical model, the historical data of the wind farm may be used. Physical method has advantages in long-term prediction while statistical method does well in short-term prediction (Kavasseri and Seetharaman, 2009). Conventional statistical models are identical to the direct random time-series model including Auto Regressive (AR) and Auto Regressive Integrated Moving Average (ARIMA) (Ramirez-Rosado *et al*., 2009) models. In the recent years, some new methods like Artificial Neural Network (ANN) (Sideratos and Hatziargyriou, 2007), fuzzy logic and neuro-fuzzy (Jursa and Rohrig, 2008; Potter and Negnevitsky, 2006), evolutionary algorithms (Potter and Negnevitsky, 2006) and some hybrid methods (Bessa *et al*., 2008; Rajasekaran and Pai, 2003) have been used to predict the wind energy.

It is observed from the ANN model that it takes long time to get the proper weights during the training. Optimal weights can be obtained and then these weights can be used in ANN. Hence, the proposed approach ANN has been used for predicting the output of wind energy conversion system. The simulation has been carried by taking the real time system data.

WIND POWER AND ENERGY

The kinetic energy of a stream of air with mass m and moving with a velocity V is given by:

$$E = \frac{1}{2} mV^2 \tag{1}$$

Consider a wind rotor of cross sectional area A_T exposed to this wind stream. The kinetic energy of the air stream available for the turbine can be expressed as:

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$$E = \frac{1}{2}\rho_a v V^2 \quad (2)$$

where, ρ_a is the density of air and V is the volume of air parcel available to the rotor. The air parcel interacting with the rotor per unit time has a cross-sectional area equal to that of the rotor (A_T) and the thickness equal to the wind Velocity (V). Hence the energy per unit time i.e., power is expressed as:

$$P = \frac{1}{2}\rho_a A_T V^3 \quad (3)$$

Equation 3 shows that the power and energy keeps on increasing as the wind speed increases. In reality it is not so. The power output of the turbine also depends on the design of the turbine i.e., it depends on the cut-in speed, rated speed, cut-out or shut-down speed. Figure 1 shows an idea of how wind power varies with wind speed.

The total energy generated over a year can be calculated by summing the power generation for all velocities (ranging from the actual windmill cut-in speed to the shut-down speed) multiplied by the number of hours the wind blows at the actual speeds.

The functioning of the wind turbine depends on the flow of air over the blades and through the rotor area. The theoretical maximum amount of energy in the wind that can be collected by a wind turbine's rotor is approximately 59% (Bhadra *et al*., 2005). This value is known as the Betz limit. If the blades were 100% efficient, a wind turbine would not work because the air having given up all its energy would entirely stop. In practice, the collection efficiency of a rotor is not as high as 59%.

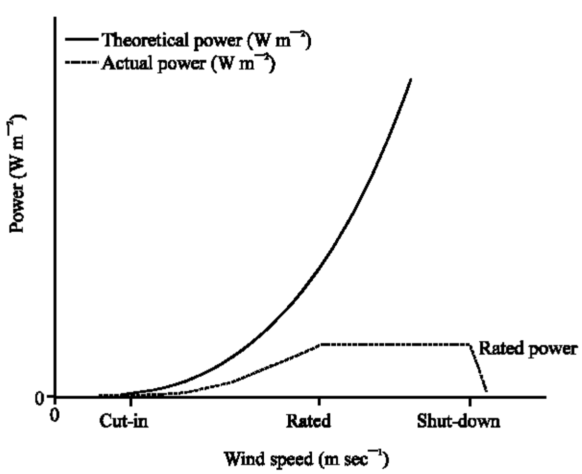

Fig. 1: Wind power density vs. wind speed

BACK PROPOGATION ALGORITHM

Back propagation algorithm: A neural network is a computational structure which resembles a biological neuron (Rajasekaran and Pai, 2003; Sivanandam *et al*., 2006). It resembles the human brain in two respects:

- Knowledge is acquired by the network from its environment through a learning process
- Interneuron connection strengths also known as synaptic weights are used to store the acquired knowledge

There are many different types of neural networks available in the literature survey. In this study, a feed-forward neural network has been used. It has layers of processing elements which make independent computations on data that it receives and passes the results to another layer and finally a subgroup of one or more processing elements determine the output from the network. Each processing element makes its computation based upon a weighted sum of its inputs. The first layer is always the input layer and the last layer is always the output layer. The layers placed between the first and the last layers are the hidden layers. A neuron is an information processing unit that is fundamental to the operation of a neural network. There are three basic elements in the neuron model namely the synapses, the adder and the activation function. Synapses between neurons are referred to as connections which are represented by edges of a directed graph in which the nodes are the artificial neurons. The adder is used for summing of the inputs, represented by the sigma. A threshold function or the activation function is sometimes used to qualify the output of a neuron in the output layer.

IMPLEMENTATION OF THE PROPOSED APPROACH

The energy generated by the wind power for the next day can be predicted using the available data. The inputs for the network should be such that it should have a strong relationship with the output of network i.e., the energy that will be generated during the next day, energy (t+1). The wind energy generated could depend on several factors like wind speed, wind direction, pressure, air density, moisture content, humidity, rainfall, cloud cover etc. Here the daily average wind speed (t) and count (t), a variable which is analogous to the minutes of lull have been selected as inputs for the network to predict the energy (t+1).

Selection of inputs and outputs: The selection of the inputs and outputs for the neural networks depends on nature of the problem. In wind energy prediction problem, daily average wind speed (t) and count (t) are taken as inputs and energy (t+1) is taken as output. The time t can be either minute, hour, day, month etc. Here, average values of the inputs for a day are used as inputs and energy generation to be expected the next day is used as output. Then the number of hidden layers and hidden neurons has to be determined.

Selection of hidden layer: Deciding the number of neurons in the hidden layers is a very important part of deciding the overall neural network architecture. Though these layers do not directly interact with the external environment, they have a tremendous influence on the final output. Using too few neurons in the hidden layers will result in under fitting. Also too many neurons in the hidden layers may result in over fitting. Obviously, some compromise must be reached between too many and too few neurons in the hidden layers. As such there is no theoretical limit on the number of hidden layers but typically they are just one or two. Here, a single hidden layer has been chosen.

There are many rule-of-thumb methods for determining the correct number of neurons to be used in the hidden layers but they generally ignore the number of training cases, the amount of noise in the targets and the complexity of the function. So ultimately, the selection of the architecture for the neural network comes down to trial and error. Using trial and error method 5 neurons were found to be apt for the network.

Selection of the neural network: A single hidden layer feed forward network with 2 inputs, 5 hidden neurons and 1 output neurons was constructed for predicting the wind energy generation. The logarithmic sigmoid function was used as the activation function in the hidden and output layers. The developed network architecture is shown in Fig. 2.

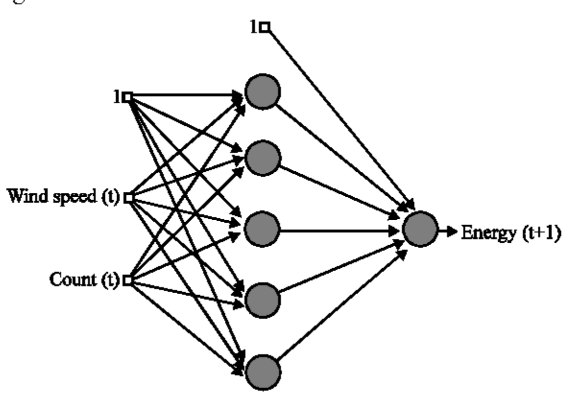

Fig. 2: The developed network architecture

Training of the network: In this model, the weights of the network are calculated by using the gradient descent method i.e., the error for each input-output training sample is propagated backwards and weights are adjusted accordingly.

To calculate the weights, the network must be trained. For the better performance of the network, appropriate care should be taken in the choice of initial weights and bias and number of iterations.

SIMULATION RESULTS

The simulations of ANN has been carried out in MATLAB (version 7.0). A real time data has been considered during the simulation study. The data obtained from the wind turbines. The capacity of the wind turbine is 10 kW. The wind speed and energy generated are measured.

The data set contains the wind speed, count and energy from 2nd of August, 2008 to 25th November, 2008. The data set from 2nd August to 15th September were used for the training of the network and from 16th of September to 25th of November has been used for validating the performance of the network. Wind speed has a high positive relation with the amount of energy generated i.e., energy generation increases with increase in wind speed.

Figure 3 shows the average wind speed for days in August (from 2nd August), September and October. The energy and wind speed from the database were plotted. The energy is represented by a cubic polynomial in terms of wind speed. The cubic polynomial is shown in Fig. 4. It is observed from the curve that the cubic fit line starts to decrease after a certain value of wind speed.

The wind speed data obtained from the turbine gives the averaged value of wind speed for each interval of 5 min. For each day, 288 average values of wind speed are

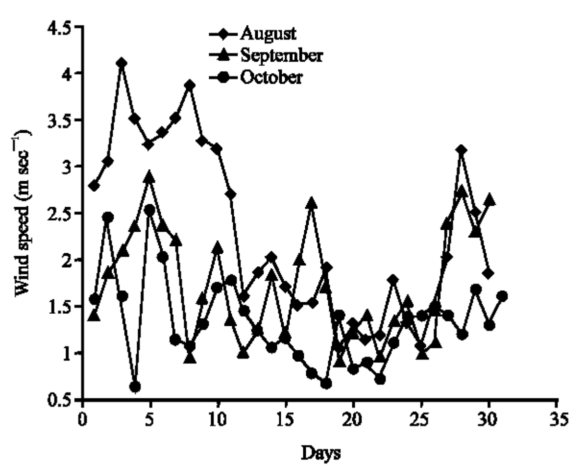

Fig. 3: Daily average wind speed

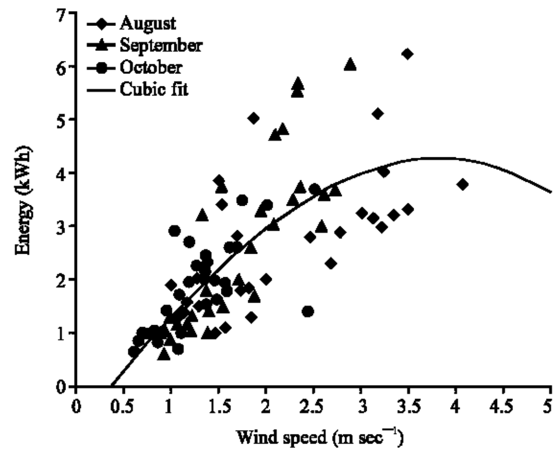

Fig. 4: A cubic relation between wind energy and wind speed from the collected data

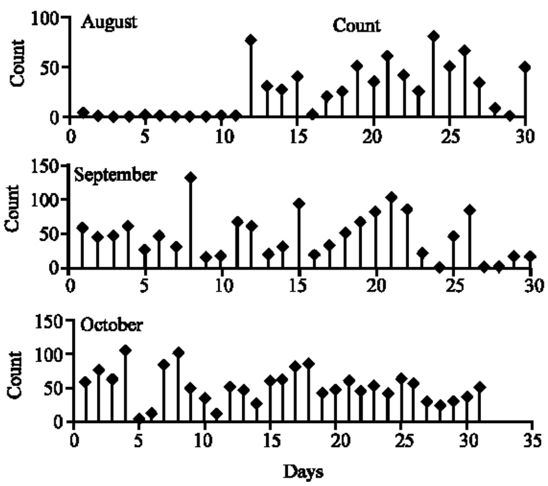

Fig. 5: Variable count during the given period

obtained. The variable count is the number of such values that is equal to or less than a constant value which depends on the characteristics of the turbine. Zero was chosen here since wind turbine had a small capacity of 3.2 kW. Turbines with higher capacity and larger cut-in speeds will have a higher value for this constant. The basic logic behind this selection is that at wind speed zero no energy is generated. This input variable can be thought to be analogous to minutes of lull i.e., number of minutes in which speed is less than a certain value, generally the cut-in speed. Correlation studies indicate a strong dependency between count and energy. The correlation coefficient was found to be -7. The negative value shows that when the value of count increases the energy generated decreases. Hence count is included as an input variable for the network. Variable count during the given period is shown in Fig. 5.

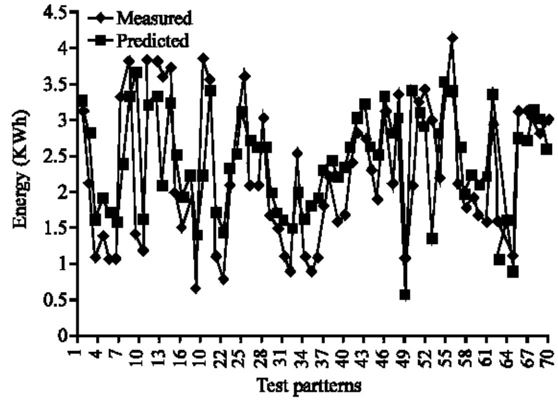

Fig. 6: Validating gradient descent method by comparing the measured and predicted values of energy

Training and validation of ANN: The network should be able to generalize and once trained it must be validated by testing its performance. The mean square error has been used as the performance function here. The simulation results in terms of measured and predicted values of energy of ANN are shown in Fig. 6. Also Mean Square Error (MSE) and Mean Absolute Error (MAE) of ANN.

MSE and MAE showing the performance of ANN:

- MSE = 0.4158
- MAE = 0.5240

The network was able to generalize for a large set of data (70 testing samples) with Mean Square Error (MSE) and Mean Absolute Error (MAE) of 0.4158 and 0.5240, respectively.

The daily average wind speed varies quite significantly resulting in quite random variations in the energy generation. The network was able to identify these variations and predict the energy generated by wind with a significant amount of accuracy.

CONCLUSION

A New approach by combining Back Propagation Algorithm (BPA) has been used for the prediction of wind energy in this study. A simple feed forward network has been used for predicting the output of wind power conversion system. In this study, wind speed and a variable (count) are taken as inputs and wind energy generated is considered as output. The ANN has been tested on real time system data. Out of the two models developed, the hybrid model showed better performance in terms of the solution time and mean square error and is preferred for prediction of wind energy in real time environment.

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