International Journal of
Scientific Engineering and Technology Research

ISSN 2319-8885
Vol.04,Issue.51,
December-2015,
Pages:11018-11022

www.ijsetr.com

Estimating Battery Reserve using Weather Forecasting and Optimization

SAI PRAVEEN VABBILISETTY[1], RAVI KISHORE REDDY. M[2], SANDEEP MEDISETTI[3], RAMPRABHAKAR. J[4]

[1]Associate Software Engineer, Amrita School of Engineering, Bangalore, India, E-mail: meet.saipraveen@gmail.com.

[2]Amrita School of Engineering, Bangalore, India, E-mail: ravikishor93@gmail.com.

[3]PG Scholar, Amrita School of Engineering, Bangalore, India, E-mail: sandeepmvsjp@gmail.com.

[4]Assistant Professor(Sr. Grade), Amrita School of Engineering, Bangalore, India, E-mail: j_ramprabhakar@blr.amrita.edu.

Abstract: Weather forecasting is the application of science and technology to soothsay the state of the atmosphere for a future time at a given location. It is carried out by amassing quantitative data about the current state of the atmosphere and past and/or present experiences. A neural network can learn intricate mapping from inputs to outputs, predicated solely on samples. In this paper, a neural network-predicated algorithm for soothsaying the wind velocity is presented. The Neural Networks package fortifies variants of training or learning algorithms. One such algorithm is Back Propagation Neural Network (BPN) technique. This method is more efficient than numerical differentiation. The results showed that this model could be applied to weather prognostication quandaries. The performance evaluation of the model carried out on the substructure of Root Mean Square Error (RMSE) showed that the BPN model yielded good results with a lower prognostication error. The energy engendered is calculated utilizing the forecasted value of wind velocity and the tolerance values are calculated according to the distinguishment between genuine and presaged values. Assuming the average load at a place is taken constant, calculation of the battery reserve for a particular day with the avail of OPTIM tool is done.

Keywords: Forecasting, BPN, Root Mean Square Error (RMSE), OPTIM.

I. INTRODUCTION

Wind energy is considered one of the most rapidly growing energy resources all over the world. It is expected that about 12% of the total world electricity demands to be supplied from wind energy resources by 2020. About 22% of the European Cumulation electricity needs are expected to be supplied from renewable energy resources, mainly wind energy, by the year 2010. Due to this expected high perforation rates of wind energy generation, wind farms are required to operate as controllable power plants.

A. Evolution of Weather Forecasting Techniques

Weather can be described as the state of the atmosphere at a given time and place. Weather forecasting entails how the present state of the atmosphere will alter. Weather forecast has been one of the most fascinating domains of study; Scientists have been endeavoring to forecast the meteorological characteristics utilizing a number of methods, some of them more precise than others. It has been one of the most scientifically used conundrums around the world in the last century. To make a precise forecast is one of the major challenges facing meteorologist all over the world. Since ancient times, weather presage has been one of the most fascinating domain. Scientists have endeavored to forecast meteorological characteristics utilizing a number of methods, some of these methods being more precise than others.

B. Methods of Forecasting

Some methods of forecasting are

Climatology Method: This method involves averaging weather statistics accumulated over many years to make the forecast. For example to predict the weather for a city on a particular day involves assembling all the weather data that has been recorded for that day over the years and taking its average. This method works well only when the weather pattern is similar to that expected for the chosen time of year. If the pattern is unusual for the given time of year, the climatology method will often fail.

Analog Method: This method is a marginally more perplexed method of engendering a forecast. It involves examining the days forecast scenario and recollecting a day in the past when the weather scenario looked similar (an analog).The forecaster would make a prediction that the weather in this forecast will behave in a certain manner similar to it did in the past. The method is arduous to utilize because it is virtually infeasible to find error free weather forecast.

Numerical Weather Prediction: This method utilizes the potency of computers to make a forecast. Complex computer programs, additionally kennedas forecast models that run on supercomputers provide forecasts on many atmospheric variables such as temperature, pressure, wind, and rainfall. With all the time taken to engender results limits the methods ability to provide very short-term forecasts. It provides more precise results for forecasting of both short and longer time steps ranging from one hour and beyond.

The mathematical models for interpretation and presaging future weather and climatic conditions are intricate non-linear dynamical systems which are currently being processed with the avail of powerful supercomputer systems running massively parallel algorithms. However, an abundance of historical data whose inceptions coincides with the advent of modern weather forecasting, which commenced with the invention of the barometer in 1644, has been gathered over the years.

II. WIND POWER CALCULATIONS AND BACK PROPAGATION ALGORITHM

Wind turbines work by converting the kinetic energy in the wind into electrical energy that can be supplied, via the national grid, for any purport around India. The energy available for conversion mainly depends on the wind speed and the swept area of the turbine. When commissioning a wind farm it is consequential to ken the expected power and energy output of each wind turbine to be able to calculate its economic viability. With the cognizance that it is of critical economic consequentiality to ken the power and therefore energy engendered by variants of wind turbine in different conditions, in this exemplar we will calculate the rotational kinetic power obtained in a wind turbine at its rated wind speed. This is the minimum wind speed at which a wind turbine engenders its rated power.

$$P = \frac{1}{2}\rho A v^3 \qquad \textbf{(1)}$$

A German physicist Albert Betz concluded in1919 that no wind turbine can convert more than16/27 (59.3%) of the kinetic energy of the wind into mechanical energy turning a rotor. To this day, this is known as the Betz Limit or Betz'Law. The theoretical maximum power efficiency of any design of wind turbine is 0.59 (i.e. no more than 59% of the energy carried by the wind can be extracted by a wind turbine). This is called the" power coefficient" and is defined as:

$$C_{p_{max}} = 0.59 \qquad \textbf{(2)}$$

Also, wind turbines cannot operate at this maximum limit. The Cp value is unique to each turbine type and is a function of wind speed that the turbine is operating in. Once we incorporate various engineering requirements of a wind turbine - strength and durability in particular – the real world limit is well below the Betz Limit with values of 0.35-0.45 common even in the best designed wind turbines. By the time we take into account the other factors in a complete wind turbine system.

A. Back Propagation Algorithm

Conceptually, a network forward propagates activation to produce an output and it backward propagates error to determine weight changes (as shown in Fig.1). The weights on the connections between neurons mediate the passed values in both directions. The Back propagation algorithm is used to learn the weights of a multilayer neural network with a fixed architecture. It performs gradient descent to try to minimize the sum squared error between the network's output values and the given target values. Fig.2 depicts the network components which affect a particular weight change. Notice that all the necessary components are locally related to the weight being updated. This is one feature of back propagation that seems biologically plausible. However, brain connections appear to be unidirectional and not bidirectional as would be required to implement back propagation.

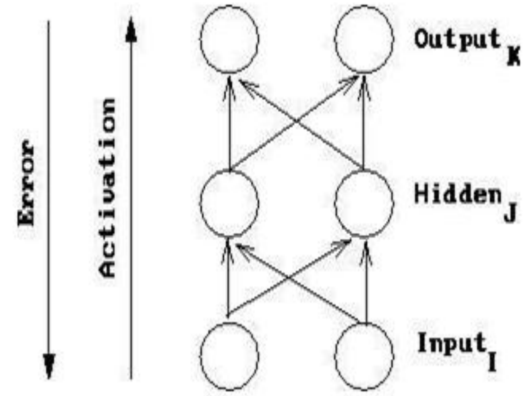

Fig.1 Neural network processing.

Notation: For the purpose of this derivation, we will use the following notation:

- The subscript k denotes the output layer.
- The subscript j denotes the hidden layer.
- The subscript i denotes the input layer.

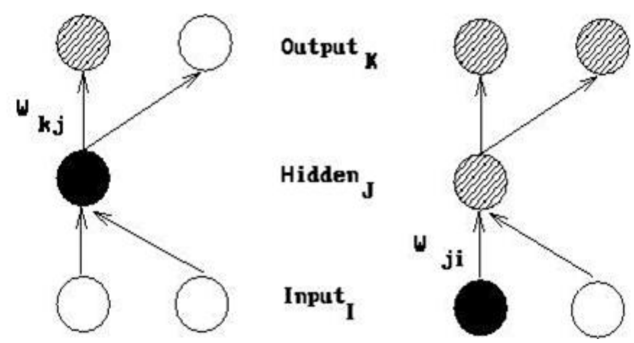

Fig.2 Neural network.

Fig.2 The change to a hidden to output weight depends on error (depicted as a lined pattern) atthe output node and activation (depicted as a solid pattern) at the hidden node. While the change to a input to hidden weight depends on error at the hidden node (which in turn depends on error at all the output nodes) and activation at the input node.

- w_{kj} denotes a weight from the hidden to the output layer.
- w_{ji} denotes a weight from the input to the hidden layer.
- a denotes an activation value.
- t denotes a target value.
- net denotes the net input.

The total error in a network is given by the following equation

$$E = \frac{1}{2}\sum_k (t_k - a_k)^2 \qquad \textbf{(3)}$$

Adjusting the network's weights to reduce the overall error

$$\Delta W \propto -\frac{\partial E}{\partial W} \quad (4)$$

Beginning with output layer at particular weight

$$\Delta w_{kj} \propto -\frac{\partial E}{\partial w_{kj}} \quad (5)$$

However error is not directly a function of weight. On expanding as follows

$$\Delta w_{kj} = -\varepsilon \frac{\partial E}{\partial a_k}\frac{\partial a_k}{\partial net_k}\frac{\partial net_k}{\partial w_{kj}} \quad (6)$$

Note that only one term of E summation will have a non-zero derivative; the one associated with the particular weight that we are considering. Derivative of error with respect to the activation

$$\frac{\partial E}{\partial a_k} = \frac{\partial(\frac{1}{2}(t_k - a_k)^2)}{\partial a_k} = -(t_k - a_k) \quad (7)$$

Derivation of activation with respect to the net input

$$\frac{\partial a_k}{\partial net_k} = \frac{\partial(1+e^{-net_k})^{-1}}{\partial net_k} = \frac{e^{-net_k}}{(1+e^{-net_k})^2} \quad (8)$$

B. Derivation of Net Input With Respect To Weight

Note that only one term of the net summation will have a non zero derivative; again the one associated with particular weight is considered.

$$\frac{\partial net_k}{\partial w_{kj}} = \frac{\partial(w_{kj}a_j)}{\partial w_{kj}} = a_j \quad (9)$$

C. Weight Change Rule For Hidden To Output Weight

Substituting the above results into the original equation

$$\Delta w_{kj} = \varepsilon(t_k - a_k)a_k(1-a_k)a_j \quad (10)$$

$$\delta_k = (t_k - a_k)a_k(1-a_k) \quad (11)$$

It looks very similar to the perceptron training rule. The only difference is inclusion of derivative function. The equation is typically simplified as shown below where the δ term represents the product of error with the derivative of activation function.

$$\Delta w_{kj} = \delta_k a_j \quad (12)$$

D. Weight Change Rule For Input To Hidden Weight

Hence determined the appropriate change for the input to hidden weight. This is more complicated because it depends on the error at all of the nodes this weighted connection can lead to

$$\Delta w_{ji} \propto -[\sum_k \frac{\partial E}{\partial a_k}\frac{\partial a_k}{\partial net_k}\frac{\partial net_k}{\partial a_j}]\frac{\partial a_j}{\partial net_j}\frac{\partial net_j}{\partial w_{ji}}$$

$$= \varepsilon[\sum_k \delta_k w_{kj}]a_j(1-a_j)a_i \quad (13)$$

$$\delta_j = \delta_k w_{kj} a_j(1-a_j) \quad (14)$$

$$\Delta w_{ji} = \varepsilon \delta_j a_i \quad (15)$$

III. LITERATURE SURVEY

Concepts cognate to the Weather forecasting techniques have perpetually been under cumbersomely hefty research and development. Weather forecasting is a major area of research in the field of renewable energy technologies. A detailed literature survey was done to understand the working and trends in this technology. Adeyemo et al.in[1] has developed an algorithm to predict the rainfall in Nigeria using SOM(self-organizing maps) clustering using Neuro XI, clustering software taking the rainfall data (1951-2008) as inputs. They also compared with the results obtained by using Co-Active Neuro Fuzzy Interference System (CANFIS). The predictions made using CANFIS technique shows that it can be used for long range weather forecasts. Govind Kumar Rahul et al.in [3] has done a comparative study review of Soft Computing Approach in Weather Forecasting. The training and forecasting of any model is dependent upon the types of the network i.e., Multi-Layer Perception (MLP), Multi-Layer Feed Forward network (MLFFN) etc., in some cases MLP may suit best or in some cases it may be MLFFN. The appropriate type of network may converse fast for prediction. The study also says that MLFFNN with BPN algorithms are the best combination for weather forecasting. The dataset selection, input variable selection, the relationships & inter-dependencies among the data, the proper training set and the proper ANN architecture are most vital for the best prediction results. Monika Sharma et al.in[2] has compared the results of several researches and some key findings that are initials for better start any soft computing model for prediction. They have used Multi-LayerPerceptron (MLP), Multi-Layer Feed Forward network (MLFFN) for their prediction. Back Propagation algorithm is found best suited with MLFFNN for forecasting the weather prediction.

IV. METHODOLOGY

In this paper, Neural Network Toolbox is utilized to design Neural Network model. These implements apply neural network techniques to data modeling. The Neural Network toolbox function constructs a Fuzzy Inference System (FIS) whose weights function parameters are tuned (adjusted) utilizing back propagation algorithm. This sanctions our fuzzy systems to learn from the data they are modeling. After forecasting the wind velocity, we have calculated the wind energy output at the turbine and the energy engendered genuinely is compared and the tolerance values are calculated. The average load demand at a place is taken and the distinguishment between power forecasted and average load demand is taken as battery reserve for that day.

V. RESULTS

The inputs (2005-2014 average wind velocities on a day of February) are loaded into the MATLAB and NNTOOL.A network with desired algorithm and adaption learning function is taken and it is created in the Network/Data manager. After creating a network with desired parameters, network is trained keeping 1000 iterations (maximum epochs), maximum 6 validation checks, Levenberg Marquardt Back Propagation Algorithm, two layers of neurons and keeping 4 neurons in each layer. Performance, Regression, Validation plots obtained after training of network are plotted. Performance plot is between the mean square error and the number of epochs (iterations) which is completely based on the test data and validation data. During training, the pattern is set according to the 80% of data which is given as target and it will test with 10% data. After this it will validate using remaining 10% data in which 60% of data is matching the actual wind velocities as shown in Fig.3. The power obtained at the output of turbine is optimized using OPTIM tool. OPTIM tool can be used efficiently if there are more variables in an equation (If Solar Output is also taken into consideration). The average load is taken as 170 KW and estimation of Battery Reserve for the month of February-2015 is done.

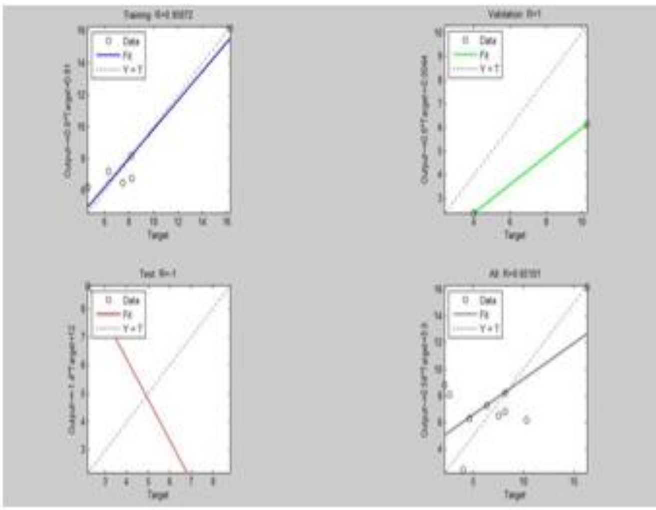

Fig.3.Regression plot obtained after the training of network.

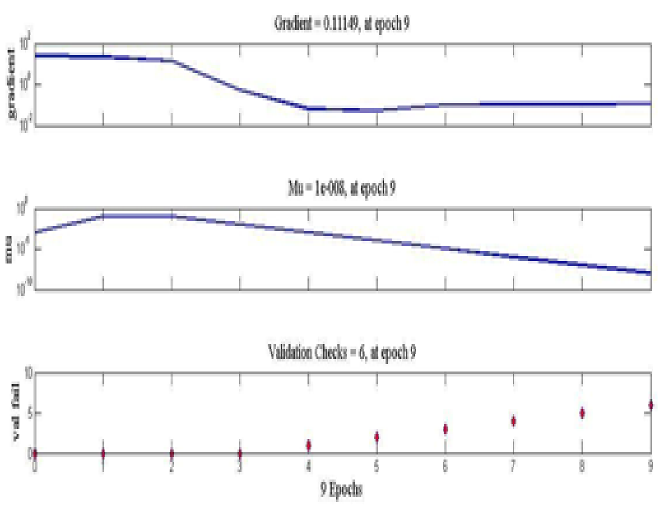

Fig.4.Training plot obtained after the training of network.

Regression is a linear expression between the output and the target which determines the error rate of the function as shown in Fig.4. The maximum value of the regression coefficient is 1. In the training state the gradient and the validation determines the error rate and maximum number of validation checks are 6 which is inbuilt in NN tool. The validations are based on the gradient, whenever it coincides is one validation check. Once the 6 validation checks are done then it stops the iterative process.

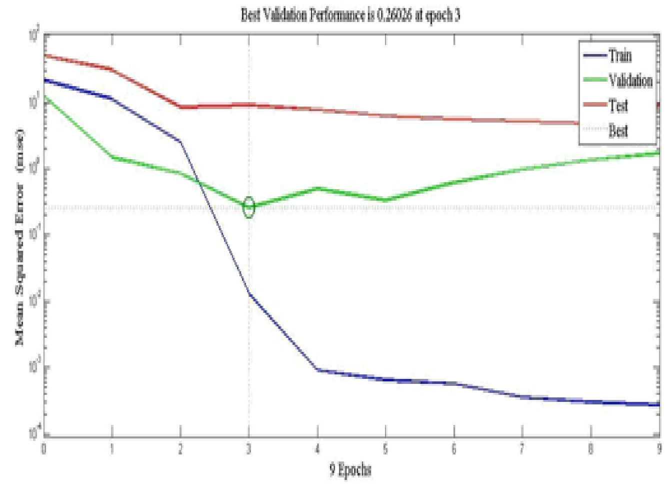

Fig.5. Performance plot obtained after training of network.

The best performance is the minimum mean square error obtained in the validation as shown in Fig.5. The forecasted wind velocity is compared with the actual wind velocity and Root Mean Square Error is calculated.

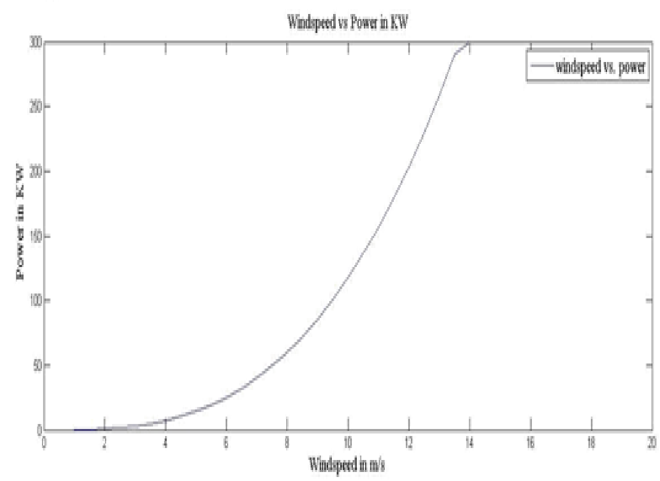

Fig.6. Actual Wind Velocity vs. Predicted Wind Velocity of Feb-2015.

The forecasted wind velocity is compared with the actual wind velocity and Root Mean Square Error is calculated. The power obtained at the output of turbine is optimized using OPTIM tool. The average load is taken as 170 KW and estimation of Battery Reserve for the month of February-2015 is done as shown in Fig.6. OPTIM tool is used for optimizing the power by taking a tolerance value of ± 10%. The predicted power is the power generated from the wind turbine considering the practical blade length of 15 meters and swept area as 550 sq.mt and air density as 1.21 and coefficient of performance as 0.35 as shown in Fig.7. Objective function is given asf=117.816*v^3considering above conditions.

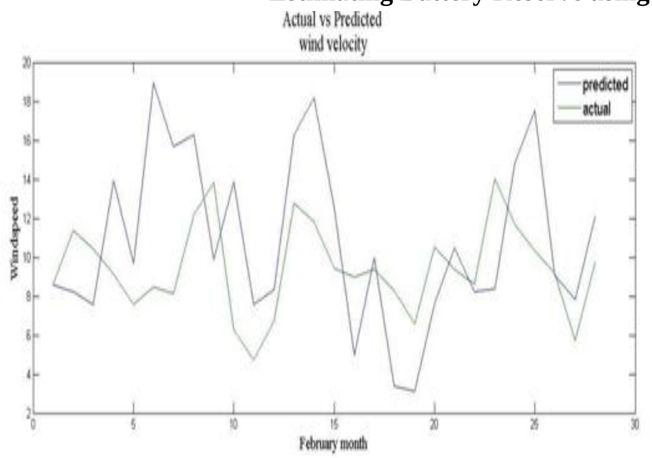

Fig.7. Wind Speed vs. Predicted Power.

Here the power is saturated, considering the rated Power capacity of a normal wind turbine is not more than 300KW. So when the turbine generates more than 300KW we will saturate it by using a control mechanism so that it won't damage the system. The graph shown in Fig.8 Power with respect to wind velocities by using the relation.

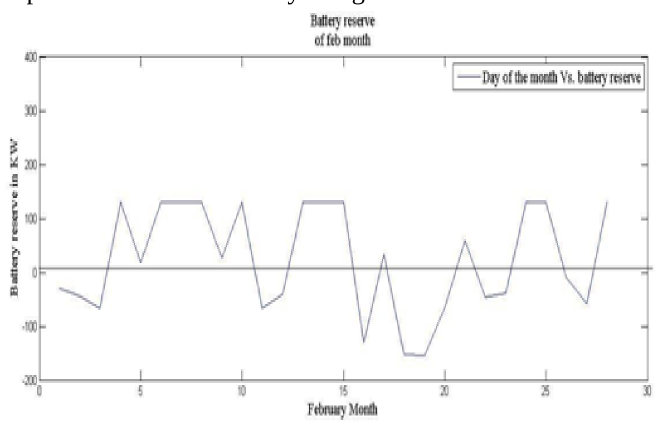

Fig.8. Battery Reserve estimated for the month of February-2015.

VI. CONCLUSION

In this report, a design for estimation of battery reserve was developed through forecasting of wind velocity using MATLAB (NNTOOL & OPTIMTOOL). A number of important model improvements have been found to be necessary through this research for effective utilization of weather forecasting methods like improved probabilistic weather forecasts and advanced algorithms that can accurately parameterize the conditions of weather. Thus, this gives an introduction to the project and also gives an idea about the various Soft Computing techniques used for weather forecasting and calculating battery reserve at a place.

VII. REFERENCES

[1]A.B. Adeyemo [2013], "Soft Computing Techniques for Weather and Climate Change Studies" IEEE Afr.J.of Comp & ICT's. Vol 6, No.2.pp 77-90.

[2]Cherkassky V. (1998), "Fuzzy Inference Systems: A Critical Review", Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications, Kayak O, Zadeh LA et al (Eds.), Springer, pp.177-197.

[3]Chowdhury A and Mhasawade S V (1991), "Variations in Meteorological Floods during Summer Monsoon Over India", Mausam, 42, 2, pp. 167-170.

[4]Fogel D. (1999), "Evolutionary Computation: Towards a New Philosophy of Machine Intelligence", 2nd Edition, IEEE press.

[5]Govind Kumar Rahul, "Comparative Study Review of Soft Computing Approach in Weather Forecasting" IJSCEVol 2, Issue 5, November-2012.

[6]Hagan M T, Demuth H B and Beale M H. (1996), "Neural Network Design", Boston, MA: PWS Publishing.

[7]Hui Zhou, Beijing Jiaotong, Mei Huang, Xinfhua Wu, "Forecast of Wind speed and power of wind generator based on pattern recognition", Proceedings of the IEEE

[8]International Conference on Industrial Mechatronics and Automation, Chengdu, pp 504-508, May, 2009.

[9]Kan Li, Yu-Shu Liu, "A Rough Set Based Fuzzy Neural Network Algorithm For Weather Prediction", Proceedings of the Fourth International Conference on Machine Learning and Cybernetics, Guangzhou, pp 1888-1892, August, 2005.

[10]Kasabov N. (1998), "Evolving Fuzzy Neural Networks - Algorithms, Applications and Biological Motivation", in Yamakawa T and Matsumoto G (Eds), Methodologies for the Conception, Design and Application of Soft Computing, World Scientific, pp. 271-274.

[11]Monika Sharma, "Weather Forecasting Using Soft Computing Techniques" IJATES Vol 2,Issue 7 ,July-2014.

[12]Oyediran O. F., Adeyemo A. B., "Performance Evaluation of Neural Network MLP and ANFIS models for Weather Forecasting Studies", African Journal of Computing & ICT, IEEE, Vol. 6, No. 1, March 2013.

[13]Paras, Sanjay Mathur, Avinash Kumar and Mahesh Chandra, "A Feature Based Neural Network Model for Weather Forecasting", International Journal for Engineering Research and Application, Vol.10, pp 66-73, Jan, 2007.

[14]"Real time data of Sotavento Experimental Wind Farm located in South West of Europe, Galicia, Spain," http://sotaventogalicia.com.nsa.html.

[15]Zadeh L A. (1998), "Roles of Soft Computing and Fuzzy Logic in the Conception, Design and Deployment of Information/Intelligent Systems", Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications, O Kaynak, LA Zadeh, B Turksen, IJ Rudas (Eds.), pp1-9.

[16]Zanchettin C., Minku L. L., Ludermir T. B., (2010), "Design of Experiments in Neuro-Fuzzy Systems", International Journal of Computational Intelligence and Applications, Vol. 9, No. 2 (2010) 137–152.

[17]European Wind Energy Association. (2002).Wind force 12,[Online].Available:http://www.ewea.org/doc/WindForce12.pdf.

[18]The Canadian Wind Energy Association. (2001).Wind visionfor Canada,[Online]. Available: http://www. canwea.ca/ pdfs/ CanWEA-WindVision.pdf.