Wind Power Prediction Using Artificial Neural Network

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Abstract— **This paper presents the application of Artificial Neural Network (ANN) in wind power prediction based on historical meteorological data. ANN which is inspired by the functional aspects of biological neural networks is employed in this project due to its strong pattern recognition capabilities and its ability to model flexible linear or non-linear relationship among variables. A three layers feed-forward back-propagation neural network has been developed to predict the wind power for the next hour. In order to get an accurate wind power prediction, several network structures, training algorithms and transfer functions have been developed and tested with different sets of data. The performance of a network will be determined by its convergence capability, and only the network with the best performance will be selected.**

Keywords - **Artificial Neural Network (ANN), wind power prediction, back-propagation, training, tested, convergence capability.**

I. Introduction

Wind power is a kind of clean, pollute-free renewable energy power generation. Wind power can be defined as the conversion of wind energy into a useful form of energy, such as using wind turbines to make electricity, wind mills for mechanical power, wind pumps for pumping water or drainage, or sails to propel ships.

Wind energy conversion systems appear as an attractive alternative for electricity generation. However, at the same time, the integration of wind farms in power networks has become an important problem for the unit commitment and control of power plants in electric power systems. The intermittent nature of wind makes it difficult to forecast wind-produced electric energy in a wind farm even in the next hours. Therefore, an accurate wind power prediction system is really important to guarantee the size of power production in the next hour.

Artificial Neural Network (ANN) is a branch of artificial intelligence (AI). With the ability to learn by example and do tasks based on training experience, it is has the capability to implement pattern recognition and forecasting tasks [3]. ANN can adjust itself when presented with appropriate input and output data relative to a specific functional relationship so that it can give a good representation of that relationship, even when the relationship is nonlinear and not well defined [3]. They also can extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [3]. Besides that, ANN-based methodology does not require any predefined mathematical models, which is hardly to obtain and not accurate for nonlinear systems. The training process using onsite measurements adapts ANNs automatically by minimizing mean square error [8].

ANN technology is promising in wind speed prediction field [10]. Therefore, this paper presents ANN-based technique for wind power prediction system based on historical wind power and meteorological data. Several ANN models will be constructed and each performance will be evaluated by comparing it to the historical wind power. This is necessary in order to choose the most accurate model among the entire models constructed. As a result, the developed ANN wind power prediction system is able to generalize well when presented new sets of input data. Consequently, prediction of the wind power using the developed ANN is the most accurate prediction and successfully done.

II. Methodology

In general, the research design for developing the wind power prediction system can be grouped into two main stages; data preparation and development of the ANN.

A. Data Collection

There were two types of data that were used in order to propose ANN. The first data was the meteorological data that were used as the input data and the second data was the wind speed data that was used as the target output. The input data of the historical meteorological data is available at http://www.wunderground.com/history/airport/WMAU/. The data are taken from Mersing (2°27'N, 103°50'E), a city in Johor state, Malaysia. The city is chosen because of its wind consistency and it is recorded to have annually wind speed at 3.1m^{s-1} [15]. The input data also consist of season indicator which represent the monsoon and inter-monsoon seasons. The data are the fundamental components because they carry the necessary information for ANN learning and testing. This will ensures that all patterns are captured for the purpose of training and testing [4]. It is important to obtain the meteorological data such as wind direction, wind speed, gust speed, dew point, humidity, temperature, and visibility because they are the common elements that are related to the speed of wind.

B. Artificial Neural Network (ANN) Development

ANNs are composed of a set of layered processing elements called neurons. The first layer is called the input layer, the last layer is called the output layer, and the layer in between are called the hidden layer [9]. The three layers were connected to each other by means of interconnection weights and biases were provided for both hidden and output layer to act upon the net input to be calculated. The input layer receives the input data, the hidden layer receives information and produce output. The output produced will be the input for the final layer. The final layer is called the output layer and it produces the desired result.

No unified theory exists for determination of such an optimal ANN architecture, and thus is achieved through computational simulations [9]. In the ANN designed three layers of network configuration chosen; where each layer has its own number of neurons. It is common to have different number of neurons in each layer. The flexibility of the ANN lies in selecting the number of hidden layers and in assigning the number of neuron to each of these layers [9].

Figure 1 shows the block diagram of the developed wind power prediction system; Meteorological data, month indicator and season indicator are cascaded together as the input data, while the wind speed will be the target output. The target output and Input data will be the input of the ANN, while the predicted wind power and wind direction for the next hour will be the output of the ANN.

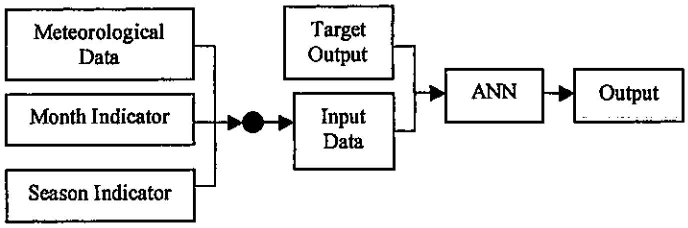

Figure 1: Wind Power Prediction Block Diagram

In order to obtain the best ANN architecture, the network configuration such as number of neurons and the types of transfer function determined by varying those configurations to get the value of regression coefficient, R close to 1. While varying the network configuration, the learning rate and momentum constant of the network are kept fixed at typical value. During the process, the number of neurons tested was set to small values in order to avoid the computation complexity of the network. The time taken for convergence and to minimize the error may be very high if that happen. The transfer function of the network also plays an important role where each of the transfer function has been tested in the network in order to obtain the best ANN architecture.

III. STAGES IN ANN DEVELOPMENT

A. Training Process

Training process is necessary in order to obtain the best network by evaluating the performance of each network. By referring to the flow chart, the input data need to be normalized by mapping each row so that they have zero means and unity deviations. This function is called 'Mean and Standard Deviation (mapstd)' [7]. After training and simulating the network, the result will be transform back to its original form through the post-processing process (de-normalize).

Another approach for scaling network inputs and targets is by normalizing their minimum and maximum value so that the value will fall within the range of [-1, 1]. This function is called 'Minimum and Maximum (mapminmax)' [7]. The network will be trained until its result gives a small error. Theoretically, the smaller the error, the better the ANN produced. The network is then saved for the testing process.

B. Testing Process

Testing process is carried out to measure the performance of the trained network, which can be measured to some extent by the errors on the training and validation sets and the testing data; or by performing a linear regression analysis between the network response and the corresponding targets [1]. The regression coefficient, R with values close to one indicates that there is a strong correlation between the targeted outputs and network outputs while the values that are close to zero indicates otherwise [1]. In order to measure network performance in terms of its R-value, the best network is trained once again using both training and validation sets as the whole training data. Its performance is then assessed using the testing data.

A fully trained network should be able to predict wind power from this set of unseen data and it is evaluated by measuring the R-value. The flowchart in Figure 16 shows the overall process of the training and testing of the developed ANN.

C. Combination of Training and Testing Process

To obtain the best ANN architecture, the network configuration such as number of neurons and the types of transfer function determined by varying those configurations to get the value of regression coefficient, R close to 1. While varying the network configuration, the learning rate and momentum constant of the network are kept fixed at typical value. During the process, the number of neurons tested was set to small values in order to avoid the computation complexity of the network. The time taken for convergence and to minimize the error may be very high if that happen. The transfer function of the network also plays an important role where each of the transfer function has been tested in the network in order to obtain the best ANN architecture.

In order to get the optimal value for learning rate (α) and momentum constant (β), trial and error technique is used. Therefore, a special program contains the combination of training and testing program is built to do this task. For 100 loops, different random value of learning rate and momentum constant ranging from 0 to 1 will be used.

The minimum regression value will be set as a threshold. If the regression value for a loop exceeds the threshold value, the looping process will stop and the value of learning rate and momentum constant will be displayed for record. If the regression value does not exceed the threshold, the training will keep looping with the next random sets of learning rate and momentum constant value. This process will keep repeating for hundred loops unless its regression value reaches the threshold regression.

To obtain the set of learning rate and momentum constant that will produce highest regression value, increase the regression threshold every time the learning process exceeds the current regression value. Setting the regression threshold too high will sometimes cause the learning program to looping for hundred times without giving any learning rate and momentum constant value.

Finally, the best pair value of the two constants obtained from the previous training stages will be used as the desirable parameter in order to obtain the best result after conducting the testing program.

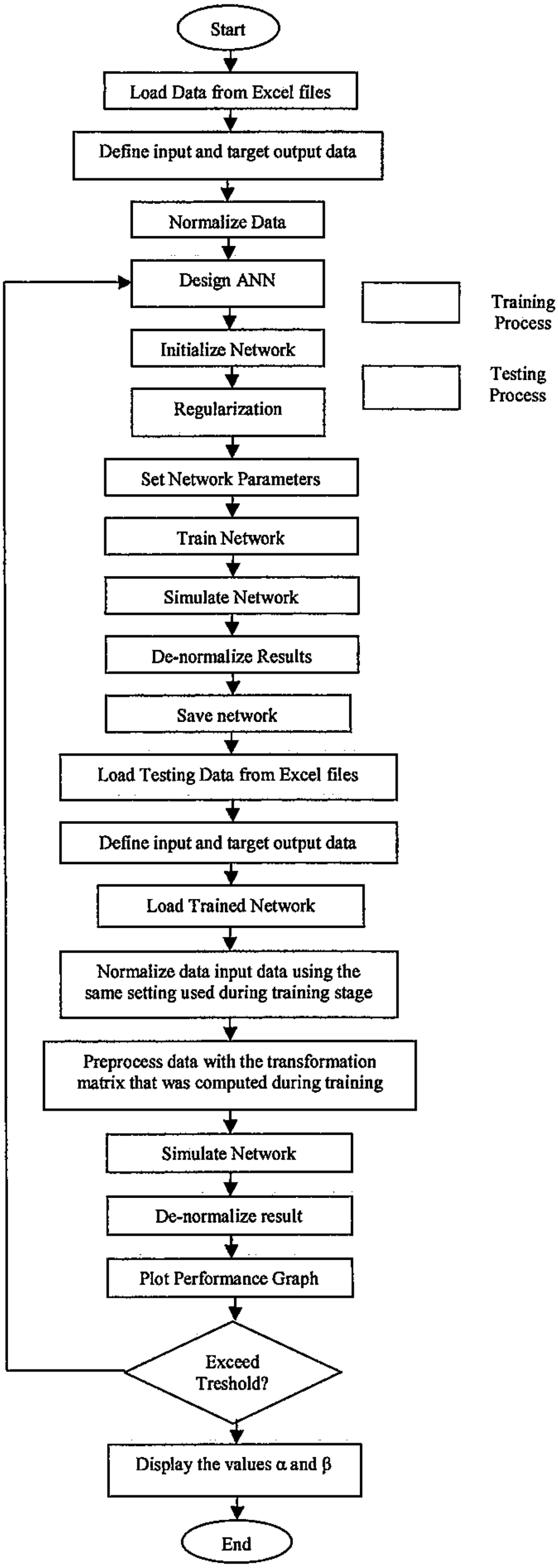

Figure 2: Flow chart for the combined process

D. Application in Wind Power Prediction

At this stage, the ANN is already been tested and the quality of prediction is acceptable and ready to be use in the real wind power prediction. A set of present meteorological data is required in order to predict the wind power for the next hour. At this stage, the target output is no longer been provided, but the network itself will display the wind power prediction for the next hour prediction. The network will implement the pattern recognition that it has been learned from the historical meteorological data throughout the training process.

The formula of wind power is as shown below;

$$\text{Wind Power}, P = 0.5 \times \rho \times A \times V^3 \times C_P \quad (1)$$

Where;

P = power in watts (W)
ρ = air density (about 1.225 kg/m^3 at sea level)
A = rotor swept area, exposed to the wind (m^2)
V = wind speed in meter/s
C_P = 0.59; theoretical maximum value of rotor efficiency

As the rotor swept area can be varying according to the type of wind turbine used by the different wind farm, the formula has been changed to a new formula so that the wind power prediction is usable for all wind farms. The new formula is as shown below;

$$\text{Wind Power density}, P = 0.5 \times \rho \times V^3 \times C_P \quad (2)$$

Where;

P = power in watts per meter square (W/m^2)
ρ = air density (about 1.225 kg/m^3 at sea level)
V = wind speed in meter/s
C_P = 0.59; theoretical maximum value of rotor efficiency [14]

Figure 3 shows the process of the application of the wind power prediction by the user. The present meteorological data must be added into the data and defined as the input data for the real application of wind power prediction. As an output for the ANN, the wind power predicted and the wind direction will be displayed.

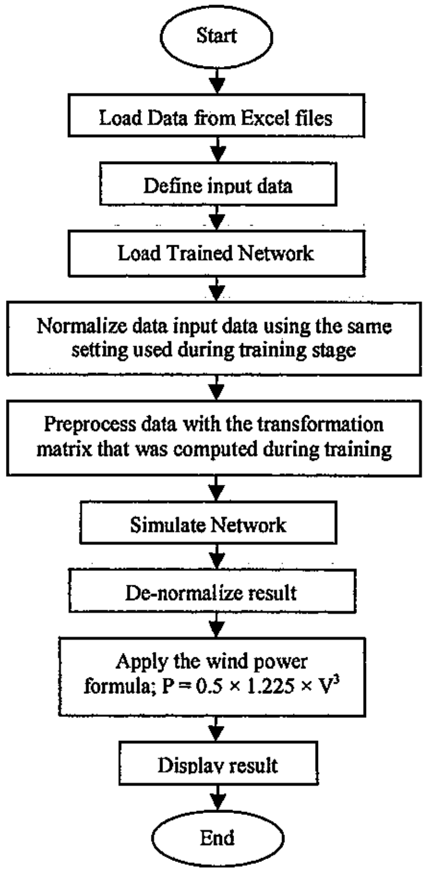

Figure 3: Flowchart for the application of Wind Power Prediction

IV. Results and Discussion

The data were collected from the meteorological data that was taken from a website, which is available at www.wunderground.com. The data used for ANN training consist of hourly meteorological data; where 1458 patterns assigned as training data while 310 patterns was chosen as the testing data.

The evaluation of the network performance can be conducted using post regression analysis where comparison between the network response and the corresponding target is made. The regression coefficient, R with values close to one indicates that there is a strong correlation between the targeted outputs and network outputs while the values that are close to zero indicates otherwise.

As the target output of the ANN have a wide variation, the ANN designed must have the ability to relate between the input and the target output to make it reliable for wind power prediction. After varying the network configuration, the number of neurons and transfer function for several times, the best five results of the network configurations were tabulated in Table 1 below.

Table 1: The Best 5 Possible Configuration

Network's Neuron Configuration	Transfer Function	Learning Rate	Momentum Constant	Regression R
13, 6, 2	logsig, tansig, purelin	0.1438	0.2426	0.81881
13, 6, 2	tansig, tansig, purelin	0.1491	0.7342	0.8179
10, 6, 2	logsig, logsig, purelin	0.1466	0.9529	0.81477
9, 6, 2	tansig, tansig, purelin	0.4164	0.6553	0.81031
12, 6, 2	tansig, logsig, purelin	0.2685	0.4991	0.81012

The best possible configuration for the prediction system developed is [13, 6, 2], using *{logsig, tansig, purelin}* as transfer function and '*Levenberg-Marquardt*' as the training algorithm. According to the configuration, there are 12 neurons in the input layer, 6 neurons in the hidden layer and 2 neurons at the output layer. The R-value achieved by this system is 0.81881, as shown in Figure 5, while the properties of the developed network are shown in Table 2.

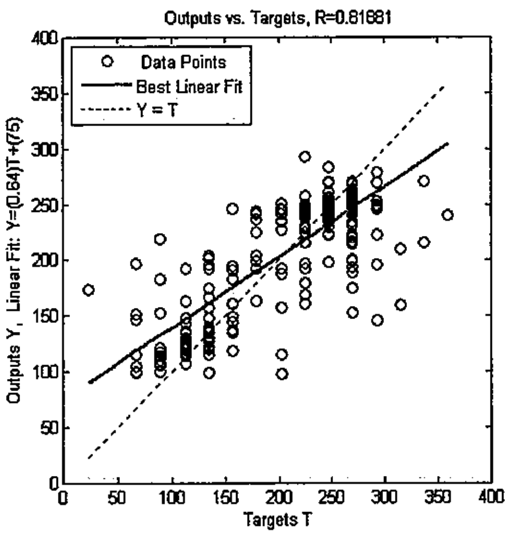

Figure 5: Result for Regression Analysis

Table 2: Properties of ANN

ANN Properties	
Network Configuration	[13, 6, 2]
Transfer Function	logsig, tansig, purelin
Learning Rate	0.1438
Momentum Constant	0.2426
Training Algorithm	Levenberg-Marquardt
No. of Epochs	2000
Training Goal	1×10^{-4}
Regression, R	0.81881
Training Patterns	1458
Testing Patterns	310
No of input variables	26

The ANN is used to predict wind power and the direction of wind for five consecutive hour pattern. The results of wind predicted are as shown in Table 3 below;

Table 3: Result of Wind Power Prediction

No.	Wind Direction (°)		Wind Power (W/m^2)	
	Actual	Predicted	Actual	Predicted
1	247.5	245.8297	6.3515	4.6990
2	270	253.6906	6.3515	4.2867
3	247.5	247.1208	1.2196	1.9773
4	270	249.5542	3.3467	2.6323
5	270	247.2545	1.2196	1.9149

V. CONCLUSION

An artificial neural network (ANN) which uses feed-forward back propagation technique to predict wind power was presented and serves as an alternative to other prediction method available.

The development of this ANN is supported by the historical meteorological data, as the ANN is trained to learn the pattern of historical wind data (meteorological data that related to wind). The testing process is required in order to prove that the training process was successfully done according to a correlation coefficient between targeted output and network output which value is close to unity. As a result, the developed ANN will be able to predict wind power for the next hour when presented with new sets of meteorological data.

VI. FUTURE RECOMMENDATION

For future development, it is recommended that the regression value could be increased as close as possible to unity in order to obtain a good network. It also recommended that the wind power prediction would be able to predict wind power for variable period, which could be implementing through Graphical User Interface, (GUI) to make it more 'user friendly'.

VII. ACKNOWLEDGMENT

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VIII. REFERENCES

[1] D. Johari, T. K. A Rahman and I. Musirin, "Artificial Neural Network Based Technique for Lightning Prediction," in The 5th Student Conference on Research and Development- SCOReD, 2007, pp 1-5.

[2] Shuhui Li, Donald C. Wunsch, Edgar A. O'Hair and Michael G. Giesselmann,"Using Neural Networks to Estimate Wind Turbine Power Generation," IEEE Trans. On Energy Conversion, vol. 3, September 2001, pp 276-282.

[3] D. Johari, T. K. A. Rahman and I. Musirin,"ANN Model Selection and Performance Evaluation for Lightning Prediction System," in Proceedings of the 2nd Seminar on Engineering and Information Technology, July 2009, pp 321-325.

[4] Dr. Ismail Musirin, "One Day Workshop on Artificial Neural Network and Evolutionary Computation Technique (ANNECT)," on ANNECT, 2007.

[5] D. Johari, T. K. A. Rahman, I. Musirin and N. Aminuddin,"Hybrid Meta-EP-ANN Technique for Lightning Prediction under Malaysia Environment," in Proceedings of the 8th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering & Data Bases (AIKED), 2009, pp 224-229.

[6] William J. Palm III, INTRODUCTION TO MATLAB 6 FOR ENGINEERS, McGraw-Hill Higher Education, 2001.

[7] MathWorks,"MATLAB – The Language of Technical Computing, Release Notes for Release 14 with Services Pack 2,"2009.

[8] Wunderground.com, "History Data," Weather Underground Incorporation, http://www.wunderground.com/, 2010.

[9] Brijesh K. Yadav, Ashok K. Keshari and Maarten A. Siebel, "Forecasting Catchment Flow for a Coastal Lake Using Artifical Neural Networks," in Proceedings of Taal2007 on The 12th World Lake Conference, 2007, pp 760-765.

[10] K. Sreelakshmi and P. Ramakanthakumar,"Neural Networks for Short Term Wind Speed Prediction," in World Academy of Science on Engineering and Technology42, 2008 pp 721-725.

[11] Wikipedia, "Wind Power," Wikipedia The Free Encyclopedia, http://en.wikipedia.org/wiki/Wind_power, 2010.

[12] Shuang Han, Yongping Yang and Yongqian Liu,"The Comparison of BP Network and RBF Network in Wind Power Prediction Application," IEEE Trans., pp173-176.

[13] X. Wang, G Sideratos, N. Hatziargyriou and H. Tsoukalas,"Wind Speed Forecasting for Power System Operational Planning," in 8th International Conference on Probabilistic Methods Applied to Power System, September 2004, pp 470-474.

[14] Shuhui Li,"Wind Power Predicton Using Recurrent Multilayer Perceptron Neural Networks," IEEE Trans., pp 2325-2330.

[15] Faridah Shafii and M. Zahry Othman,"COUNTRY REPORT: WIND LOADING FOR STRUCTURAL DESIGN IN MALAYSIA," unpublished.