Short Term Wind Speed Forecasting Using Artificial Neural Network: A Case Study

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***Abstract*—The intermittency of wind speed is very challenging in order to produce wind energy via wind turbine to synchronize with the power system. The accurate wind forecasting models are very important for effective power system management. There are many ways have been introduced for short term accurate wind forecasting. In this paper, Artificial Neural Network (ANN) is used with feed forward back propagation algorithm to forecast short-term wind speed of Asian Institute of Technology (AIT). After simulating the model in MATLAB, the result shows that the mean absolute percentage error (MAPE) between the predicted and measured wind speed is quite low and noteworthy. It represents the high prediction correctness of short-term wind speed forecasting using the above mentioned model.**

***Keywords—component; formatting; style; styling; insert** (key words)*

I. INTRODUCTION

In order to reduce fuel energy, one country needs to exploit energy from renewable energy sources. Wind energy is important source for power generation because a wind power plant is operated without fuel consumption, has economical operation [1]. The investment cost of wind power plant depends on various factors including the location, the type of wind turbine and its generator. Wind power generation has total installed capacity of 318.5GW in 103 countries in 2013 and is projected to share one third of the world's electricity by 2030. Currently, wind power contributes nearly 4% to the world electricity demand [2]. Thailand just started using electricity generated by wind turbine in 2010 when the first wind power plant was built. The total capacity of all wind power plants in December 2013 was 193 MW, while the peak demand in year 2014 was 26,942.10 MW [3]. Among all the renewable energy sources wind (speed) needs more forecasting approach due to its higher intermittency rate. In order to ensure the efficient installation, operation and continuation and to have reduced influence on wind power projects in severe weather, the magnitude of wind power forecasting has become a vital issue. Again due to forecasting in energy market trading one gets a heads up and can decrease imbalance charges and fines.

II. BACKGROUND

The randomness of wind speed is very challenging in order to produce wind energy via wind turbine to harmonize with the power system. The precise wind predicting models are very important for effective power system management. Many ways for short-term accurate wind forecasting have been instigated to get the most out of wind power. However, it is a very tough problem due to the high uncertainties from surrounding environment and the current weather forecast capability. The most straightforward and traditional solution is using the wind variables from real time forecasts of a full-physics atmospheric model , but it is very limited to meet the requirement of a local wind farm. Recently, several attempts have been made by using full physics atmospheric models, statistical approaches or neural network (NN) varieties [4].

An ANN contains of simple processing units called neuron [5]. The computational capabilities are excellent determined by the connection weights, network architecture and training algorithm. ANN is excellent tool for researching field; it can solve non- linear function, data classification, clustering, simulation, prediction, and load forecasting and restoring missing wave measure [6]. ANNs have been used in different fields of science and technology including prediction of different environmental parameters like solar radiation, wind speed etc. and power forecasting [7]. ANN extracts information from data to develop complex relationship between input and output. The inputs variables are multiplied by connection weights and its products, biases are added and delivered through transfer functions for generating output. The network is decided by architecture, exciting function and training algorithm. The architecture determines connection pattern among neurons. During training, the values of connection weights and biases are updated to reduce the mean square of output error. The wind speed prediction accuracy is determined by mean absolute percentage error (MAPE).

The hourly mean wind speed data of January 2016 is used in the ANN model. The data are taken from the automatic wind monitoring station of the Energy field building, School of Environment Resources and Development (SERD), Asian Institute of Technology (AIT), Pathumthani, Thailand (latitude:14.0796^{0}N, longitude:100.6127^{0}E, altitude:14m above mean sea level). The wind speed range during that period was recorded from 0.04m/s to 4.04 m/s (figure 1).

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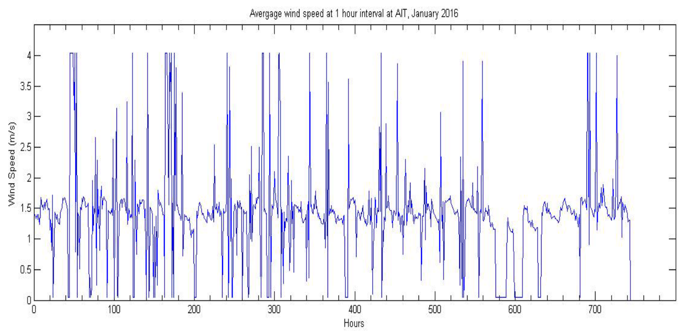

Fig. 1. The hourly variation of wind speed averaged in 01hour interval at AIT Energy building during January, 2016.

III. System Model

In this project, neural network toolbox (**nntool**) of MATLAB R2014a is used to forecast hourly 24 hour ahead wind speed with Levenberg-Marquardt Feed forward Back Propagation Algorithm.

The input contains 24 samples which is exactly the same as time period in one day (putting in column of the workspace in MATLAB. Each sample (column) has 30 rows representing the wind speed in the past 30days. Among these 24 samples, there are three groups of data. First group is train data, which contains 60% sample and is selected randomly by nntool. Second group is the validation data which contains 20%sample; it measures the network in general by feeding it with new data. The last group is the test data which contains 20% sample and measures the neural network performance independently in terms of Mean Square Error (MSE). MSE is the square of the difference between predicted value and target value. Thus, it is always positive.

Therefore, this model has 3 layers-first layer is input layer which has 30 neurons corresponding to 30 days of January 2016, second layer is hidden layer which has 20 neurons and the third is output layer which has 1 neuron corresponding to the predicted day. The model simulation is implemented in four scenarios which 01st, 11^{th}, 22^{nd} and 31th day of January 2016 is set as the target accordingly.

Proposal Formulation

The wind speed forecasting accuracy is determined by MAPE attained from the following equation:

$$MAPE = \left(\frac{1}{n} \sum_{i=1}^{n} \frac{\left| ws_{i(ANN)} - ws_{i(measured)} \right|}{\left| ws_{i(measured)} \right|} \right) \times 100$$

Where, n is input and output pair numbers (which can be vector quantities); $Ws_{i(measured)}$ is measured wind speed for I hour; $Ws_{i(ANN)}$ is predicted wind speed for i hour.

The level of prediction accuracy judged by MAPE are less than 10% (high prediction), 10%-20% (good prediction) and over 50% (inaccurate prediction) [8].

IV. Result And Discussion

A. Scenario 01

The performance plot of ANN model demonstrates that the MSE is 0.0002 as shown in figure 2. It means the error between predicted value and the measured value is very small correlation coefficient (R-value) shows the association among output and target value of ANN model The perfect fit indicates the data should fall along 45^0 line (Slope is equal to 1), means network output is equal to target. The R-value is 0.98 and slope is 0.98, achieve during whole data set, proved that the prediction close to measured value as shown in figure 3.

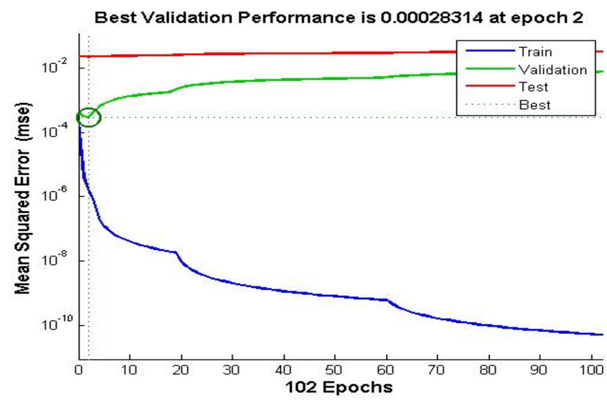

Fig. 2. Performance plot of wind speed prediction in 01st January 2016.

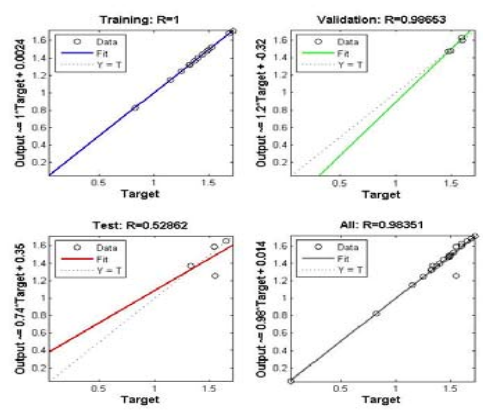

Fig. 3. Regression plot of wind speed prediction 01st January 2016.

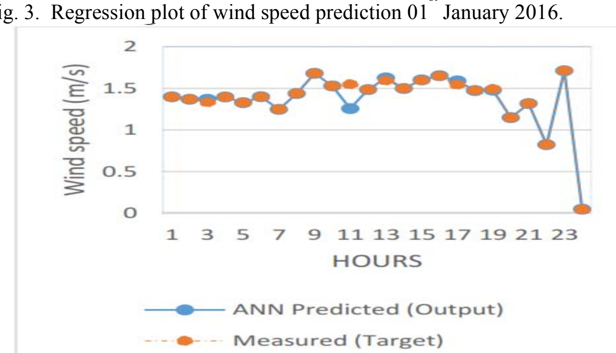

Fig. 4. Comparison between predicted and measured wind speed in AIT on 01^{st} January 2016.

TABLE I
CALCULATION OF MAPE IN 01st JANUARY 2016

Hour	**Wind Speed (m/s)**	
	Predicted	***Measured***
1	1.40	1.40
2	1.37	1.37
3	1.37	1.33
4	1.40	1.40
5	1.33	1.33
6	1.40	1.40
7	1.25	1.25
8	1.44	1.44
9	1.68	1.68
10	1.53	1.53
11	1.26	1.55
12	1.48	1.49
13	1.62	1.59
14	1.50	1.50
15	1.60	1.60
16	1.65	1.65
17	1.59	1.54
18	1.47	1.48
19	1.48	1.49
20	1.15	1.15
21	1.32	1.32
22	0.82	0.82
23	1.71	1.71
24	0.05	0.05
MAPE	**1.1%**	

In this table, there are three columns; the first column shows the number of hours in that day while the second column presents the predicted wind speed value that is prepared using nntool and the measured wind speed value is in last column. The result is 1.1% which indicates high accuracy prediction.

B. Scenario 02

The performance plot of ANN model shows that Mean Square Error (MSE) is 0.014 (figure 5). It means the error between prediction value and the measure value is very small. The R-value is 0.86 and slope is 1, achieved during whole dataset, proved that the prediction close to measured value as shown in figure 6. The MAPE is calculated by comparing predicted and measured data which is 13.7%, showing good prediction of ANN model.

In this table, there are three columns; the first column shows the number of hours in that day while the second column presents the predicted wind speed value that is prepared using nntool and the measured wind speed value is in last column. The result is 1.1% which indicates high accuracy prediction.

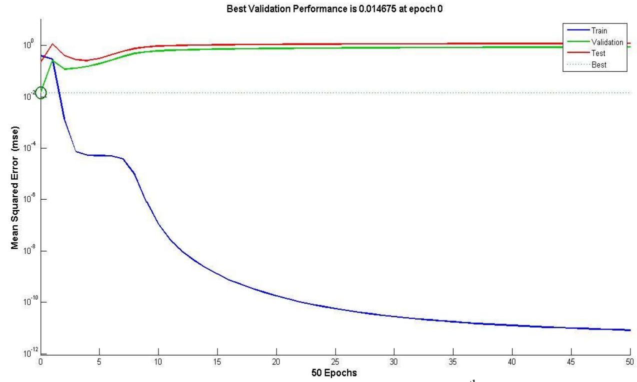

Fig. 5. Performance plot of wind speed prediction on 11th January, 2016.

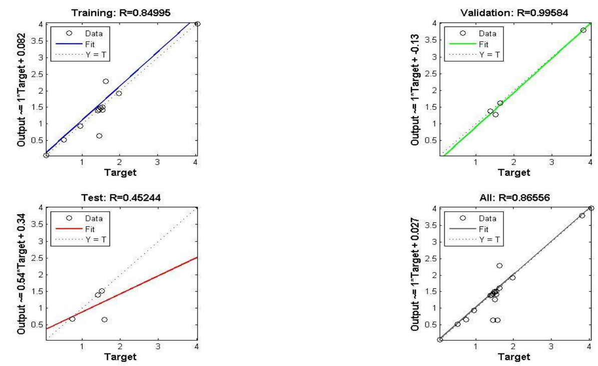

Fig. 6. Regression plot of wind speed prediction on 11th January 2016.

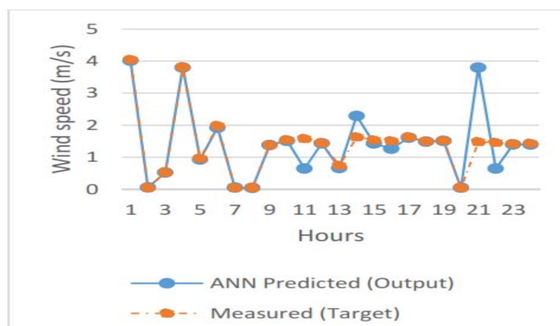

Fig. 7. Comparison between predicted and measured wind speed.

C. Scenario 03

The performance plot of ANN model demonstrates that the mean square error (MSE) is 0.004 as shown in figure 8. It means the error between prediction value and the measure value is very small. The correlation coefficient (R-value) shows the association among output and target value of ANN model. R value is 0.9 and slope is 0.85 which leads to MAPE of 5.1%.

TABLE II
CALCULATION OF MAPE IN 31st JANUARY 2016

Hour	**Wind speed(m/s)**	
	Predicted	***Measured***
1	1.26	1.26
2	1.32	1.32
3	0.79	0.61

4	2.76	3.07
5	1.64	1.64
6	1.04	1.18
7	1.45	1.62
8	0.42	0.34
9	0.76	1.59
10	1.63	1.63
11	1.60	1.60
12	1.62	1.62
13	1.63	1.63
14	1.66	1.66
15	1.72	1.64
16	1.71	1.71
17	1.60	1.60
18	1.82	1.55
19	1.52	1.52
20	1.50	1.50
21	1.46	1.46
22	1.41	1.41
23	1.45	1.45
24	1.42	1.42
MAPE	**5.1%**	

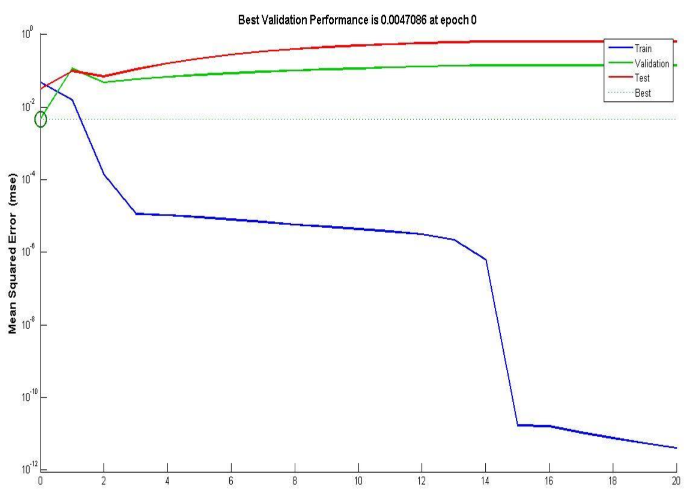

Fig. 8. Performance plot of wind speed prediction on 22nd January, 2016.

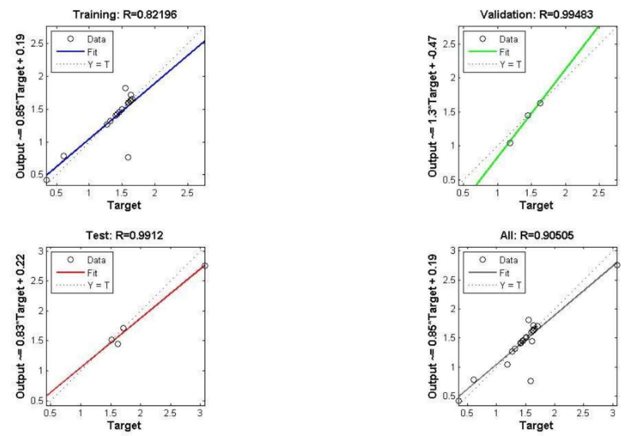

Fig. 9. Regression plot of wind speed prediction on 22nd January 2016.

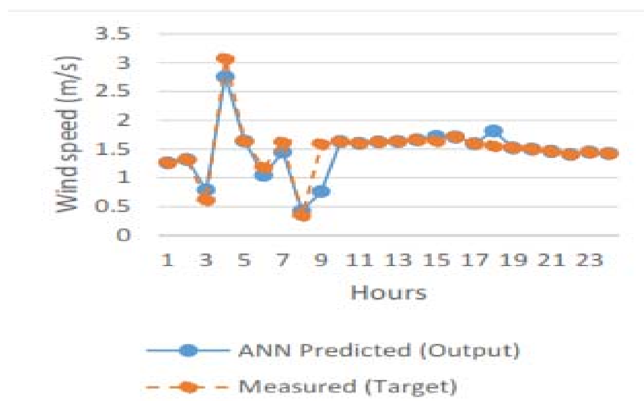

Fig. 10. Comparison between predicted and measured wind speed.

D. Scenario 04

It is clear from the performance plot of ANN model that Mean Square Error is 0.0167 which is very less. The R-value is 0.97 and slope is 0.88, achieved during whole dataset, proved that the prediction close to measured value as shown in figure 9. The MAPE is 4.08%, showing high accuracy of ANN model as shown in figure 10 and table III.

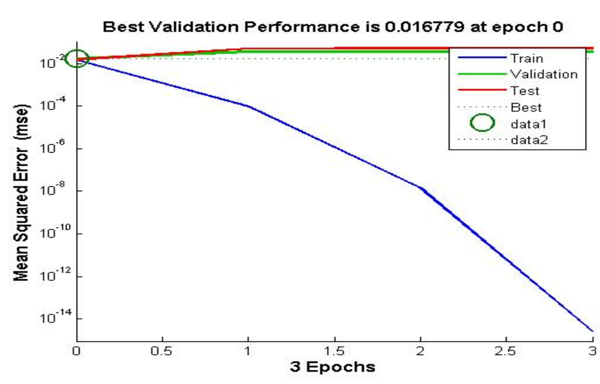

Fig. 11. Performance plot of wind speed prediction on 31st January 2016.

TABLE III
CALCULATION OF MAPE IN 31st JANUARY 2016

Hour	Wind Speed (m/s)

	Predicted	*Measured*
1	1.26	1.31
2	1.47	1.41
3	1.98	1.98
4	1.28	1.32
5	1.39	1.35
6	1.49	1.37
7	2.19	2.61
8	3.89	4
9	1.51	1.48
10	1.67	1.54
11	1.53	1.60
12	1.63	1.59
13	1.74	1.69
14	1.28	1.03
15	1.49	1.60
16	1.47	1.51
17	1.49	1.45
18	1.53	1.56
19	1.49	1.51
20	1.45	1.45
21	1.38	1.41
22	1.36	1.29
23	1.31	1.31
24	1.53	1.31
MAPE	**4.08%**	

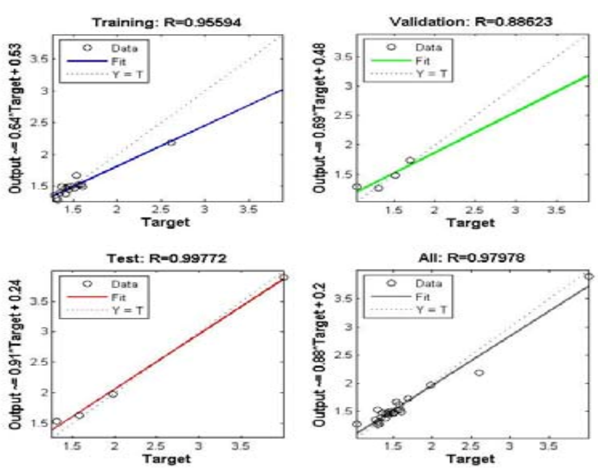

Fig. 12. Regression plot of wind speed prediction on 31st January 2016.

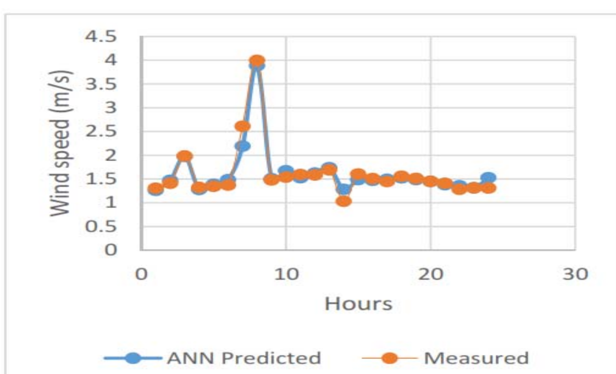

Fig. 13. Comparison between predicted and measured wind speed on 31st January 2016.

V. Conclusion

ANN model with feed-forward back propagation algorithm is used to forecast hourly wind speed in AIT. The MAPE of the day 01, 11, 22 and 31 are 1.1%, 13.7%, 5.1% and 4.08% respectively which indicates the high prediction accuracy. It means that this model works well with short-term wind speed prediction. Future study can be focused not only on wind velocity prediction but also on parameters of other renewable sources prediction. Furthermore, the comparison between this method and other methods like Levenberg-Marquardt with Bayesian Regularization or Scale Conjugate Gradient or Support Vector Machine (SVM), Decision tree and Random Forest (RF) can be studied for forecasting.

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