Detailed Analysis for Implementing a Short Term Wind Speed Prediction Tool Using Artificial Neural Networks

Aubai Alkhatib
University of Kassel
REMENA
Kassel, Germany
alkhatibaubai@yahoo.com

Siegfried Heier
University of Kassel
REMENA
Kassel, Germany
heier@uni-kassel.de

Melih Kurt
Fraunhofer IWES
Kassel, Germany
mkurt@iset.uni-kassel.de

***Abstract* - Wind speed forecasting is an essential prerequisite for the planning, operation, and maintenance works associated with wind energy engineering. This paper attempts to forecast fluctuations based only on observed wind data using the data-driven artificial neural network approach. Wind fluctuations with varying lead times ranging from a half year to a full year are predicted at Al-Hijana, Syria with the pre-preparation for the available data. Two layers of feed-forward back-propagation networks were used along with the conjugate gradient algorithm and other tested training functions. The results show that artificial neural network models perform extremely well as low values of errors resulting between the measured and predicted data are obtained. The present work contributes to previous work in the field of wind energy independent power producer market and may be of significant value to Syria, considering that the country is currently in the process of transitioning into a free energy market. It is likely that this modeling approach will become a useful tool to enable power producer companies to better forecast or supplement wind speed data. Two main types of wind speed prediction tool is discussed in this paper. One prediction tool with no time shift and the other prediction tool with time shift, where in the second type two different time periods were used to show the different between long term prediction and short term prediction.**

Keywords - Artificial Neural Networks; Wind Speed; Mean root square error; Training functions; Short term prediction; Long term prediction.

I. INTRODUCTION

The wind-energy spread usage in recent years is an attempt to address the environmental problems that result from the consumption of energy and especially from nuclear power plant disasters like the one that recently occurred in Fukushima, Japan [1]. The IPCC (Intergovernmental Panel on Climate Change) indicated that [2] human activities are directly related to increased atmospheric levels of greenhouse gasses, i.e., carbon dioxide, methane, chlorofluorocarbons, and carbon monoxide. Additionally, a correlation also exists between global warming involving greenhouse gas and environmental problems. It is generally agreed that of those harmful greenhouse gasses, carbon dioxide contributes the most to global warming. The main artificial source of carbon dioxide discharge is derived from fossil fuels (conventional power plants). Therefore, much recent research has focused on reducing the consumption of fossil fuels and replacing those with renewable, environment-friendly energy sources. Currently, wind energy is considered as one of the most promising energy sources. However, since wind is difficult to manage, generating wind energy is still a challenge. Due to a variety of factors, the wind speed characteristic curve can change with time, location and height. Wind blows as a result of an imbalance in the quantity of heat on the earth by the energy from the sun. Experimentally, it is known that wind speed is intermittent, irregular, and frequently fluctuates in the short term. Since wind energy is directly related to the cubic value of the wind speed, any changes in the wind speed will greatly impact the amount of the energy. In order to better support the transition to a free energy market, a more accurate means of estimating the energy generated from the wind farm and pumped in the grid is needed.

This paper thus introduces an ANN (Artificial Neural Networks) for wind speed predictions to estimate the wind speed in a suggested location in Syria that involves two main approaches.

1- No time shift approach.
2- Time shift approach: which contain:
   a. A one year prediction tool (old approach – long term-).
   b. A half year prediction tool (new approach, see the next point -3-).
3- Time shift new approach (short term): is suggested in is work as result of analysis the outputs generated from the previous tools.

Also, the different possible ways that can be used in order to improve the prediction output (e.g., choosing different training functions, which are introduced by Matlab). This paper also introduces a model for energy estimation using the output of the wind speed prediction tool as an input for the energy model. Using the Matlab computing program for building the suggested ANN is one of the future computing methods for wind prediction.
Finally the steps needed for building the suggested wind speed prediction tool & the energy module are presented in the same order as done is this research, from the part of getting the row data and analyzing the importance of every used input using speerman analysis, till getting the final results obtained from the energy module. A suggestion for new approach is ales presented in this paper for predicting

the wind speed (with time shift) taking into consideration the unexpected changes in the wind speed function

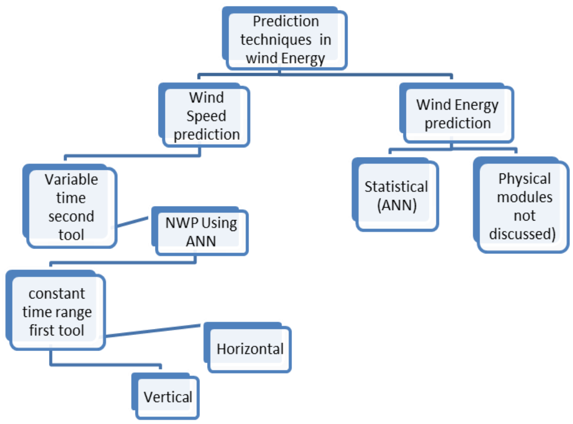

Figure 1. Prediction techniques

Figure 1 shows the different prediction techniques used in the wind energy field. The physical module in wind energy prediction section is not discussed in this paper and the variable time prediction technique is the time shift tool (old and new approach). The constant time range is the not time shift approach.

II. WIND SPEED PREDICTION TECHNIQUES

In this part a detailed description will be illustrated for the actual steps used in this research in order to build an acceptable wind speed prediction tool using the artificial neural networks approach.

A. *state of the art*

The wind speed characteristic can be considered a non-linear fluctuation. Therefore, the forecasting of this function using traditional methods (e.g., numerical weather prediction (NWP) which is used in Germany nowadays) can be very difficult and time consuming. In this case, the intelligent engineering represented by a neural network, a chaos fractal, and a genetic algorithm, etc. can be applied. While these techniques are already adopted in numerical predictions, the usage of the ANN gives a better performance in terms of pattern recognition and finding location peculiarities, especially when information on the used wind turbine and power curve is given [3]. That is why the focus in this work will be on developing an acceptable wind speed prediction tool using ANN's and showing the different possibilities of sizing this tool with a new approach for minimizing the errors resulting from the used prediction tool.

B. *The usage of the proposed wind speed prediction tool*

There are two different types of wind speed predictions [4]:

The vertical wind speed prediction or the prediction of the expected wind speed curve in one point on the geographical map with different height. This can be seen, for example, when the wind measurement device is at a height of 40 m and the wind turbine is installed in the same location yet in a different hub height like 105 m

The horizontal wind speed prediction or the prediction of the expected wind speed curve in one point on the geographical map that has a horizontal difference from the point of measured data. This is witnessed when the wind measurement device is in one location and the wind turbine is installed in another location (top of a mountain where the measurement is very difficult to be obtained) [5].

In both cases the no time shift tool can be used in order to get the predicted wind speed at the height of the used wind turbine in a new location with no available measurements. In this tool it is enough to know the pressure and temperature of a nearby location (not at the same place of the location of interest).

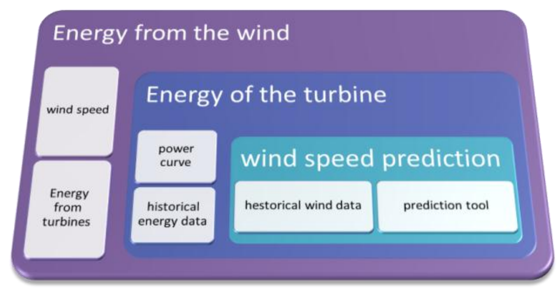

Figure 2. Wind speed prediction and energy module connections

The historical wind data shown in Figure 2 indicates that the atmospheric parameter measurements such as the pressure and temperature that were available for the location in our case. The energy historical data indicates a previous energy output for a previous wind turbine installed in the location of interest, which was not available in our case (as this was the first wind farm to be installed in this location).

Finally a wind prediction tool was built in order to predict the wind speed in locations where no wind speed measurement devices are available which means to predict the wind speed from the available data of a specific site (Like pressure, temperature …etc.). In this case no time shift is introduced, which mean that the prediction is done for the measured data for the same time.

C. *Feed Forward Neural Network with Backpropogation*

A neural network is a computational structure that resembles a biological neuron. It can be defined as a "*massively parallel distributed processor made up of storing processing units, which has a natural propensity for storing experimental knowledge and making it available for use*" [6].

A feed-forward neural network consists of layers. Every layer will be connected to the previous once with more than one connection that has a weight to determine the importance of this connection. Every network has at least three layers. These include the input layer, output layer, and the hidden layer(s). The strength of a set of inputs can be determined by the activation function after adding the whole input signals as shown in Figure 3.

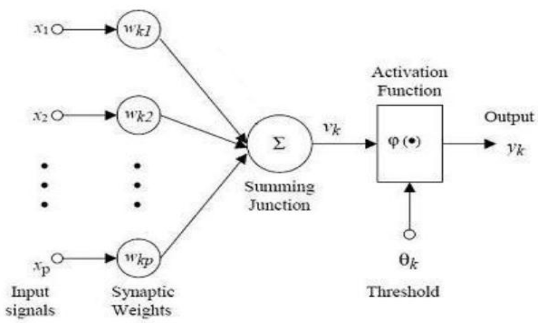

Figure 3. Basic structure of a neuron [6]

The raw data was provided in a form of Excel file. Patterns were generated and a statistical analysis performed to get a good correlation among the input values. Some data was fed as an input in the prediction network for training purposes while other data was specifically employed for network testing purposes.

The following steps were taken to get the wind speed prediction:

1- Data Acquisition & Pre-processing.
2- Data conversion & Normalization.
3- Statistical Analysis.
4- Design of the Neural Network &Training.
5- Testing.

D. Data Acquisition, Pre-processing, and Data Conversion

The different weather parameter values were collected from the used measurement devices in the location of interest [7]. Time series was provided for every ten minutes with the help of the Syrian National Energy Center for Research and Development. The values of three different parameters were utilized to include the pressure, temperature and wind direction as shown in Table I.

TABLE I. LIST OF NETWORK PARAMETERS[8]

station	day	hour	speed 40 s wvt	direct 40 dl wvt	direct 40 sd1 wvt	speed 40 max	speed 40 std	speed 10 avg	speed 10 max	speed 10 std	temp	pressure
14	1	0	1.656	199.8	8.55	2.01	0.183	1.184	1.57	0.142	3.344	947.24
14	1	10	1.549	185.6	9.74	1.91	0.164	1.136	1.47	0.097	3.581	947.1
…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…
14	366	2230	2.803	278.1	8.74	4.71	0.643	2.579	3.73	0.48	3.624	945.58
14	366	2240	3.069	282.2	7.22	4.29	0.385	2.593	3.55	0.379	3.392	945.68

During the data acquisition stage, the maximum value among each parameter was computed after that normalization was carried out for all the used parameters [9].

During the visit to the Syrian National Energy Center we have learned that not in all cases a wind speed data is available, which means that sometimes it is needed to predict the wind speed from the available information in location of interest, that is why a scenario of wind speed prediction tool with no time shift is introduced and compared with that used for wind speed prediction with time (the ANN is trained with the available wind speed data and get as a results the wind speed for the next year or six months).

E. Statistical Analysis

Since the amount of available data is massive and the characteristic curve of the wind speed continually changes with time, a statistical analysis is needed in order to measure the extent of the relationship between each of the meteorological values and to get rid of the redundant values that might be present in the data set. Therefore, a "*Spearman rank correlation*" was applied. The amount of correlation in a sample (of data) is measured by the sample coefficient of correlation, generally denoted by 'r' or by 'ρ'.

This analysis is very important for the "no time shift scenario". The results of this analysis can determine, which data are a must for the wind speed prediction tool (As input) and which data have a secondary effect on the output of the prediction tool. As a result of this analysis the measurement devices that should be installed in any location can be determined.

F. Spearman's Correlation

Spearman's correlation allows testing the direction and strength of a relationship [10]. For example the relationship between the pressure and the wind speed will be shown (one of the inputs of the prediction tool and the output) to help determine the importance of this parameter on the output of the prediction. This in turn can give a good vision of the expected output of the suggested ANN tool. This approach can also be applied to problems in which data cannot be measured quantitatively but in which a qualitative assessment is possible. In this case, the best individual is given rank number 1, the next rank 2, etc. (In our case the highest wind speed, which is the rated wind speed for the wind turbine in which the wind turbine generate its rated power in kW, will get the rank number 1).

The correlation coefficient takes values between [1,-1]. A value of /1/ indicates that the relationship between the two different parameters is very strong and has a positive effect (when "X" increases, "Y" value will also increase). The value/-1/ has the same strength meaning of /1/ yet the relation is inverse. A value of /0/ means that no relationship exists between the two different studied parameters.

Steps for achieving a Spearman's ranking:

A- Rank both sets of data from highest to lowest value (make sure to check for tied ranks - readings of the same value and to obtain the same sequence of readings).

B- Subtract the two sets of ranking data to get the difference /d/.

C- Square the values of /d/.

D- Add up the squared values of the differences.

E- Calculate the values using Spearman's Ranking Formula [10]:

$$\boldsymbol{R = 1 - \frac{6 \times \Sigma D^2}{n(n^2 - 1)}} \qquad (1)$$

Table II shows the results obtained from this analysis for one year data (2008). It can be seen that the pressure has an inverse influence on the wind speed and that the temperature has an indirect effect on the wind speed through an inverse relationship with the pressure [11].

TABLE II. SPEARMEN'S RANKING RESULTS FOR 2008

		2008		
Correlation	**Wind Speed**	**Direction**	**Temperature**	**pressure**
Wind Speed	**1**			
Direction	**0.232188687**	**1**		
Temperature	**0.257124942**	**0.214808385**	**1**	
pressure	**-0.49489753**	**-0.29900903**	**-0.70568132**	**1**

Figure 4 gives a statistical analysis for 6 years of available data. The figure can be used to clarify the results obtained from the prediction tool as it shows that the atmospheric parameters and the character curve of the wind speed changes on a yearly basis. The information obtained from Spearmen's ranking can help determine which data should be selected as training data in order to contain the best possible situation and get better prediction results for this specific location. What is more it can be noted that the pressure has the most direct influence on the wind speed so it should be used as an input for the prediction tool in any case (with or without time shift scenarios). Although the temperature has no big effect on the wind speed as the pressure it still should be included in the wind prediction tool as it has a good effect on the pressure.

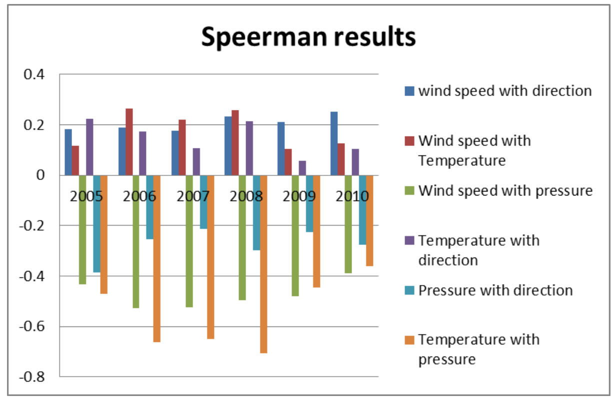

Figure 4. Spearman's analysis

It is important to mention that some ANN tool uses a "helping function". The helping function is normally determined by carrying out a statistical analysis (in our case speerman). This helping function works as pre-determining function, which will help the ANN tool by telling what the expected output should look like avoiding unexpected outputs by the ANN tool. Unfortunately this approach was not used in this work as the purpose of this work was to get the differences of using different internal parameters used in the ANN tool itself (e.g. Training functions, number of neurons, number of the hidden layers, Activation functions, …etc.).

G. *Design of the Neural Network & Training*

Designing the neural network means sizing the network in order to fit our need. Unfortunately, there is currently no mathematical equation for sizing the network or determining which training functions to use [12]. Thus, engineers often rely on trial and error and personal experience to solve these issues. In our case, the sizing of the number of hidden layers, training functions, activation functions, number of neurons in the hidden layers, and determining the best training input pattern was accomplished through trial and error and, as shown in Figure 5, a comparison of the results. Finally, 2 hidden layers with feed forward activity were chosen (as the differences in the results between 2 and 3 hidden layers were very small and neglectable see Table III in comparison to Table IX).

TABLE III. RMS VALUES WHEN USING 3 HIDDEN LAYER PREDICTION TOOL

one year input with three hidden layers and different training data																				
Description	max					min					average					RMSD				
Year		2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
year 2008 training	21.036	21.04	20.37	13.31	9.594	-18.1	-18.1	-17.6	-18	-12.8	3.94646	3.946	-4.51	-0.947	0.057	0.137	0.137	0.1406	0.115	0.049
year 2007 training	13.467	13.47	16.78	9.242	16.71	-15.5	-15.5	-8.71	-7.96	-10.2	-5.5216	-5.52	1.734	0.003	5.963	0.143	0.143	0.0959	0.043	0.135

Using the back propagation algorithm in each training set, the weights were modified in order to reduce the root mean squared error (deviation) (RMSE/D/) between the predicted values and the actual readings as target values. Thus, the modification takes place in the reverse direction from the output layer until the terminating condition is reached. The steps are:

- Initialize the weights.
- Propagate the inputs forward.
- Back propagate the error.
- Terminating condition.

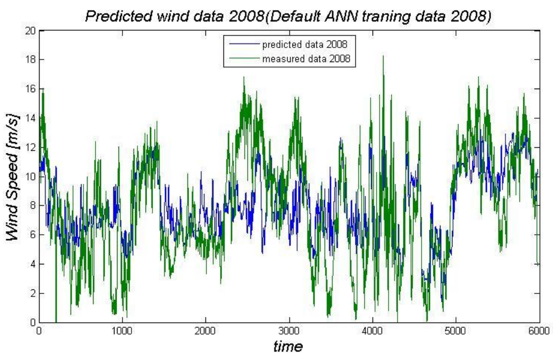

Figure 5. Deviation of predicted and measured wind speed for 2008

Figure 5 shows both the predicted wind speed and the measured wind speed for the year 2008. It is clear that in some points the measured wind speed takes a drastic change is speed (between X=2000 and X=3000 on the time axis in Figure 5) that the prediction tool did not expect, in this case a helping function can be useful to correct the prediction tool results.

H. Testing

Testing is the final stage needed to finalize the proposed wind speed prediction tool. While different methods can be used to evaluate the results obtained from the prediction tool, in this case the Mean Square Error method was used [13].

TABLE IV. RMSE OF THE WIND PREDICTION TOOL WITH DIFFERENT INPUT POSSIBILITIES FOR DIFFERING YEARS.

different inputs with time																				
Description	max					min					average					RMSD				
Years	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Wind data input	0	17.331	17.479	7.866	11.819	0	-7.8058	-9.7378	-10.206	-7.7274	0	-0.0814	1.14062	-0.0161	1.48332	0	0.0623	0.0824	0.05091	0.0749
all as input	0	11.573	15.195	5.447	11.485	0	-16.792	-16.34	-13.66	-9.8059	0	-5.5984	-2.2118	-3.7902	-0.0325	0	0.13893	0.1214	0.0916	0.0597

TABLE V. RMSE OF THE WIND PREDICTION TOOL WITH DIFFERENT TRAINING DATA FOR DIFFERING YEARS.

two year input for prediction with time tool																				
Description	max					min					average					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
two year 2007-2008	NP	15.68	15.21	8.52	9.099	NP	-17.5	-13.9	-7.88	-10.4	NP	-0.36	-1.6	0.098	0.065	NP	0.098	0.057	0.038	0.057
two year 2006-2007	NP	17.61	15.89	8.731	15.56	NP	-22.7	-8.23	-8.03	-10.6	NP	-0.42	-0	0.257	5.677	NP	0.159	0.0441	0.068	0.127

TABLE VI. RMSE OF THE DIFFERENT YEARS WIND PREDICTION TOOL WITH DIFFERENT TRAINING FUNCTIONS.

different training functions with time																				
Description	max					min					average					RMSD				
Years	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Bayesian Regulation	0	16.856	14.09	12.35	10.101	0	-10.119	-11.103	-12.967	-10.662	0	-0.6578	-0.4479	-0.7117	-9E-05	0	0.07538	0.0791	0.07472	0.0669
Fletcher-Reev	0	17.202	13.017	8.371	11.139	0	-8.9468	-10.426	-10.182	-8.418	0	-9E-05	-0.3887	-0.7026	0.04619	0	0.07435	0.0786	0.07087	0.067
Marquardt	0	20.416	12.621	11.05	9.8743	0	-18.207	-9.7308	-10.111	-8.6624	0	1.59405	-0.4967	-0.9127	-0.063	0	0.1548	0.0787	0.06833	0.0669
Quasi-netwton	0	16.916	13.239	11.34	10.486	0	-9.0429	-9.3813	-9.9776	-8.5122	0	-1.241	-0.486	-0.8636	-0.0545	0	0.07359	0.0786	0.06932	0.067

The previous tables give the results of the differing sizing possibilities that can be used for the prediction tool. It can be seen that the usage of the pressure, temperature and wind direction as inputs for the prediction tool is more effective than using each parameter alone. Also, the 2007-2008 input data gives better results than the 2006-2007 data because the MSE is better in the first case. After determining which training data to be used as input for the suggested prediction tool, different training functions are tested in order to see which training function results in the lowest RMS values. The next step will be to determine the activation function which is very important to determine which input summation is enough to get a high output values. More information about the different training function and activation function can be found in Matlab help, with a definition of the different properties of every function.

The results for using the "no time shift scenario" are as follows:

TABLE VII. RMSE OF THE WIND PREDICTION TOOL WITH DIFFERENT ACTIVATION FUCNTIONS.

different activation functions (no time prediction)																				
Description	max					min					avarage					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
purelin Act.	14.46	16.4	14.9	7.6	9.977	-7.77	-8.1	-7.95	-17.6	-8.07	0.18	-1.29	-0.48	-1.41	-0.07	0.069	0.0666	0.079	0.061	0.069
logsig Act.	21.04	10.6	10.5	8	9.518	-18.1	-17	-15.9	-17.2	-11.1	3.95	0.982	-3.31	-5.6	-0.03	0.137	0.1043	0.105	0.124	0.056
MSE Perf.	5.703	13.6	11.9	9.17	11.01	-17.2	-15	-16.5	-16.8	-10.4	-7.2	1.473	-2.81	-2.83	0.011	0.15	0.0964	0.098	0.094	0.056
sum Perf.	13.23	13.2	9.79	9.07	10.76	-13.2	-13	-13.1	-17.4	-11.7	-1.1	-1.11	-3.01	-2.49	-0	0.071	0.0715	0.101	0.08	0.062

TABLE VIII. RMSE OF THE WIND PREDICTION TOOL WITH DIFFERENT TRAINING FUCNTIONS.

different training functions (no time prediction)																				
Description	max					min					average					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Bayesian Regulation	12.227	16.531	18.456	10.86	10.02	-17.98	-18.296	-17.041	-18.297	-10.928	-8.3043	-9.6229	-1.7939	-5.3751	-0.0492	0.17806	0.20016	0.1247	0.1671	0.0515
Fletcher-Reev	18.0054	17.237	17.458	8.371	10.334	-16.149	-16.123	-11.41	-11.64	-11.409	-1.2824	-0.0492	-1.5887	-1.0298	-0.0376	0.11547	0.12557	0.1026	0.07491	0.056
Marquardt	22.7813	20.416	16.424	13.31	10.017	-17.549	-18.207	-17.974	-17.832	-11.179	3.2116	1.59405	-5.3782	-2.0494	0.02095	0.1733	0.1548	0.1513	0.13921	0.0505
Quasi-netwton	20.6997	13.824	8.5364	11.16	9.5953	-17.654	-18.182	-13.513	-18.29	-10.257	-5.948	-6.6341	-4.2221	-3.2991	-0.0501	0.15514	0.15158	0.112	0.10729	0.0533

TABLE IX. RMSE OF THE WIND PREDICTION TOOL WITH DIFFERENT TRAINING DATA.

default type of ANN with different training data (2008-2007) (no time prediction)																				
Description	max					min					average					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
2008 training data	15.531	13.959	12.466	8.525	9.5902	-16.225	-17.764	-15.76	-18.238	-10.675	-1.8815	4.10261	-3.013	-4.0005	-0.0306	0.12767	0.12201	0.1051	0.10668	0.054
2007 training data	22.7516	15.671	17.515	8.371	12.153	-15.23	-15.547	-7.4397	-8.5895	-9.8371	4.3987	-4.0795	1.35332	-0.0386	0.09141	0.16641	0.13326	0.0901	0.04862	0.0761

It is clear from the above tables that the RMS errors of a wind speed prediction tool without time shift is better than the one done with time shift, which lead to the conclusion that the same tool can be used for both type of prediction (with or without time shift with acceptable errors).

The most important conclusion that can be driven from the data in the previous tables is that if the error to be reduced a new approach is needed in order to overcome the errors generated from the unaccounted character changes of the wind speed. In this new approach is to take only half a year into account. Also this half year was divided among collecting testing (or validation) data and training data. The half year period was divided into days, with one day allocated for training and the next one for testing and so on as shown in Figure 6.

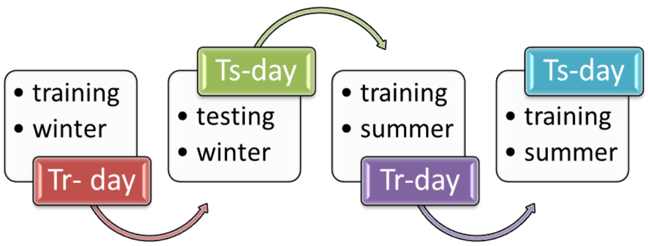

Figure 6. The new wind prediction tool (Tr= training, Ts= testing).

The new approach can be described as a short term prediction tool with a nonconventional way of selecting the training and testing data. The old approach can be described as a conventional long term approach.

Figure 7 compares the results of the old approach with the results of the new one. The first two columns shows the results of the old approach along with the best results from the different input data and training data respectively (shown in the previous RMS results tables) , and the second two columns show the same results but for the new approach. An error of /RMSD=0.0449/ was obtained.

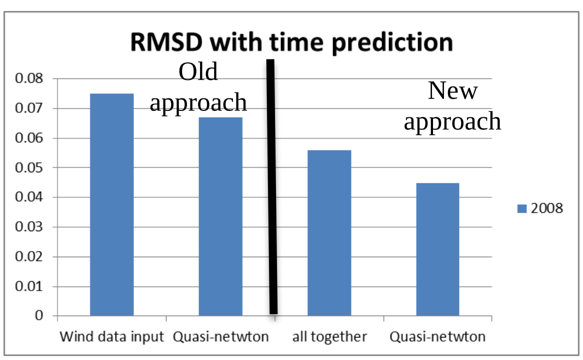

Figure 7. The error reduction due to the usage of the new approach.

Although the results shown in Figure 7 only describe one year (2008), if applied to more than one year as shown in Figure 8 it can be seen that the RMSD for the old approach is better than the new approach. However, since the purpose of this research is for energy calculations and the energy market (in other words, for engineering not meteorological applications -short term prediction is enough in this case-) the approach needs to have a very small value of error. For this reason, the new approach can be considered more effective in this situation as shown in Figure 5 or Figure 9, which show the deviation between the measured and predicted wind speed using the old and new approach respectively.

It should be mentioned that in the European energy market a 4 day wind energy prediction is needed and considered as a short term prediction period. Every grid operator should be able to provide the expected available energy for the next day in order to finish the bidding on the energy soled amount (this process normally takes one day).

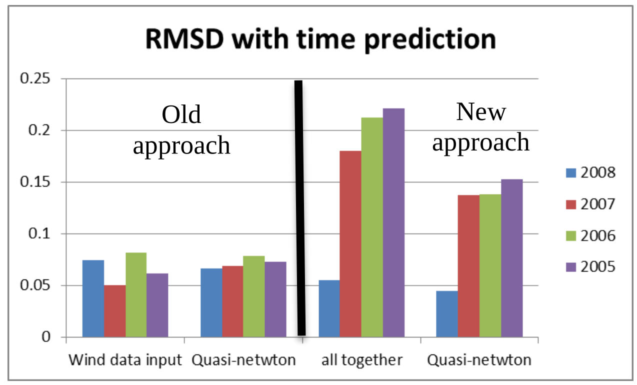

Figure 8. Comparison of the RMSE for the old and new approach for differing years.

Thus the usage of proposed prediction tool has a great influence on the selection of which scenario to work with.

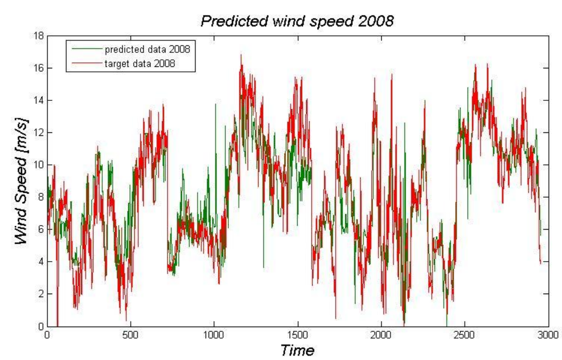

Figure 9. Measured and predicted wind speed for 2008 using the new approach using the preasure, the temperature and the wind speed diraction as an input.

When comparing the different prediction scenario's results (with time shift and without time shift) in Figure 8 and Figure 11, it can be seen that the RMS values of the not time shift scenario are lower than the other one for the whole year range which lead to the conclusion that the used input variables (pressure, temperature) are good enough for getting a reliable output (wind speed). Those results were also compared with the WASP program calculation for the wind speed with a result of /RMS=0.004/ (as the WASP program uses NWP module in order to calculate the vertical wind speed difference between the measurement mass and the wind park selected location).

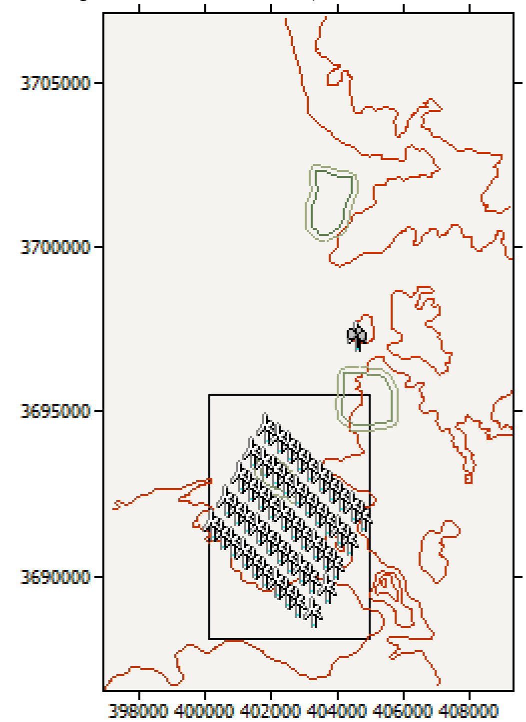

Figure 10. the location of the suggested wind park as designed by WASP program

The difference in the location between the measurement mass and the wind park is clear in Figure 10, which shows the map of wind park location in Syria using the WASP program for calculating the expected energy output from the suggested wind park.

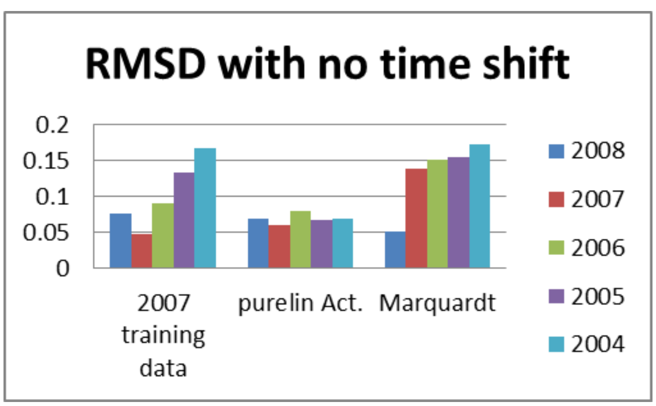

Figure 11. The best errors values that are resulting from using different training fucntion and training data and activation fucntion .

The best training function selection is done by comparing the regression figures of the different training functions, like in Figure 12 where the fit line shows the trend line of training, validation, testing and all. The more the trend line is adjacent to the orange line (Y=T) the better prediction results can be obtained from the ANN prediction tool. The dotted line presents the case where the output results of the ANN tool are the same of with the target data which mean the best case scenario for the prediction tool.

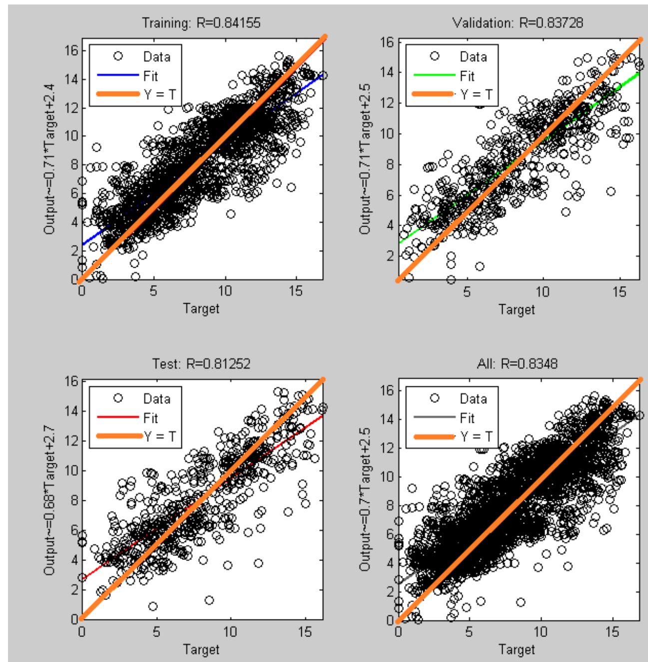

Figure 12. The best errors values that are resulting from using different training fucntion and training data and activation fucntion

Finally it should be mentioned that comparing Figure 9, which shows a comparison between measured wind speed values and the predicted one for the new approach, and Figure 5, which shows the same information for the old approach, for the same time interval (e.g. same moth) will reveal the fact that the new approach give a better output results. And it is also necessary to emphasis that the prediction errors can fall into two main categories:

1- Amplitude errors: This type of error results from the difference between the predicted wind speed value and measured wind speed value for the same point of time (same point on the x-axis).
2- Time shift errors: This type of error results from the difference between two wind speed points with the same value.(different X-axis /time/ values but the same Y-axis /wind speed in m/s/ values).

The second type of errors is more critical compared to the first one. As the results of this prediction will be used after that to determine the available energy that can be produced, which in its turn will be sold in an energy market. Assuming that the first type of errors (Amplitude errors) appears during a real time situation the conserved energy should be able to cover the difference (this is the case in European energy market) yet if the other type of errors accurse in a real time situation it might result in a complete black out as the preserved energy may not be able to cover difference in energy values (Y-axis /wind speed that results eventually in Energy/ has a big difference in values (Amplitude) at the same time point on the x-axis that is not expected and not taken into consideration during the biding period done earlier) that is not considered.

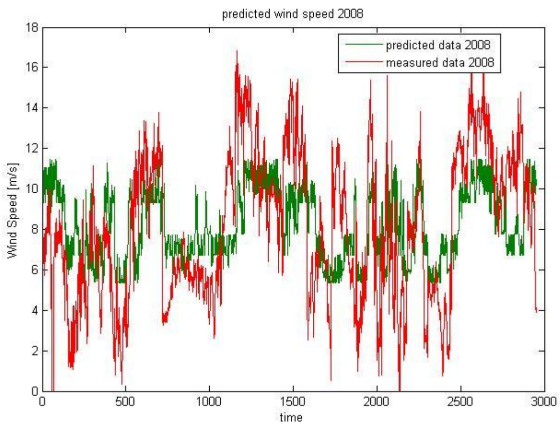

Figure 13. Measured and predicted wind speed for 2008 using the new approach and wind speed as input data

In other words, it is difficult to overcome an unexpected shortage in the energy (Like, in the second error type) than to overcome an expected value of shortage in the energy (Like, in the first error type). Figure 13 is a good example for showing the time shift error, which occur between X=0 and X=500 s. it was expected (predicted) that we will have about Y= 10 m/s wind speed but in realty we got only Y=8 m/s this difference will be tripled in the energy point of view and in its turn will result is some kind of problem to the Grid operator when no enough reserved energy is available to cover this difference.

I. Energy Module

After getting acceptable results as an output from the previously built prediction tool, those results are used as an input for the energy module. Figure 14 shows the suggested energy model, which has the following components:

1. A signal Builder: contains the predicted wind speed data.
2. Lookup Table: contains the power curve data of the used power turbine [14].
3. Integrator: is used to get the output energy from the wind turbine [15].
4. Scope: is used to show the results in Figure 14.
5. Display: is used to show the accumulated value of the energy.

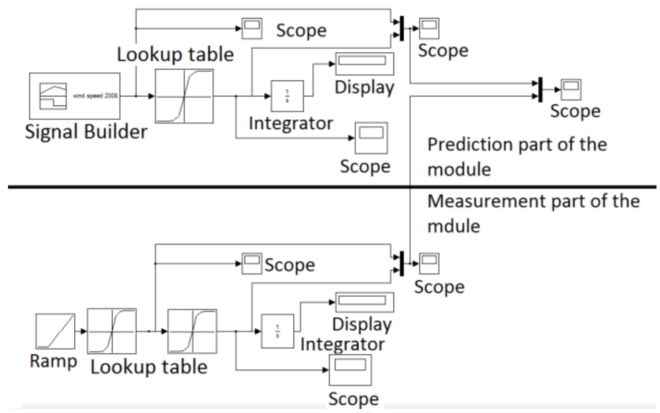

Figure 14. Block diagram of the energy module.

Putting the previous component together give us the energy which can be produced by the used turbine. As the energy is the area under the power curve of an electrical generation unit. The integration of the power function over a certain time period can result with the energy generated in the same time period. The energy calculated in this module results from the integration of the combined wind speed data (one input is the predicted values and the other input is the measured values) and the power curve of the used wind turbine (in order to make sure that only the useful wind speed values will result in the corresponding power).

Vestas Wind System /V90/ was selected as the working wind turbine with a 90 m rotor diameter, 105 m height, and 2 MW power [8]. Figure 15 shows the power curve of this wind turbine.

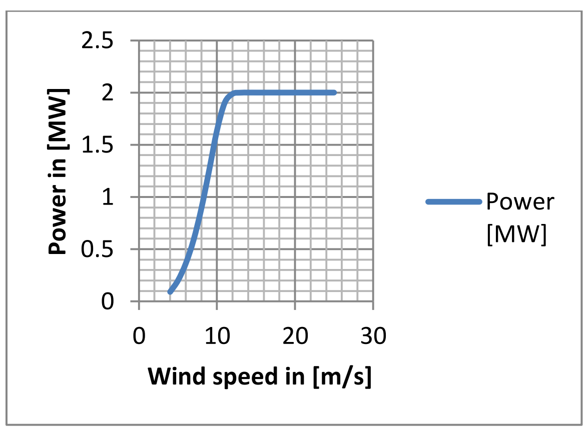

Figure 15. Power curve of V90 wind turbine.

Using all of above information, the energy can be obtained as shown in Figure 16 where the error is tripled due to the relation between the energy and the cubic wind speed. For this reason, the error of the predicted wind speed should be at its minimum with no time deviation errors [16][17].

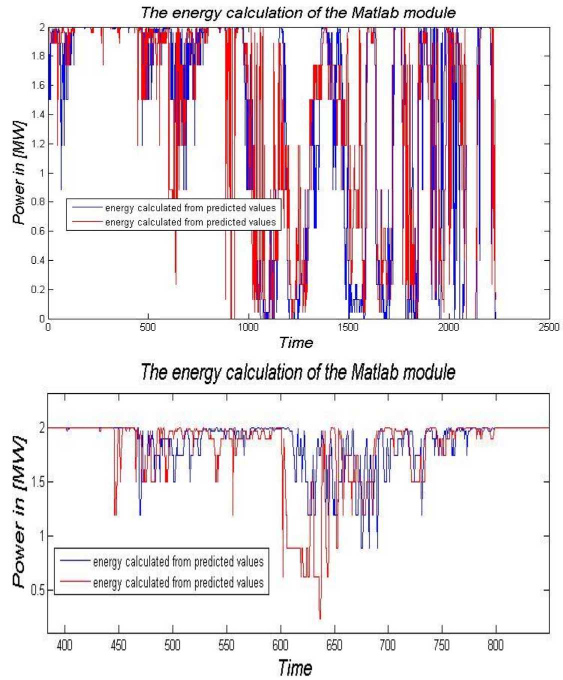

Figure 16. The difference between the energy calculated from the predicted and measured wind speed

It is important to mention here, that integrating the wind turbine curve in the energy module helped to avoid using the yield energy equation from the wind speed (the energy equation [17]) where other parameters like the density of the air is not included.

III. CONCLUSION

As a conclusion of this work it is observed that the prediction errors can be reduced by the usage of same characteristic properties of the predicted wind speed and that in its turns will lead to less errors in the Energy module (the error of the energy is cubical to the wind speed errors due to the cubic relationship between the Energy and the wind speed). More understanding of the data lead to better results in the prediction tool that is why spearman's analysis is an important method of determining the strength of connection between the different data used as input to get the output of the prediction tool. Finally, the short term prediction helps of reducing the errors in the prediction tool and also the work load on the computing device.

From all the information presented in this work it can be concluded that the time shift wind speed prediction tool is used in order to estimate the wind speed changes in the future in the location where the measurement is available. After that the no time shift wind speed prediction tool can be used to transfer these results from the previous tool to the location of interest and the height of the wind turbine's hub. Finally those results can be used as input for the energy module which in its turn will results in the estimated energy that will be generated from the chosen wind turbine in the future (the same time interval as the one predicted by the time shift wind speed prediction tool).

REFERENCES

[1] *A. Alkhatib, S. Heier, and M. Kurt"The development and Implementation of a short Term Prediction Tool Using Artificial Neural Networks" Published for ComputationWorld 2011, IARIA, Rome, Italy ,2011*

[2] *J.T. Houghton, L.G. Meira Filho, B.A. Callander, N. Harris, A. Kattenberg, and K. Maskell " Climate Change 1995, The Science of Climate Change, Contribution of WGI to the Second Assessment Report of the Intergovernmental Panel on Climate Change" Published for the Intergovernmental Panel on Climate Change, Cambridge University Press, 1995, pp. 27-73.*

[3] *Dr. K. Rohrig and R. Jursa "Online-Monitoring and prediction of wind power in German transmission system operation centers" Königstor 59, D-34119, Kassel: IWES, pp. 1, 2002.*

[4] *Dr. M. Lange and Dr. U. Focken" State of the art in wind power prediction in Germany and international developments"Marie-Curie-str.1, D-26129 Oldernburg: Oldenburg uni.,pp. 2-3, 2009.*

[5] *T. Burton, D. Sharpe, N. Jenkins, and E. Bossanyi "Wind energy handbook" London: John Wiley & Sons, Ltd., 2001.*

[6] *M. Kumar" SHORT-TERM LOAD FORECASTING USING ANN TECHNIQUE" Rourkela-769008: National Institute of Technology,pp. 9, 2009.*

[7] *Ministry of Electricity, "Request for qualification (RFQ)" Damascus: Syrian Arab Republic, 2009.*

[8] *Decon "Pre-feasibility study AL hijana. Damascus" Syrian Energy Center, Damascus, Syria, 2005.*

[9] *S. Mathew" Wind Energy Fundamentals, Resource Analysis and Economics" Springer, 2007.*

[10] *S.Chand. Managerial statistcs. AMIT ARORA, 2009.*

[11] *K.Sreelakshmi and P. Ramakanthkumar" Neural Networks for short term wind speed prediction" World Academy of Science ,Engineering and technology, pp.724, 42 2008.*

[12] *J. R.Rabunal and J.Dorado "Artificial neural network in real-life application" London: Idea Group Publishing, 2006.*

[13] *Wikipedia®. (2010). http://en.wikipedia.org/wiki/Root_mean_square_deviation.*

Retrieved 06,12, 2012, from www.wikipedia.com: www.wikipedia.com

[14] K.Sreelakshmi, P. Ramakanthkumar" Neural Networks for short term wind speed prediction" World Academy of Science ,Engineering and technology, pp.724, 42 2008.

[15] A. Kumar Mishra and L. Ramesh "Application of Neural networks in wind power (Generation) Prediction" IEEE, pp. 3, 2008.

[16] M. Hayashi and B. Kermanshahi "Application Artificial neural network for wind speed and determination of wind power generation output" Nakamachi, Koganei-shi,Tokyo 184-8588, Japan: Tokyo Uni.,pp.2-3, 2009.

[17] M.C. Mabel and E.Fernandez" Estimation of Energy Yield from Wind Farms Using Artificial Neural Networks" IEEE, pp. 3, 2009.

[18] A. Alkhatib "Developing a Wind speed prediction tool using artificial neural networks and designing Wind Park in Syria using WASP software" Kassel university, pp.6, 2010.