The Development and Implementation of a Short Term Prediction Tool Using Artificial Neural Networks

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***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.

Keywords-Artificial Neural Networks; Wind Speed; Mean root square error; Forecasting.

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. The IPCC (Intergovernmental Panel on Climate Change) indicated that [1] human activities are directly related to increased atmospheric levels of greenhouse gasses, i.e., carbon dioxide, methane, chlorofluocarbons, 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. 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- A one year prediction tool.
2- A half year prediction tool.

Also, the different possible ways that can be used in order to improve the prediction output (e.g., choosing different training functions). 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.

II. WIND SPEED PREDICTION TECHNIQUES

A. *Introduction*

The wind speed characteristic can be considered a non-linear fluctuation. Therefore, the forecasting of this function using traditional methods 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 [2].

There are two different types of wind speed predictions [3]:

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,

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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) [4].

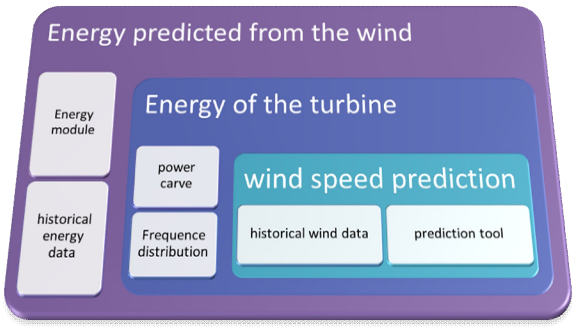

Fig. 1 Wind speed prediction and energy module connections

The historical wind data shown in Fig. 1 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).

B. *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*"[5].

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 Fig. 2.

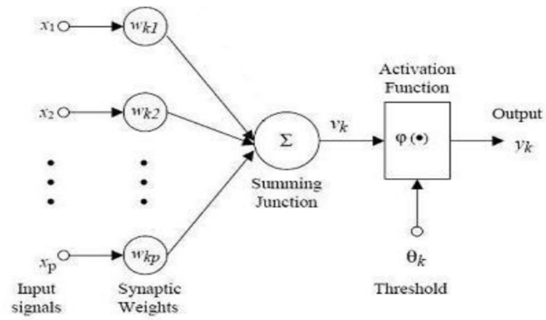

Fig. 2 Basic structure of a neuron [5]

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.

C. *Data Acquisition, Pre-processing, and Data Conversion*

The weather parameter values were collected at a weather station at the location of interest [6]. 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 d1 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 and normalization was carried out for all of those parameters [7].

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D. 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'

E. Spearman's Correlation

Spearman's correlation allows testing the direction and strength of a relationship [9]. 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.

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, the "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 [9]:

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

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 [12].

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**

Fig. 3 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.

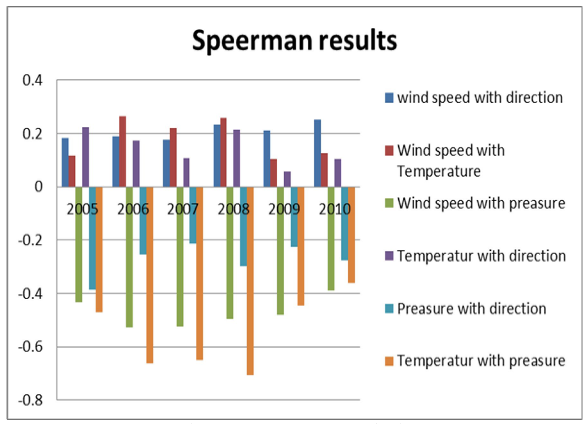

Fig. 3 Spearman's analysis

F. 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 [10]. 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 Fig. 4, a comparison of the results. Finally, 2 hidden layers with feed forward activity were chosen. 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.

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- Terminating condition.

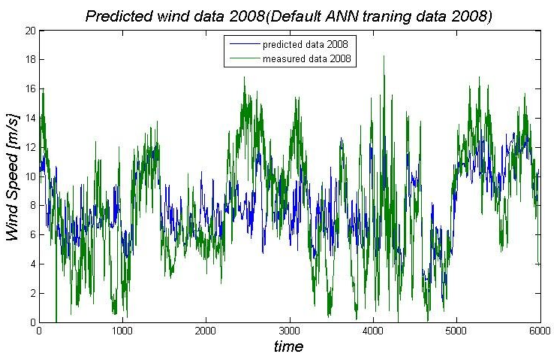

Fig. 4 Deviation of predicted and measured wind speed for 2008

G. 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 [11].

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

different inputs with time																				
Description	max					min					avarage					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	17.33	17.48	7.866	11.82	0	-7.81	-9.74	-10.2	-7.73	0	-0.08	1.141	-0.016	1.4833	0	0.062	0.0824	0.051	0.07493
all as input	0	11.57	15.19	5.447	11.49	0	-16.8	-16.3	-13.7	-9.81	0	-5.6	-2.21	-3.79	-0.0325	0	0.139	0.1214	0.092	0.05967

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

two year input for prediction with time tool																				
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
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 V RMSE OF THE DIFFERENT YEARS WIND PREDICTION TOOL WITH DIFFERENT TRAINING FUNCTIONS.

different training functions																				
Description	max					min					avarage					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	16.86	14.09	12.35	10.1	0	-10.1	-11.1	-13	-10.7	0	-0.66	-0.45	-0.712	-9E-05	0	0.075	0.0791	0.075	0.06691
Fletcher-Reev	0	17.2	13.02	8.371	11.14	0	-8.95	-10.4	-10.2	-8.42	0	-0	-0.39	-0.703	0.0462	0	0.074	0.0786	0.071	0.066973
Marquardt	0	20.42	12.62	11.05	9.874	0	-18.2	-9.73	-10.1	-8.66	0	1.594	-0.5	-0.913	-0.063	0	0.155	0.0787	0.068	0.066888
Quasi-netwton	0	16.92	13.24	11.34	10.49	0	-9.04	-9.38	-9.98	-8.51	0	-1.24	-0.49	-0.864	-0.055	0	0.074	0.0786	0.069	0.066996

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.

The most important conclusion that can be derived from the data in the previous tables is that if the error is 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 Fig. 5.

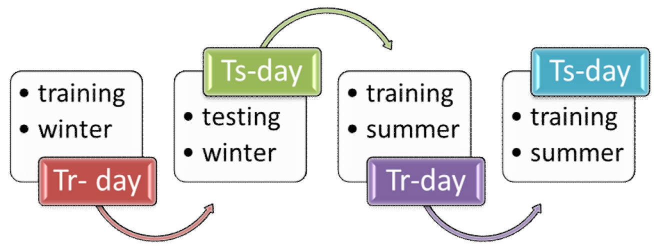

Fig. 5 The new wind prediction tool (Tr= training, Ts= testing).

Fig. 6 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, and the second two columns show the same results but for the new approach. An error of /RMSD=0.0449/ was obtained.

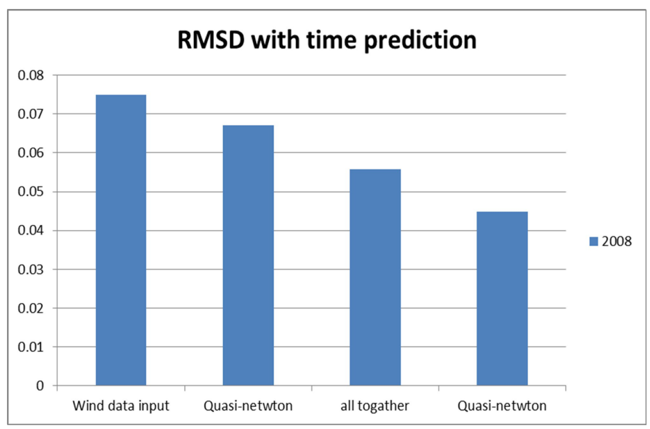

Fig. 6 The error reduction due to the usage of the new approach.

Although the results shown in Fig. 6 only describe one year (2008), if applied to more than one year as shown in Fig. 7 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) the approach needs to have a very small error. For this reason, the new approach can be considered more effective in this situation as shown in Fig. 6 or Fig. 8, which show the deviation between the measured and predicted wind speed.

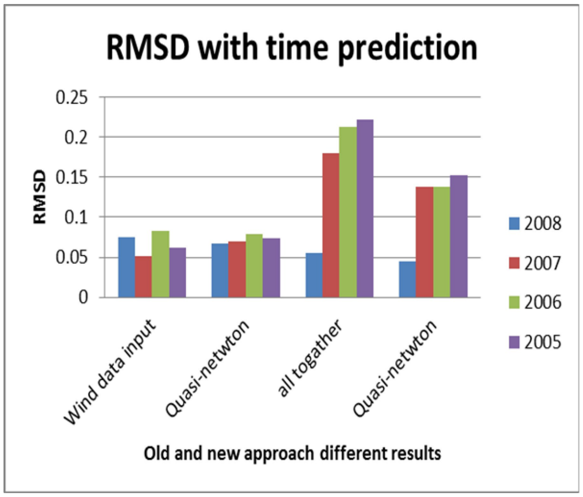

Fig. 7 Comparison of the RMSE for the old and new approach for differing years.

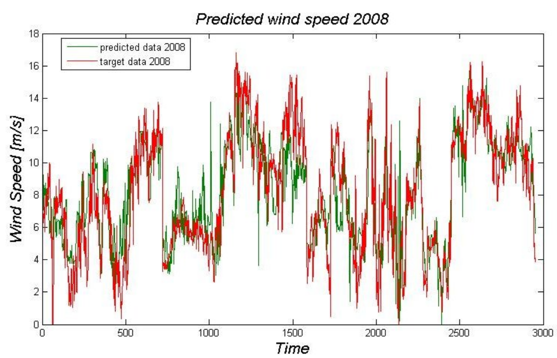

Fig. 8 Measured and predicted wind speed for 2008 using the new approach.

H. *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. Fig. 9 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 [12].
3. Integrator: is used to get the output energy from the wind turbine [13].
4. Scope: is used to show the results in Fig. 11.
5. Display: is used to show the accumulated value of the energy.

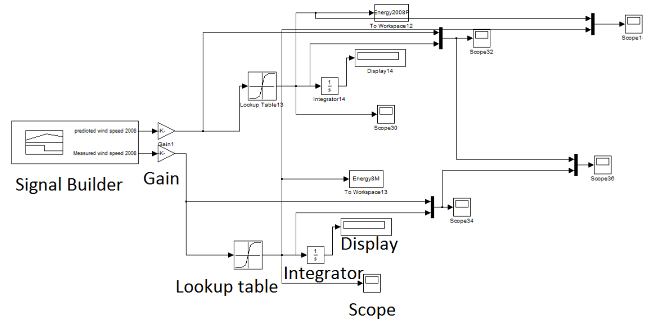

Fig. 9 Block diagram of the energy module.

Putting the previous component together give us the energy that can be produced by the used turbine.

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]. Fig. 10 shows the power curve of this wind turbine.

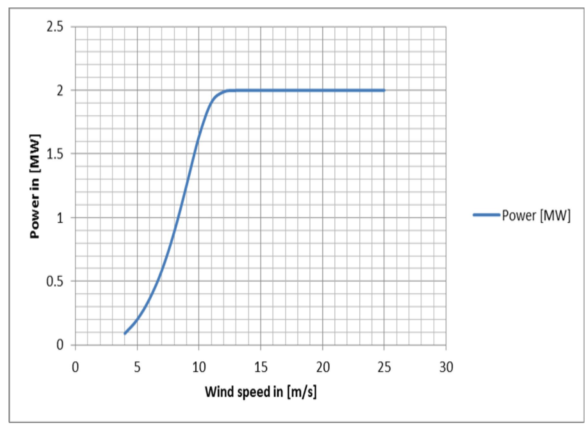

Fig. 10 Power curve of V90 wind turbine.

Using all of above information, the energy can be obtained as shown in Fig. 11 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 [14][15].

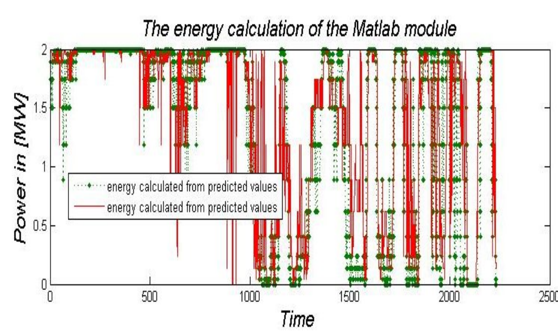

Fig. 11 The difference between the energy calculated from the predicted and measured wind speed

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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.

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