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EDITORIAL

Wind Power Generation Prediction for a 5Kw Wind turbine

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ABSTRACT
Renewable energies such as wind energy and solar energy are the most attractive sources of energy in the world. Researchers may need to prepare an inventory on the availability of wind energy in an area where there is no measured wind power data. In this study, air temperature, relative humidity, and wind speed data for a period of 10 years (2001–2011) for Bandar-Abass city, were used to predict wind power generation by a 5 Kw wind turbine using ANNs. The measured data between 2001 and 2009 were used as training data set and the remained data (i.e. 2010 and 2011) used as testing dataset. In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. Eventually, logistic sigmoid transfer function for both hidden layers, linear transfer function for output layer and LM training algorithm were found to have a good performance.
Keywords: *Artificial Neural Networks, Prediction, Bandar-Abass, Wind Power, Wind Turbine.*

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INTRODUCTION

The power of wind has become the world's fastest growing green energy source of electricity generation. Accurate information of dynamic wind at the wind farm site is crucial for the operations and management of wind energy conversion systems. However, due to the stochastic nature of wind speed from time to time and from site to site, prediction of wind power at the intended site is of great importance [1, 2].

Literature Reviews

Significant research efforts have been devoted to developing efficient forecasting methods for the prediction of wind speed or power.

Barati et al., presented a wind speed model using multilayer perceptron neural networks for South Coasts of Iran [3]. In a different work same authors used Genetic Algorithm (GA) to train an MLP network to predict wind power for same location [4]. In both works, they used month of the year, monthly mean daily air temperature, relative humidity and vapor pressure data as input and monthly mean daily wind speed as the output of the network. The measured data between 1994 and 2003 were used as training and the remained data (i.e. 2004 and 2005) used as testing dataset. Riahy and Abedi

presented a new linear prediction method for short-term wind speed forecasting. They used a linear prediction method in conjunction with filtering of the wind speed waveform to forecast wind speed based on the observation that filtering out less effective frequency components from a wind speed spectrum can increase the correlation between real and predicted winds [5]. Sancho et al., suggested a method of exploiting the diversity in input data using banks of artificial neural networks for accurate short-term wind speed prediction, which yields better results compared to those obtained from a system using single neural networks [6]. Mohandes et al., introduced a support vector machines (SVM) algorithm for wind speed prediction and compared its performance with multilayer perceptron (MLP) neural networks. The results indicated that SVM compares favorably with the MLP model based on root mean square error testing between actual mean daily wind speed data from Madina city, Saudi Arabia and predicted data [2]. Barbounis and Theocharis proposed a locally feedback dynamic fuzzy neural network (LF-DFNN) model using spatial wind speed information from remote measurement stations at wind farms to estimate multi-step ahead wind speed from 15 min to 3 h ahead. Furthermore, they trained the LF-DFNN models using an optimal online learning scheme, the decoupled recursive prediction error algorithm (DRPE). It was shown that DRPE outperformed three gradient descent algorithms: the back propagation through time, real-time recurrent learning, and recursive back-propagation algorithms, in training of recurrent LF-DFNN forecast models [7]. Mohammad et al., proposed a new strategy in wind speed prediction based on fuzzy logic and artificial neural networks. They trained their new strategy on real wind data measured in Rostamabad in northern Iran from 2002 to 2005 [8]. The experimental results demonstrated that the proposed method not only provided significantly less rule base but also increased the estimated wind speed accuracy when compared to traditional fuzzy and neural methods. In this study, air temperature, relative humidity, and wind speed data for a period of 10 years (2001–2011) for Bandar-Abass city, were used to predict wind power generation by a 5 Kw wind turbine using ANNs.

NEURAL NETWORKS

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large number of interconnected neurons. Each neuron is capable of performing only simple computation [9]. Any how, the architecture of an artificial neuron is simpler than a biological neuron. NNs are constructed in layer connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. Learning in ANNs is achieved through particular training algorithms which are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of biological system [10].
However, the necessary components to establish a neural network are the following [11]:

(a) Its architecture (the number of layers and units in the network and connections among them).

(b) The activation function (that describes as each unit combines its inputs to obtain the desired outputs).

(c) The cost function (a measurement of the accuracy of the prediction like the average squared error).

(d) The training algorithm to find the values of the parameters that diminish the cost function.

Fr more details the readers are referred to [12-15]

SIMULATION AND RESULTS

In this study, air temperature, relative humidity, and wind speed data, collected by Bandar-Abass Meteorological Office between 2001 and 2011, are used for wind power generation by a 5 Kw wind turbine prediction using ANNs. Specification of the applied wind turbine is given in Table 1.

Table 1.Specification of the applied wind turbine

Manufacturer	ReDriven	
Power capacity	kW	5.0
Number of turbines	-	1
Hub height	m	30.0
Rotor diameter per turbine	m	6
Swept area per turbine	m^2	32
Energy curve data	-	Standard
Shape factor	-	2.0
Airfoil losses	%	5.0%
Miscellaneous losses	%	5.0%
Availability	%	95.0%

The following combinations of data are considered for this study:
1. Month of the year, air temperature, and relative humidity as inputs and wind power as output; and
2. Month of the year, air temperature, relative humidity, and wind speed as inputs and wind speed as output.

The measured data between 2001 and 2009 were applied for training and the 24 months of data of 2010 and 2011 were used for testing. The data for testing were not applied for training the neural networks.
In this article, wind speed, air temperature, relative humidity, and vapor pressure are normalized in the (0, 1) range. Figs. 1 to 4 show the values of air temperature, relative humidity, wind speed, and wind power for Bandar-Abbas city (2001–2011).

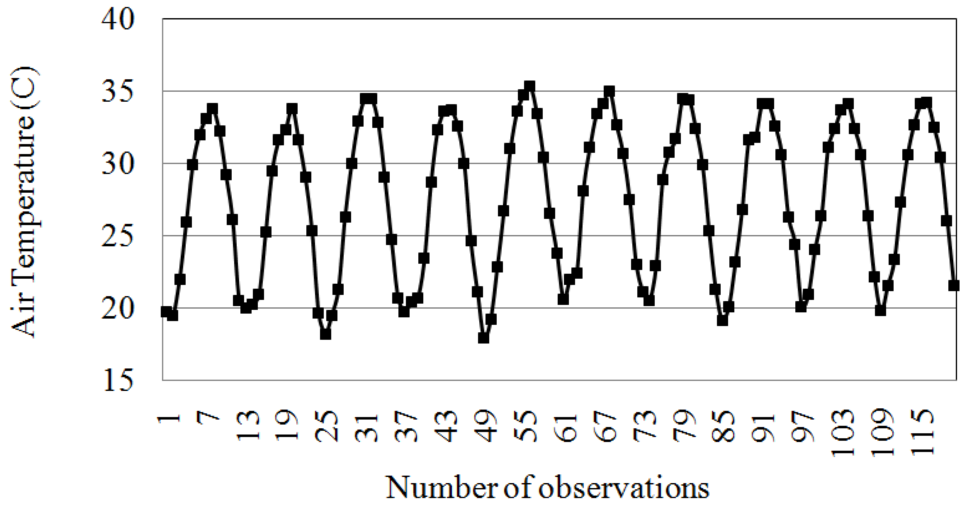

Fig. 1. Values of air temperature for Bandar-Abbas city between 2001 and 2011.

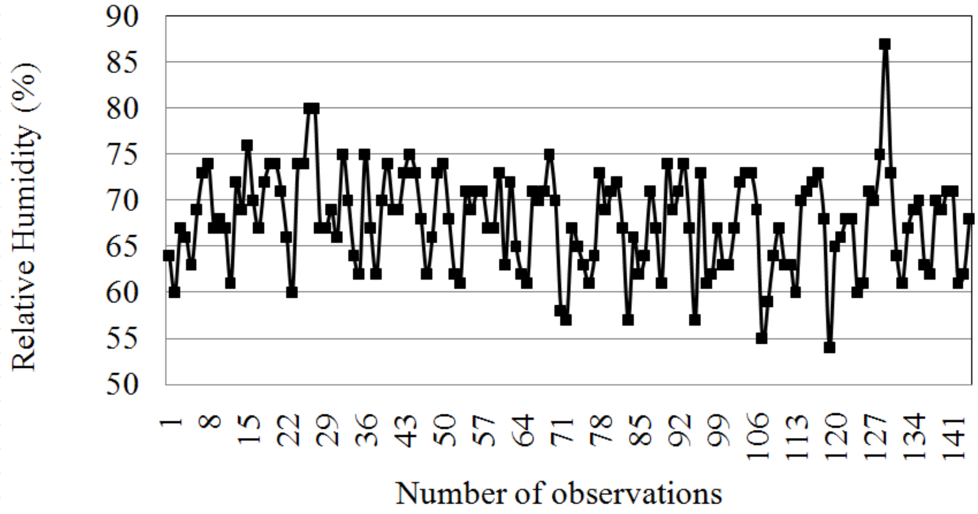

Fig. 2. Values of relative humidity for Bandar-Abbas city between 2001 and 2011.

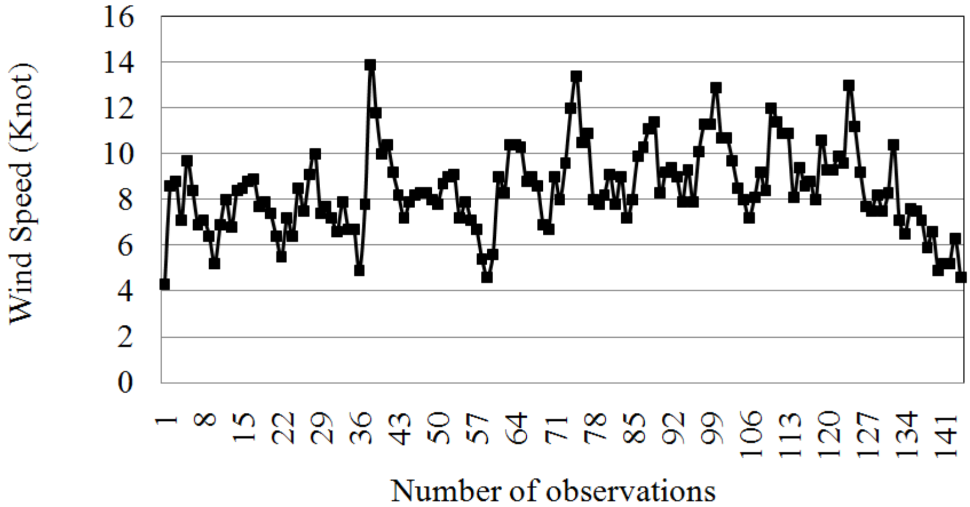

Fig. 3. Values of wind speed for Bandar-Abbas city between 2000 and 2011.

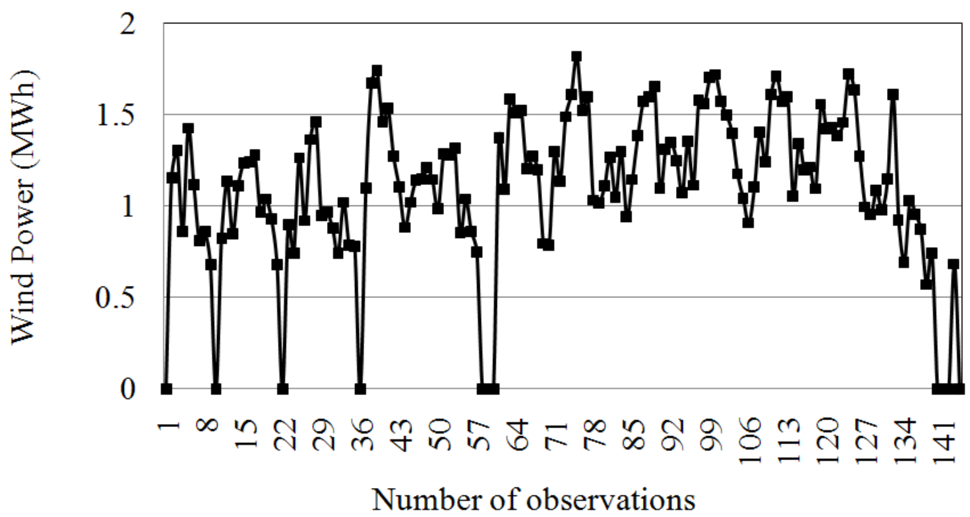

Fig. 4. Values of wind power for Bandar-Abbas city between 2000 and 2011.

ANN models were implemented in MATLAB 2010 (Math Works, Natick, MA) and in order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. For both combinations based on a MLP network, logistic sigmoid transfer function (logsig) for hidden layer, linear transfer function (purelin) for output layer, and LM (Levenberg–Marquardt) train were found to perform reasonably good. Table 2 shows the performance of some trained networks for first combination while Table 3 shows training and testing errors of some trained networks for the second combination.

Table 2. Training and testing errors for first combination

#	Neuron in hidden layer	Transfer function	Training		Testing	
			MAPE (%)	R^2 (%)	MAPE (%)	R^2 (%)
1	5	sigmoid	23.54	97.02	24.51	96.43
2	6	sigmoid	21.12	97.35	23.13	97.09
3	**7**	**sigmoid**	**20.32**	**98.01**	**21.34**	**97.21**
4	8	sigmoid	20.91	97.81	22.52	97.44
5	9	sigmoid	22.13	97.11	24.19	97.01
6	5	tanh	25.23	96.64	25.98	96.51
7	6	tanh	24.14	96.85	25.07	96.47
8	7	tanh	22.09	97.16	23.76	96.67
9	8	tanh	23.65	97.07	24.97	96.06
10	9	tanh	24.18	96.33	25.55	96.14

Table 3. Training and testing errors for second combination

#	Neuron in hidden layer	Transfer function	Training		Testing	
			MAPE (%)	R^2 (%)	MAPE (%)	R^2 (%)
1	5	sigmoid	17.12	98.21	18.11	97.31
2	6	sigmoid	16.93	98.54	17.15	97.95
3	7	sigmoid	16.19	98.93	16.93	98.05
4	**8**	**sigmoid**	**15.87**	**99.06**	**16.11**	**98.99**
5	9	sigmoid	16.12	98.97	16.52	98.11
6	5	tanh	18.26	97.98	19.07	97.44
7	6	tanh	17.33	98.05	18.01	97.77
8	7	tanh	17.07	98.34	17.96	98.03
9	8	tanh	16.45	98.77	17.07	98.26
10	9	tanh	17.11	98.23	17.53	97.85

As it can be seen in this table, the optimum networks for first combination and second combination have

Mean Absolute Percentage Errors (MAPE) of 21.34% and 16.11% and correlation coefficient (R2) of 97.21% and 98.99% on testing period, respectively.
Figures 5 and 6 show the comparison between predicted wind power values based on MLP and measured values on testing data (2010 and 2011) for both of combinations.

CONCLUSION

Numerous research efforts have been devoted to improving the accuracy of wind Power forecasting through the optimization of parameters and further analysis of factors that have a significant impact on the final output in these models. In this paper, a new model was proposed to forecast the monthly average wind power for a period of time. Monthly wind power was forecasted according to measured values of air temperature, relative humidity, wind speed.
This is of great importance because above parameters are commonly accessible. Data for Bandar-Abbas city, from 2001 to 2009 were used for training ANNs networks and data for 24 months (i.e. 2010 and 2011) were used for testing the operation of the ANNs networks.
For one case, month of the year, air temperature and relative humidity are considered as inputs and wind power generation as output.
In second case, month of year, air temperature, relative humidity and wind speed are considered as inputs and monthly wind power delivered to the grid as output. Obtained results indicate that using wind speed along with the month of the year, air temperature, and relative humidity has the mean absolute percentage error of 16.11% and correlation of coefficient of 98.99% on testing data sets and has better performance than another case.

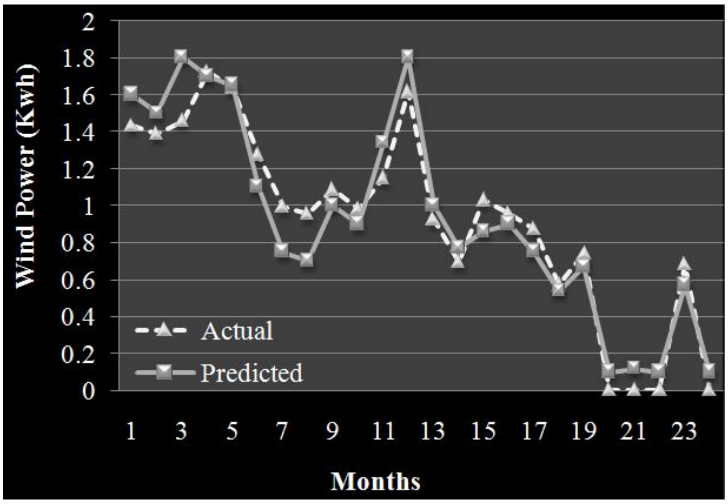

Fig. 5. Comparison between predicted wind power values based on the best ANN model for first combination and measured values on testing data (2010 and 2011) for Bandar-Abbas city.

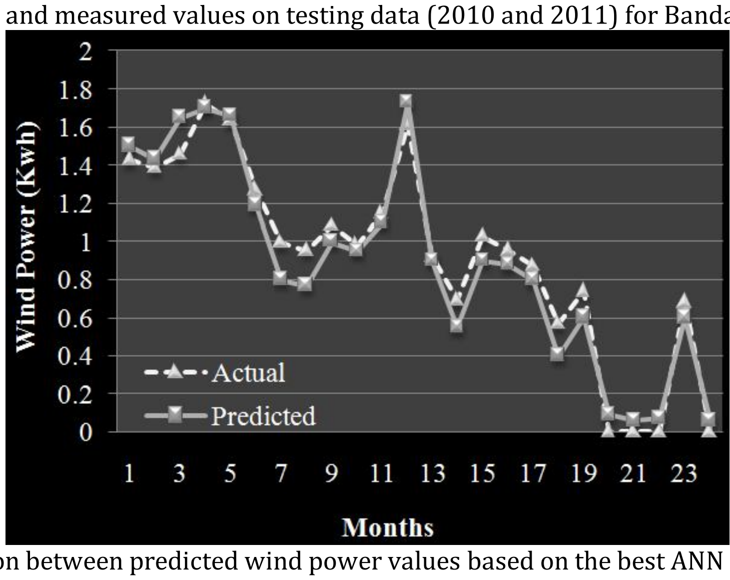

Fig. 6. Comparison between predicted wind power values based on the best ANN model for second combination and measured values on testing data (2010 and 2011) for Bandar-Abbas city.

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