WIND SPEED ESTIMATION IN SAUDI ARABIA USING THE PARTICLE SWARM OPTIMIZATION (PSO)

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ABSTRACT

Particle Swarm Optimization (PSO) is used in this paper to train a neural network to estimate wind speed 24 hours ahead based on the previous wind speed at 72 hours. Four years of hourly wind speed data at Rowdat Bin Habbas, Saudi Arabia, between 2006 until 2009 are divided into three groups 50% is used for training, 25% for validation and 25% for testing. The validation data set is used to select the network architecture and other PSO user defined parameters. The testing data is used only to assess the generalization capability of the network on future unseen data that has never been used for training or model selection. Twenty four networks, each for wind speed at one future hour are used. Close agreements were found between the PSO predicted and measured hourly mean wind speed. For testing data set, the RSME varied from 0.0140 to 0.1826 at hours 14 and 18 while MBE from 0.1657 to 0.5550 corresponding to hours 1 and 8. Performance indicates that the proposed algorithm is viable for predicting wind speed.

Keywords**:** Wind speed, Particle swarm optimization (PSO), artificial neural networks (ANN), prediction

1. INTRODUCTION

Power of the wind has become a center of attraction and implementation for all ranges of applications starting from roof top mounted wind turbines to multi-megawatt installed capacity grid connected wind farms. The reality behind this achievement is the commercial acceptability of the wind power technology and ease of installation and maintenance. Furthermore, power of the wind is a clean, abundance, a free source of energy, available everywhere, and has no political or geographical boundaries. For proper and optimal utilization of wind power, accurate knowledge of wind speed variation with time, height, and in spatial domain over a region or a country is of prime importance. Accurate wind speed forecasts in future time domain greatly contribute to the smooth integration of wind power into existing power systems. A 2% error in wind speed measurements or estimation results in 8% error in wind power density estimation. Moreover, the wind is a highly fluctuating meteorological parameter and varies with time of the day, season of the year, height above ground, and geographical location. Hence a sincere effort towards accurate estimation of wind speed is a critical issue for wind energy yield and cost of wind energy estimation. It is practically impossible to conduct wind measurements everywhere and different heights over entire time spatial domains and hence empirical, statistical, numerical, and modern learning methods are employed to estimate the wind speed in future time and spatial domains which in turn are used to estimate the energy yield and cost of wind energy.

The above requirement motivates researchers, engineers, and clean energy developers for the understanding, analysis, and prediction of wind speed and thereof power generation. Several studies have been reported related to estimation and prediction of wind power produced by wind turbines. Bechrakis and Sparis [1] developed a model for the estimation of wind speed at a location by utilizing the wind speed data available at nearby station and using sample cross correlation function (SCCF) of wind speed in time domain and an artificial neural network. The results showed that the higher the SCCF value between two sites, the better simulation achieved. Aksoy et al. [2] proposed a new wind speed data generation method using wavelet transformation and compared the results with some of the existing wind speed generation schemes such as normal and Weibull distributed independent random numbers, the first- and second-order autoregressive models, and the first-order Markov chain.

Castino et al. [3] coupled autoregressive processes to the Markov chain and simulated both wind speed and direction. Kaminsky et al. [4] compared different alternative approaches used in the generation of simulated wind speed time series. Riahy and Abedi [5] presented a linear prediction method for wind speed forecasting. The proposed scheme utilized the linear prediction method in conjunction with filtering of the wind speed waveform. The predicted values were compared with real wind speed data based on experimental results and demonstrated the effectiveness of the linear prediction method. Sfetsos [6] used adaptive neuro-fuzzy inference systems and neural logic networks and compared performance with the autoregressive moving average models. Numerous other methods have been used for wind speed prediction [7-9].

The present study uses the Particle Swarm Optimization (PSO) algorithm to train neural networks to predict 24 hours ahead wind speed in the future at Rowadat Bin Habbas (RBH), a city in Saudi Arabia.

2. PARTICLE SWARM OPTIMIZATION (PSO)

The PSO algorithm was motivated by the behavior of insect swarming, fish schooling, and bird flocking [10]. It includes several individuals (called particles) that keep refining their position in the space of the problem at hand. Every particle is a potential solution to the problem, and is specified by its position in the space. The position of the particles is changed in a multidimensional space to find better fitness positions. The PSO algorithm is initialized with a random set of particles that represent possible solutions. The positions and velocities of the particles are initialized randomly. During the learning stage, each particle saves the best position it has encountered so far (its local best solution). However, the whole population saves the best position found among all particles local best solutions (the global best). To guarantee a balance between the local and the global exploration of the search space, inertia weight is introduced. This inertia weight is decreased during the search process to guarantee global exploration at the initial iterations and then local search at the last iterations. The PSO algorithm is computationally efficient and easy to implement. The PSO algorithm is summarized in the flowchart shown in Fig. 1. Additional details about PSO algorithm can be obtained from [10, 11].

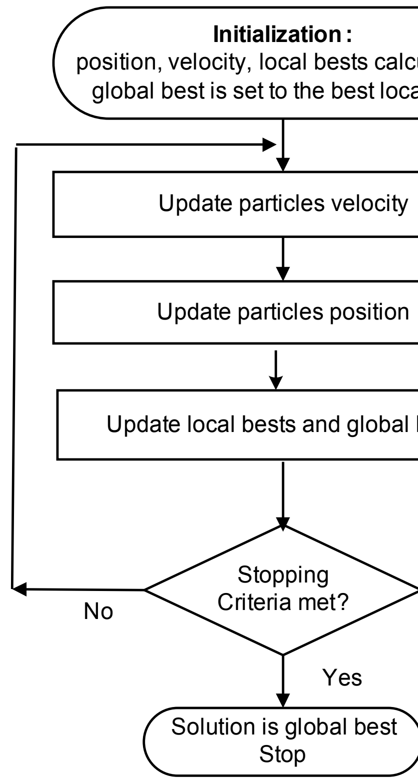

Fig.1. Flowchart of the PSO algorithm

3. WIND SPEED PREDICTION

The available data is 4 years of hourly wind speed at 20 m height starting at hour 0:00 on 1/1/2006 until hour 23:00 on 12/31/2009 for a total of 35064 hours, as shown in Fig.2. The cross correlation of wind speed at an hour and the previous 72 hours is shown in Fig.3. The figure indicates that the wind speed data is highly correlated during early hours and decays with the hours with an increase at multiple of 24 hours. Therefore, hourly wind speed data of the previous 72 hours are considered to predict the wind speed at the next 24 hours.

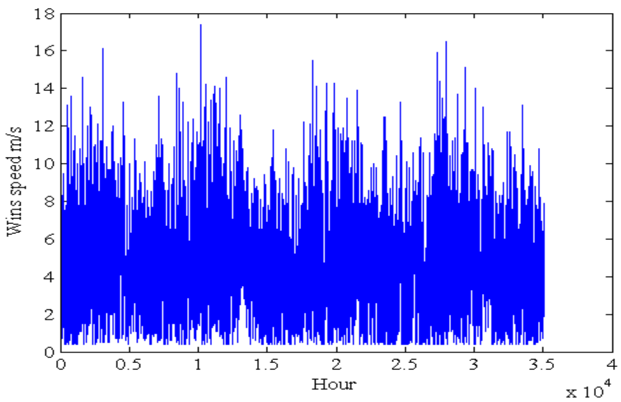

Fig.2 Hourly wind speed data in RBH for 4 years

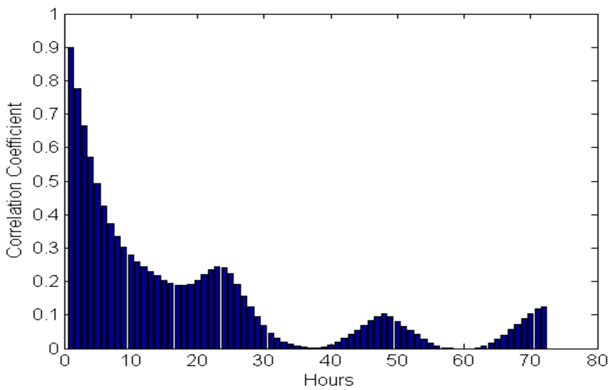

Fig. 3. Correlation coefficients of hourly wind speed with previous 72 hours

The available hourly wind speed at Rowadat Bin Habbas (RBH) is divided into three groups one for training consisting of 50% of the data, one for cross validation consisting of 25% of the data, and the remaining 25% is used to evaluate the generalization capability of the developed system. After several experiments on network structures, it was observed that a network with 72 inputs, 48 hidden units and one output unit performed reasonably well on the training data. The inputs are: The average WS at each of the previous 72 hours and the output is the estimated WS at one of the next 24 hours. To ease the training process, the inputs and output are normalized by dividing all values by the maximum wind speed recorded in RBH. The training continues to run until the mean squared error drops below a pre-specified number or the number of iterations reaches 1200.
A total of 8760 data points were used for testing the model which corresponds to 365 testing points for each hour. The comparison between the PSO predictions ahead of time and the measured hourly mean wind speeds, for first 100 values out of 265, for 24 hours of the day are shown in Figures 4 and 5. A close look of the first top most figure for hour 1 (Figure 4) indicates an excellent match between the two and of particular interest is the trend which PSO method was able to produce comparable to the measurements. Wind is a highly fluctuation and most difficult meteorological parameter to model but in the present paper, the PSO was able to capture these fluctuation features at hour 1. For hour 1, the mean square error (MSE) for training and testing were 0.0052 and 0.0757 and the respective mean biased errors (MBE) values were 0.1394 and 0.1657, respectively, as given in Table 1. Almost similar type of close comparisons was observed at hour 2, hour 3, and hour 4 though MSE and MBE values increased by an acceptable margin.
Ideally speaking, the values of RMSE and MBE should have followed an increasing trend with the passage of each hour but in actual case due to highly random nature of wind speed these values were not able to show a definite trend but were found to be random as well. The best part of these results was that the values of RMSE and MBE remained within reasonably acceptable limits. The maximum values of RMSE and MBE for training of the model were 0.1786 and 0.4238 corresponding to hours 20 and 5, respectively while the respective minimum values were 0.0006 and 0.1394 corresponding to hours 6 and 1, as can be seen from Table 1. For testing data set, the RSME varied from 0.0140 to 0.1826 at hours 14 and 18 while MBE from 0.1657 to 0.5550 corresponding to hours 1 and 8.

4. CONCLUSION

Particle swarm optimization algorithm is used in this paper to train neural networks to predict hourly mean wind speed at future 24 hours based on wind speed at previous 72 hours. A separate network is trained for each of the 24 future hours. Available wind speed data at Rawdat Bin Habbas, Saudi Arabia for 4 years is divided as 50% for training, 25% for cross validation, and the remaining 25% for testing the performance. Root Mean Squared Error (RMSE) and Mean Biased Error (MBE) are used for performance evaluation. The minimum, mean, and maximum RMSE on testing data are 0.01, 0.08, 0.18, respectively, while the minimum, mean, and maximum MBE on the testing data is 0.16, 0.38, and 0.55, respectively. Results show good agreements between estimated and measured hourly wind speed values.

Table 1. Summary of RMSE and MBE for 24 hours

Hour	RMSE		MBE	
	Training	Testing	Training	Testing
1	0.0052	0.0757	**0.1394**	**0.1657**
2	0.0131	0.1557	0.2381	0.3159
3	0.0297	0.0835	0.3104	0.3136
4	0.0080	0.0871	0.3563	0.3575
5	0.0011	0.0269	**0.4238**	0.4688
6	**0.0006**	0.0906	0.3671	0.4761
7	0.0027	0.0614	0.3793	0.4864
8	0.0314	0.0949	0.4024	**0.5550**
9	0.0194	0.1813	0.4189	0.5280
10	0.0217	0.0947	0.4100	0.5113
11	0.0256	0.0776	0.4215	0.4196
12	0.0741	0.0721	0.3796	0.3891
13	0.0380	0.0519	0.3447	0.3671
14	0.0105	**0.0140**	0.2874	0.3383
15	0.0449	0.1009	0.2720	0.2997
16	0.0092	0.0346	0.2961	0.3373
17	0.0046	0.1378	0.3354	0.4716
18	0.1081	**0.1826**	0.3035	0.4510
19	0.0443	0.0272	0.3054	0.4110
20	**0.1786**	0.0809	0.1610	0.3047
21	0.0567	0.0531	0.1761	0.2524
22	0.0285	0.0159	0.1734	0.2652
23	0.0141	0.0780	0.2654	0.4343
24	0.0049	0.0701	0.2393	0.3835

5. ACKNOWLEDGEMENT

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6. 6. REFERENCES

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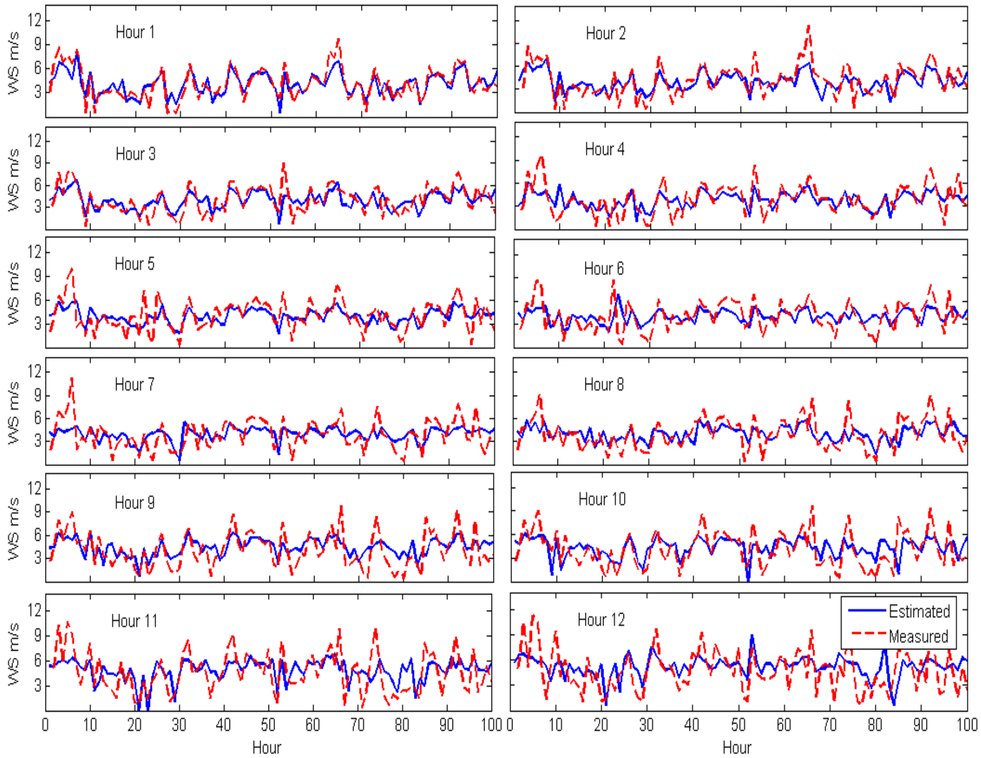

Fig. 4. Comparison between PSO predicted and measured hourly mean wind speed (Hour 1-12)

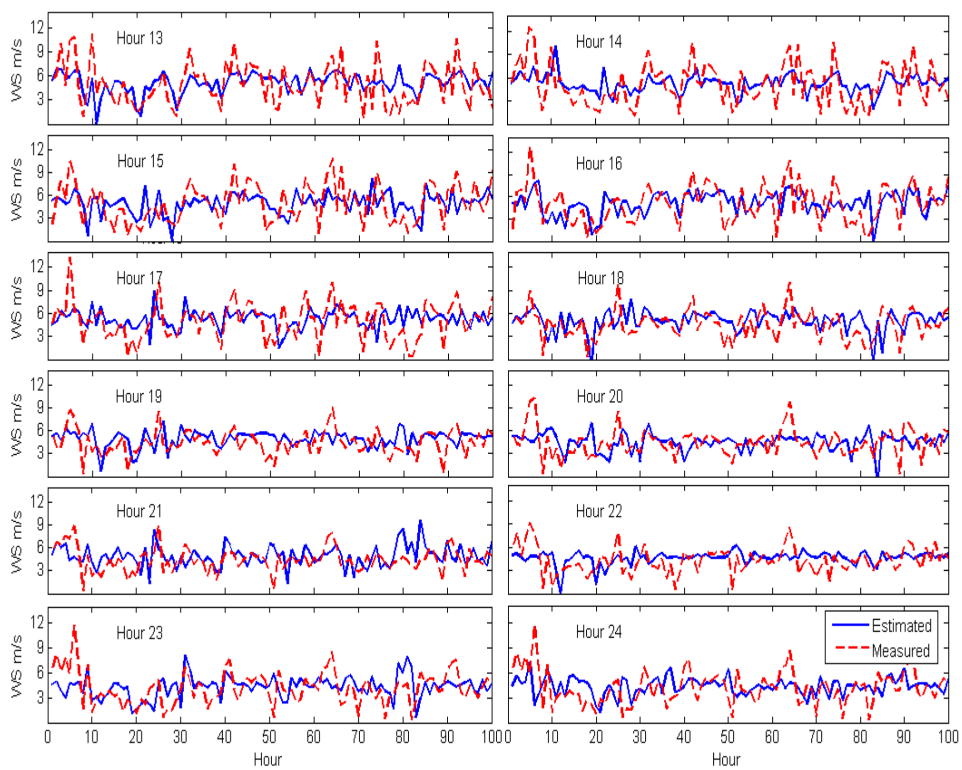

Fig. 5 . Comparison between PSO predicted and measured hourly mean wind speed (Hour 13-24)