Wind Speed Behavioral Modeling for Economical Energy Generation using Windmills

K. Aboul-Seoud, Alaa El-Din Sayed Hafez, Mohamed Abd El-latif, A. Abou-Raya

Abstract— the energy generation using windmills depends mainly on the wind speed which has a random behavior so; it is difficult to create statistical approaches with prior and deterministic parameters. Since wind speed is directly affected by some factors such as seasons, years, solar activities and land breeze, the behavioral modeling can be achieved. Prediction of wind speed is essential in order to protect systems in-action from the effects of strong winds. In this paper, data represent wind speed in Alexandria, Egypt has been obtained over a time window of twenty years. The frequency spectrum of the wind speed data have been obtained using Fourier transform (FT). The spectrum is fitted by twelve Gaussian distributions which are transformed back to the time domain. The central amplitudes are modified to accurately represent the actual time domain data using two different approaches. The proposed model is tested through the prediction of wind speed profile over the next two years following the available data window. The predicted data are compared with the actual ones. The constructed model showed a great consistency and high accuracy in modeling the wind speed behavioral in the selected site.

Index Terms— Wind speed prediction, Wind power generation, Power systems

1 INTRODUCTION

The energy is a vital input for the social and economic development of any nation. With increasing agricultural and industrial activities in the country, the demand for energy is also increasing. Formulation of an energy model will help in the proper allocation of widely available renewable energy sources as solar, wind, bioenergy and hydropower in meeting future energy needs. A study of the energy models helps energy planning, research and policy making. The use of wind energy has been developed significantly throughout the world, in order to get an electric power without pollution. Wind speed is non-linear fluctuation. So; forecasting is very difficult in normal method. Many techniques can be used in solving a nonlinear problem such as the intelligent engineering represented by a neural network, a genetic algorithm, a chaos fractal. Literature reports provide different models for wind speed prediction [1-7]. Tore et al. used first order Markov chain models for synthetic generation of hourly wind speed time series in the Corsica region [8]. Youcef Ettoumi et al. have modeled wind speed and wind direction data by means of Markov chains [9].

Shamshad et al. have generated a wind speed model using wind speed data measured from two different regions in Malaysia [10]. Recently, Hocaoglu et al. also modeled the wind speed data [11]. This paper proposes a wind speed model for Alexandria, Egypt over a window of twenty years. This model is used to evaluate the economy, size and specifications of windmills to be installed. The predictive model is developed and tested for the region of Alexandria on the northern coast of Egypt.

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2 PROPOSED MODEL FOR WIND SPEED PREDICTION

Data represents the wind speed at Alexandria area over twenty years window were obtained and stored as a data base. This data was used to construct the proposed model. Fourier transform is used to introduce the frequency spectrum and phase angle of the wind speed data at maximum amplitudes. Figure - 1 clarifies the frequency spectrum obtained where it forms a continuous function having twelve peaks in the frequency range between one hour to twenty years. The average wind speed is taken as a pole at zero frequency. The different peaks were fitted as Gaussian functions with complex amplitudes and real arguments given by the following equation,

$$W(f) = a_0 + \sum_{n=1}^{n=12} a_n exp[(f - f_n)/2\sigma_n^2] \qquad (1)$$

where:

W(f) is the Fourier transform of the wind speed along a window of twenty years, (f) is the frequency, (f_n) is the central frequency of the Gaussian function, (σ_n) is the standard deviation of the n_{th} Gaussian function, (a_0) is the average wind speed, and (a_n) is the maximum value of the n_{th} Gaussian distribution. Due to the above assumption the predictive wind speed function in time domain can be described as follows:

$$W(t) = b_0 + \sum_{1}^{12} b_n\, exp\, j(2\pi f_n t + \emptyset_n)\, exp - \left(\frac{\sigma_n^2 t^2}{2}\right) \qquad (2)$$

where:

W(t) is the inverse Fourier transform of W(f), (b_0) is the average wind speed, and (b_n) is the coefficient in time domain corresponding to frequency domain coefficients. The real exponen-

ISSN 2229-5518

tial term decays to zero as time tends to infinity. This means that the predicted value will be vanished with time. To overcome this problem, a time series can be written in the form,

$$W'(t) = b_0 + \sum_{1}^{12} C_n \ Cos(2\pi f_n t + \emptyset_n) \qquad (3)$$

where:

W'(t) is the modified predicted wind speed function. (b_0) is the average wind speed; (C_n) is a coefficient used in minimizing the difference between the proposed model and the actual data. The coefficient C_n in the above equation can be obtained using two different approaches.

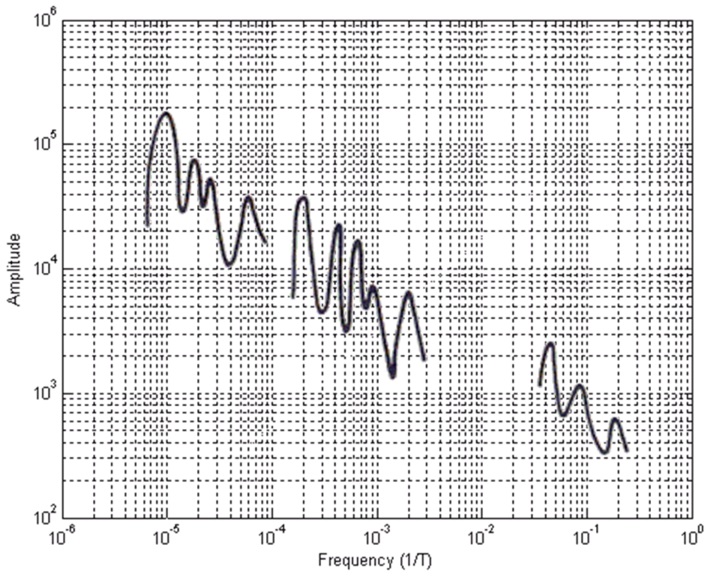

Fig.1. Frequency spectrum of wind speed data ranging between 1- Hour and twenty years in Alexandria- Egypt

2.1 Model Fitting

The cooefeicient C_n that is used to minimize the difference between the prosed model and actual data can be calculated using two approaches , the first one is a delta function where in time domain , the real part of Gaussian function is approximated by a delta function in the form :

$$C_n = \sqrt{2\pi}\, A_n \sigma \qquad (4)$$

The second approach to calculate the fitting parameter C_n is the time seires where in time domain both the frequencies of the cosine series and the phase angles corresponding to the peaks detected in the frequency spectrum is constructed. The cooefiecient are determined using a least root mean square (LMS) regression technique based on the available hourly data of the twenty years window.

3 SIMULATION RESULTS

The power spectrum plot of figure -1 can be represented by a set of Gaussian functions given in table-1. The two models can be constructed as explained before. The different values of the coefficient (C_n) are calculated.

TABLE- I

GAUSSIAN FUNCTIONS FITTING THE WIND SPEED SPECTRUM

Frequency (Hz)	Amplitude (m/sec)	Standard deviation	Phase Angel (rad)	Coef.C_n 1st Model	Coef.C_n 2nd Model
1.10E-5	2.81E+5	1.60E-6	1.169	0.1090	0.118
1.82E-5	8.01E+4	2.00E-6	1.174	0.0630	0.205
2.50E-5	5.02 E+4	2.58E-6	1.214	0.0540	-0.129
6.30E-5	3.8 E+4	9.00E-6	1.703	0.1450	-0.115
2.02E-4	3.9E+4	2.20E-5	1.010	0.3700	-0.224
4.5E-4	2.41E+4	2.70E-5	1.106	0.2800	-0.176
6.4E-4	1.81E+4	3.57E-5	5.230	0.2800	-0.122
9.01E-4	7.06E+3	8.47E-5	0.575	0.3180	0.043
2.06E-3	6.5E+3	4.00E-4	5.503	1.4000	0.107
4.57E-2	2.45E+3	7.15E-4	0.477	6.3000	0.0157
8.53E-2	1.32E+3	2.53E-2	3.604	10.400	0.007
1.97E-1	1.59E+2	2.60E-2	3.687	6.4100	0.0031

The actual data for the wind speed in Alexandria- Egypt through the 21st and 22nd years were obtained and compared with the calculated predicted data using the above two models, a high accuracy results have been obtained . To evaluate the proposed model performance, a cross correlation function at $\tau = 0$ between the predicted and actual data in the 21th and 22th years have been calculated, the equation used can be written as follows:

$$R_{ap}(0) = \int_{0}^{one\ Year} W_a(t).W_p(t).dt \qquad (5)$$

where:

$W_a(t)$ and $W_p(t)$ are the actual and the predicted data of wind speed for Alexandria, Egypt respectively. The obtained results are shown in tables (2-3).

TABLE-2

NORMALIZED CROSS CORRELATION COEFFICIENTS BETWEEN THE ACTUAL AND PREDICTED WIND SPEED DATA FOR THE 21TH YEAR

Month	Cross correlation using first approach			Cross correlation using second approach			First approach	Second approach
	Night	Day	Total	Night	Day	Total		
Jan	0.79	0.76	0.77	0.86	0.85	0.85		
Feb	0.80	0.79	0.80	0.86	0.87	0.87		
Mar	0.79	0.82	0.80	0.87	0.84	0.88		
Apr	0.78	0.84	0.82	0.85	0.90	0.88		
May	0.77	0.88	0.83	0.86	0.94	0.91		
Jun	0.81	0.91	0.86	0.88	0.95	0.92	0.79	0.87
Jul	0.74	0.90	0.83	0.81	0.92	0.88	**Winter**	
Aug	0.77	0.90	0.85	0.87	0.94	0.91	0.83	0.89
Sep	0.73	0.91	0.84	0.79	0.92	0.87	**Spring**	
Oct	0.80	0.82	0.81	0.84	0.88	0.86	0.83	0.89
Nov	0.74	0.81	0.78	0.78	0.88	0.84	**Summer**	
Dec	0.81	0.77	0.79	0.84	0.86	0.85	0.80	0.89
Total	0.75	0.81	0.79	0.82	0.88	0.85	**Autumn**	

TABLE –3

NORMALIZED CROSS CORRELATION COEFFICIENTS BETWEEN THE ACTUAL AND PREDICTED WIND SPEED DATA FOR THE 22TH YEAR

Month	Cross correlation using first approach			Cross correlation using second approach			First approach	Second approach
	Night	Day	Total	Night	Day	Total		
Jan	0.74	0.75	0.75	0.78	0.81	0.79		
Feb	0.84	0.81	0.82	0.87	0.89	0.88		
Mar	0.84	0.78	0.80	0.86	0.89	0.87		
Apr	0.85	0.89	0.87	0.90	0.94	0.93		
May	0.79	0.86	0.84	0.87	0.91	0.89		
Jun	0.77	0.86	0.83	0.82	0.92	0.88	0.78	0.84
Jul	0.79	0.88	0.84	0.85	0.93	0.89	**Winter**	
Aug	0.79	0.89	0.85	0.85	0.94	0.90	0.84	0.90
Sep	0.77	0.88	0.84	0.84	0.91	0.88	**Spring**	
Oct	0.77	0.91	0.86	0.88	0.94	0.92	0.84	0.89
Nov	0.73	0.89	0.83	0.86	0.92	0.89	**Summer**	
Dec	0.71	0.81	0.76	0.82	0.83	0.83	0.84	0.92
Total	0.77	0.83	0.80	0.83	0.88	0.86	**Autumn**	

From the above tables, it is clear that the proposed model fit the actual data with very high accuracy. Comparison of wind speed cross correlation value of the proposed model using two different approaches is shown in figures (2-3).

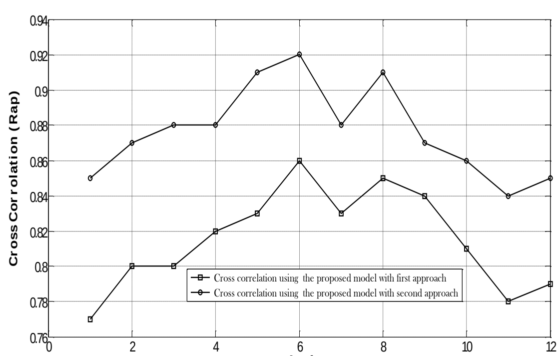

Fig .2 Comparison of wind speed cross correlation values of the proposed model using two different approaches for the 21th year

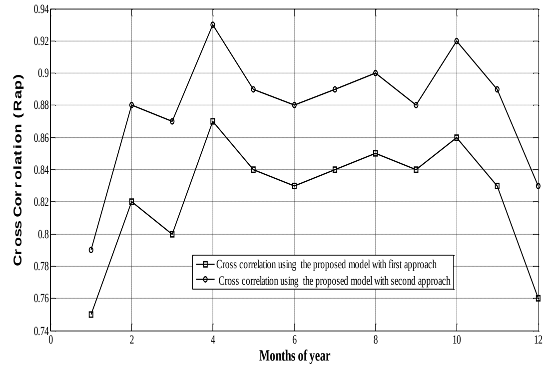

Fig.3 Comparison of wind speed cross correlation values of the proposed model using two different approaches for the 22th year

It is clear that a better correlation have been obtained using time series approach for the 21th and 22th years.

The proposed model using in wind speed prediction and windmills output is shown in figure – 4

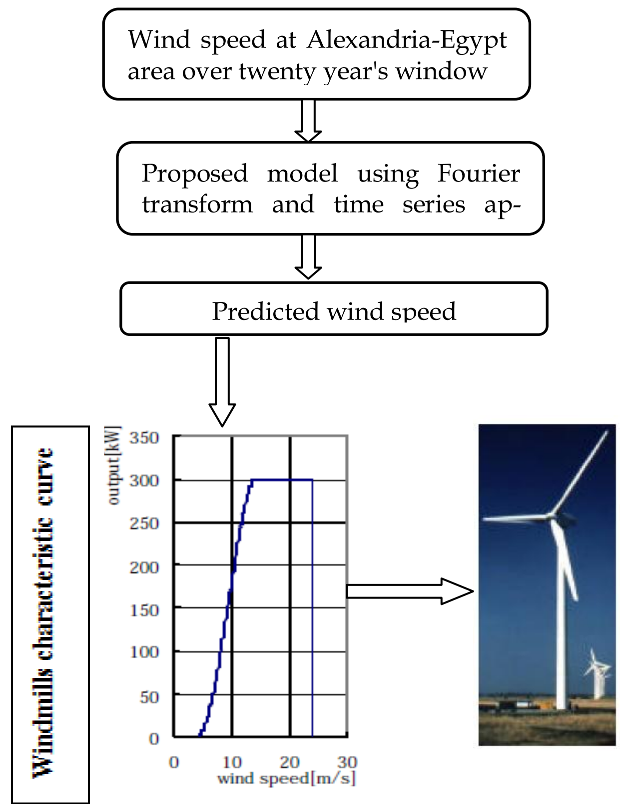

Fig.4 Wind speed prediction and windmills output determination

4 CONCLUSION

In this paper, a predictive model for wind speed in Alexandria-Egypt is constructed. The model performance is evaluated by cross correlating the predicted and the actual data for two years. It has been found that the predicted data has a higher cross correlation values during day times rather than night times. It has also been found that smaller cross correlation is obtained in the winter months compared to those of summer months. This is due to the weather nature stability during the summer season. The proposed model which has been constructed using the time series method showed superiority over many published techniques. A very important advantage obtained using the suggested model is that, moving away from the data window has no effect on the predicted data.

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