(6) First and Second Order Markov Chain Models for Synthetic Generation of Wind Speed Time Series

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Abstract

Hourly wind speed time series data of two meteorological stations in Malaysia have been used for stochastic generation of wind speed data using transition matrix approach of the Markov chain process. The transition probability matrices have been formed using two different approaches; the first approach involves the use of the first order transition probability matrix of a Markov chain, and the second involves the use of a second order transition probability matrix that uses the current and preceding values to describe probabilistically the next wind speed value. The algorithm to generate the wind speed time series from the transition probability matrices is described. Uniform random number generators have been used for transition between successive time states and within state wind speed values. The ability of each approach to retain the statistical properties of the generated speed are compared with the observed ones. The main statistical properties used for this purpose are mean, standard deviation, median, percentiles, Weibull distribution parameters and the autocorrelations of wind speed values. The comparison of the observed wind speed and the synthetically generated ones shows that the statistical characteristics are satisfactorily preserved.

1. Introduction

The increasing demand of energy, the growing environmental concern and rapidly depleting reserves of fossils fuel have made planners and policy makers think and search for ways to supplement the energy base with renewable energy sources. Wind is one of the potential renewable energy sources and has emerged as the world's fastest growing energy source. In Malaysia a lot of wind speed data on hourly basis at several locations is being collected by Malaysian Meteorological Stations. Designing a proper wind energy system requires the prediction of wind speed statistical parameters [1]. Besides, wind energy parameters are important for designing of wind sensitive structures and for air pollution studies.

For Markov process the probability of the given condition in the given moment is possible to be deduced from information about the preceding conditions. A Markov chain represents a system of elements making transition from one state to another over time. The order of the chain gives the number of time steps in the past influencing the probability distribution of the present state, which can be greater than one. Many natural processes are considered as Markov processes [2]. In fact, the probability transition matrix is a tool for describing the Markov chains behaviour. Each element of the matrix represents probability of passage from a specific condition to a next state. The Markov chain modelling approach has frequently been used for the synthetic generation of rainfall data. Thomas and Fiering [3] first of all used a first order Markov chain model to generate stream flow data. Srikanthan McMahon [4] and Thyer and Kuczer [5] used and recommended a first order Markov chain model to generate annual rainfall data. Shamshad et al. [6] compared performance of stochastic approaches for forecasting of river water quality. However, very little work has been done on the synthetic generation of wind speed data using Markov chain models. Kaminsky et al. [7] compared alternative approaches including Markov chain models for the synthetic generation of wind speed time series using the wind speed data for a short period of eight hours sampled at a rate of 3.5 hertz. In recent studies, Sahin et al. [8] and Torre et al. [9] used first order Markov chain model for synthetic generation of hourly wind speed time series.

For accounting dependence in the wind speed time series, a first order Markov chain model has generally been used for modeling and data simulation. It is expected that the second order or higher Markov chain model can improve the results of synthetically generated wind speed data. In this paper the synthetic time series are generated using hourly wind speed data of six years from 1995 to 2000 at two meteorological stations located in Mersing and Kuantan by first and second order probability transition matrices of Markov chain models. In order to validate and compare the performance of the models, several statistical tests have been carried out.

2. Markov Chains

Markov Chains are stochastic processes that can be parameterized by empirically estimating transition probabilities between discrete states in the observed systems [2]. The Markov chain of the first order is one for which each next state depends only on immediately preceding one. Markov chains of second or higher order are the processes in which the next state depends on two or more preceding ones.

Let $X(t)$ be stochastic process, possessing discrete states space $S = \{1, 2, \ldots\ldots, K)$. In general, for a given sequence of time points $t_1 < t_2 < \ldots < t_{n-1} < t_n$, the conditional probabilities should be[10]:

$$Pr\,\{X(t_n) = i_n | X(t_1 = i_1, \ldots, X(t_{n-1}) = i_{n-1}\} = \Pr\{X(t_n) = i_n | X(t_{n-1}) = i_{n-1}\} \tag{1}$$

The conditional probabilities $Pr\,\{X(t) = j | \; X(s) = i\,\} = P_{ij}\,(s,\, t)$ are called transition probabilities of order $r = t - s$ from state i to state j for all indices $0 \leq s < t$, with $1 \leq i, j \leq k$ [2]. They are denoted as the transition matrix P. For K states, the first order transition matrix P has a size of KxK and takes the form:

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,k} \\ \cdots & \cdots & & \cdots \\ p_{k,1} & p_{k,2} & \cdots & p_{k,k} \end{bmatrix}$$

The state probabilities at time t can be estimated from the relative frequencies of the k states. A second order transition probability matrix can be shown symbolically as below:

$$P = \begin{bmatrix} p_{1.1,1} & p_{1.1,2} & \cdots & p_{1.1,k} \\ p_{1.2,1} & p_{1.2,2} & \cdots & p_{1.2,k} \\ \vdots & \vdots & & \vdots \\ p_{1.k,1} & p_{1.k,2} & \cdots & p_{1.k,k} \\ p_{2.1,1} & p_{2.1,2} & \cdots & p_{2.1,k} \\ p_{2.2,1} & p_{2,2,2} & \cdots & p_{2.2,k} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ p_{k.k,1} & p_{k.k,2} & \cdots & p_{k.k,k} \end{bmatrix}$$

In this matrix the probability p_{ijk} is the probability of the next wind speed state k if the current wind speed state is j and the previous wind speed state was i. This is how the probability of making a transition depends on the current state and on the preceding state [7]. These matrices become the basis of future likely wind speed. The probability in any state varies between zero and one. The summation of row in a transition matrix is always equal to one. If the transition probability in the $i.j^{\text{th}}$ row at the k^{th} state is $p_{i.j,l}$, then the cumulative probability is given by

$$\mathrm{P}_{ijk} = \sum_{l=1}^{k} p_{ijl} \tag{2}$$

This cumulative probability helps in determining the future wind speed states by using random number generator.

3. Formation of Transition Matrices

The analysis of the wind speed hourly data has been carried out in two ways using: (i) first order Markov chain model, and (ii) second order Markov chain model. Initially, the wind speed time series are converted to wind speed states, which contains wind speeds between certain values. B ased on the visual examination of the histogram of the wind speed data, the wind speed states have been adopted with an upper and lower limit difference of 1 m/s of wind speed. The first state is started with the lower limit zero. For wind speed time series at Mersing, the wind speed transition probability matrix (12 x 12) for first order Markov chain model has been shown in Table 1. The second order transition probability matrix is of size 144 x 12, which is partly shown in Table 2. In the first order matrix (Table 1) each element shows the probability of next wind speed state based on the current wind speed state. It reveals that the highest probability occurs on the diagonal of the matrix. Thus, if the current wind speeds are known, it is most likely that the next wind speed will be in the same category. Further more, all the transition probabilities are around the diagonal, which means that transitions from one state to another far distant state are rare. By examining Table 2 in parts of 12 x12, it is clear that the highest probability occurs on the diagonal. Therefore, if the current and the preceding wind speeds are known, it is most probable that the next wind speed will be in same category.

4. Synthetic Generation of Wind Speed

The generation of synthetic values becomes easy if the elements of transition matrix take all values varying between 0 and 1. Using Equation 2, the cumulative probability transition matrix, P_c, both for the first order and the second order Markov process have been formed. The probability transition matrix of first order Markov process for Mersing is presented in Table3 in which each row ends with 1. Due to the extra large size of second order cumulative probability transition matrix, it has not been shown here.

For generating the sequences of wind speed states, the initial state, say state i, is selected randomly. Then random values between 0 and 1 are produced by using a uniform random number generator. For next wind speed state in first order Markov process, the value of the random number is compared with the elements of the i^{th} row of the cumulative probability transition matrix [8]. If the random number value is greater than the cumulative probability of the previous state but less than or equal to the cumulative probability of the following state, the following state is adopted. In case of second order Markov process the first wind speed state is also adopted randomly. However, the next wind speed state is not searched in the i^{th} row. The row is decided based on the current and preceding states in which current state will be the previously selected state.

The wind speed states have been converted to the actual wind speed using the following relationship:

$$V = V_l + Z_i(V_l - V_r) \tag{3}$$

where V_l and Vr are wind speed boundaries of the state and Z_i is the uniform random number (0, 1). In this manner the time series of wind speed of any length can be generated. The initial 1000 values of observed time series have been plotted in Figure 1. A time series of wind speed data equal to the number of wind speed data (61368) was generated. A few initial (about 1000) synthetically generated wind speed values by first and second order Markov chain models have been shown in Figures 2 and 3, respectively. The frequency of each element of the generated probability transition matrix for both methods is presented in Table 5 with the frequency of the corresponding element of transition probability matrix of the observed data. While, for second order transition matrix the sum of frequencies of elements of the row for observed and the generated wind speed data is presented in Table 6. The Markov models appear to be quite accurate in maintaining the frequencies of the generated data.

5. Validation of the Model

In addition to the acceptance procedures described above, the synthetic wind speed time series were thoroughly examined to determine their ability to preserve the statistical properties and to assess the applicability of Markov chain models for wind speed generation. In this context the important statistical properties are the general parameters (mean, standard deviation etc.), the probability distribution and the autocorrelation functions of the time series.

5.1 General Statistical Parameters

In order to test the accuracy of first order and second order Markov modelling approaches, the general statistical parameters such as mcan, standard deviation, minimum and maximum values and the percentiles of the synthesized values are presented together with the observed ones in Table 7. It is clear from the comparison of the corresponding observed and generated parameters that the first order and second order Markov chain models are sufficient to preserve most of the parameters values. However, as expected, no significant improvement has been observed in the statistical parameters of the second order Markov chain model as compared to the first order model.

5.2 Probability distribution of wind speed

The synthetically generated data, by first and second Markov chain models, have been compared qualitatively and quantitatively in terms of probability distribution with those of the observed values. For qualitative assessment, the frequency distributions for the observed and the generated time series by two different modeling approaches have been examined. The frequency distributions of data at Mersing is shown in Figure 4. The visual examination of the bars of this figure reveals that the probability at different wind speed time series have almost the same values. The probability distribution of the observed and generated wind speed is characterized by Weibull distribution. The similar behaviour has been observed for wind speed data collected at Kuantan.

For quantitative assessment, the Weibull distribution parameters have been computed for the observed and the generated data. It is a well accepted and widely adopted distribution in wind energy analysis [11-13]. The Weibull distribution function is given by:

$$p(V) = \frac{K}{V}\left(\frac{V}{C}\right)^{k-1} \exp\left\{-\left(\frac{V}{C}\right)\right\}^{k} \tag{4}$$

where $p(V)$ is the frequency or probability of occurrence of wind speed V, k the shape parameter that specifies how sharp is the peak of the curve, while c is the weighted average speed which is more useful in power calculation than the actual wind speed. The Weibull parameters of both stations for the observed and the generated wind speed time series are presented in Table 7 for comparison. The Table shows that both the wind speed data generation methods have preserved Weibull parameters.

5.3 Autocorrelation

To determine the persistence structure in the observed and the generated wind speed data, the autocorrelation function has been used. The autocorrelations at lag time lag k have been determined using the following equation [14]:

$$\rho_k = \frac{\frac{1}{N-K}\sum_{i=1}^{(N-K)}(x_i-\bar{x})(x_{i-k}-\bar{x})}{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})(x_i-\bar{x})} \tag{5}$$

where, $\bar{x}$ is the mean of wind speed time series $(x_i,\ i=1,2,\ldots\ldots,N)$. The autocorrelations for both stations for the observed and generated wind speed data were computed and compared. Figure 5 shows the autocorrelation functions of the observed and generated data of Mersing. It can be seen that the observed wind speed is correlated over a long period of time than the wind speed generated by both the Markov chain models. It appears that the observed wind possesses long period information than the first order and the second order synthetic Markov chains. It is also observed that the synthetic wind speed time series have lower autocorrelation values at the same time lag than the observed time series as shown in the figure. The general behaviour of the autocorrelation function of the synthetic data of both the methods is almost similar. However, for initial lags the values of autocorrelations of synthetic series by second order Markov model are closer to the observed ones than first order Markov model. Thus, the performance of data generated by the second order method has improved. It is because the second order wind speed *remembers* more about its history than the first order model. The algorithm for data generation can be improved if more than two previous wind speed states were to be *remembered.*

6. CONCLUSION

A Markov chain represents a system of elements making transition from one state to another over time. The order of the chain gives the number of time steps in the past influencing the probability distribution of the present state. The method utilized involves the use of first order and second order transition probability matrix of a Markov chain and an algorithm to produce the time series of wind speed values. Depending upon the wind speed time series, it was felt that at least twelve states of size 1 m/s would be needed to capture the shape of the probability density function (PDF). The manners in which Markov models can be used to generate wind speed time series are described. The models have been used to generate hourly synthetic wind speed time series. The time series have been examined to determine their ability to preserve the properties of the observed wind speed time series. A satisfactory accordance has been noted between the observed and the generated wind speed time series data from all the angles. The overall comparison of the two generated data shows that the wind speed behaviour slightly improved by the second order Markov model. The synthetic hourly wind speed time series may be utilized as the input for any wind energy system.

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Table 1

Probability transition matrix of first order for Wind speed time series at Mersing

P =

0.371	0.407	0.174	0.036	0.009	0.002	0.001	0.001	0.000	0.000	0.000	0.000
0.166	0.446	0.313	0.059	0.012	0.004	0.000	0.001	0.000	0.000	0.000	0.000
0.051	0.243	0.504	0.163	0.028	0.008	0.002	0.001	0.000	0.000	0.000	0.000
0.017	0.083	0.304	0.390	0.160	0.035	0.008	0.002	0.000	0.000	0.000	0.000
0.010	0.034	0.099	0.277	0.381	0.158	0.031	0.007	0.001	0.001	0.000	0.000
0.006	0.021	0.043	0.108	0.294	0.343	0.146	0.030	0.005	0.002	0.000	0.000
0.005	0.016	0.027	0.047	0.110	0.302	0.325	0.142	0.021	0.004	0.002	0.000
0.006	0.016	0.030	0.033	0.055	0.127	0.365	0.239	0.105	0.022	0.002	0.000
0.009	0.019	0.014	0.019	0.042	0.065	0.140	0.326	0.270	0.079	0.014	0.005
0.014	0.055	0.055	0.014	0.027	0.027	0.041	0.205	0.288	0.164	0.082	0.027
0.000	0.000	0.000	0.040	0.000	0.000	0.080	0.120	0.160	0.240	0.280	0.080
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.200	0.000	0.200	0.600	0.000

Table 2

Probability transition matrix of second order for Wind speed time series at Mersing (few rows of 144 x 12 matrix)

P =

0.417	0.403	0.144	0.027	0.006	0.000	0.001	0.000	0.000	0.000	0.000	0.000
0.184	0.438	0.302	0.066	0.008	0.003	0.000	0.000	0.000	0.000	0.000	0.000
0.078	0.250	0.442	0.186	0.037	0.003	0.003	0.000	0.000	0.000	0.000	0.000
0.033	0.114	0.333	0.352	0.129	0.033	0.000	0.005	0.000	0.000	0.000	0.000
0.040	0.160	0.340	0.260	0.140	0.040	0.020	0.000	0.000	0.000	0.000	0.000
0.000	0.455	0.182	0.273	0.091	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.000	0.000	0.400	0.600	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.333	0.000	0.333	0.000	0.333	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.354	0.424	0.179	0.032	0.008	0.002	0.000	0.000	0.000	0.000	0.000	0.000
0.168	0.480	0.295	0.044	0.010	0.003	0.000	0.001	0.000	0.000	0.000	0.000

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Table 4

Cumulative probability transition matrix of first order for Wind speed time series at Mersing

$$
P_c = \begin{bmatrix}
0.371 & 0.778 & 0.952 & 0.988 & 0.997 & 0.998 & 0.999 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 \\
0.166 & 0.612 & 0.924 & 0.983 & 0.995 & 0.999 & 0.999 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 \\
0.051 & 0.294 & 0.798 & 0.961 & 0.989 & 0.997 & 0.999 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 \\
0.017 & 0.100 & 0.403 & 0.794 & 0.954 & 0.989 & 0.997 & 0.999 & 1.000 & 1.000 & 1.000 & 1.000 \\
0.010 & 0.045 & 0.144 & 0.421 & 0.803 & 0.960 & 0.991 & 0.998 & 0.999 & 1.000 & 1.000 & 1.000 \\
0.006 & 0.027 & 0.070 & 0.178 & 0.473 & 0.816 & 0.962 & 0.993 & 0.997 & 1.000 & 1.000 & 1.000 \\
0.005 & 0.021 & 0.048 & 0.095 & 0.205 & 0.507 & 0.831 & 0.973 & 0.994 & 0.998 & 1.000 & 1.000 \\
0.006 & 0.022 & 0.052 & 0.085 & 0.140 & 0.267 & 0.632 & 0.871 & 0.976 & 0.998 & 1.000 & 1.000 \\
0.009 & 0.028 & 0.042 & 0.060 & 0.102 & 0.167 & 0.307 & 0.633 & 0.902 & 0.981 & 0.995 & 1.000 \\
0.014 & 0.068 & 0.123 & 0.137 & 0.164 & 0.192 & 0.233 & 0.438 & 0.726 & 0.890 & 0.973 & 1.000 \\
0.000 & 0.000 & 0.000 & 0.040 & 0.040 & 0.040 & 0.120 & 0.240 & 0.400 & 0.640 & 0.920 & 1.000 \\
0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.200 & 0.200 & 0.400 & 1.000 & 1.000
\end{bmatrix}
$$

Table 5

Frequencies of the elements of transition matrix for observed and generated wind speed data of first order Markov model

States																							
1		2		3		4		5		6		7		8		9		10		11		12	
Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.
2180	2167	2393	2391	1022	1033	210	221	50	41	11	14	5	3	3	1	1	1	0	0	0	0	0	0
2452	2419	6602	6436	4627	4567	867	892	180	183	61	58	5	5	8	10	1	2	1	0	0	0	0	0
980	1017	4658	4618	9657	9650	3122	3094	539	574	154	139	40	36	13	13	6	6	2	2	0	0	0	0
171	177	845	832	3100	3090	3985	4064	1636	1674	360	376	80	93	22	17	3	3	4	7	0	0	0	0
60	59	197	192	565	609	1586	1619	2181	2224	902	968	177	179	39	37	7	4	3	1	1	1	0	0
18	17	66	71	134	127	337	345	917	987	1069	1068	456	451	94	91	15	15	7	3	1	1	0	0
7	9	25	20	41	44	72	72	168	172	460	456	495	463	216	225	32	19	6	6	3	5	0	0
4	4	10	6	19	20	21	21	35	23	81	85	232	230	152	134	67	64	14	10	1	2	0	0
2	3	4	3	3	5	4	4	9	10	14	11	30	26	70	56	58	51	17	14	3	2	1	0
1	0	4	3	4	4	1	1	2	5	2	1	3	4	15	13	21	12	12	6	6	8	2	0
0	0	0	0	0	0	1	0	0	0	0	0	2	1	3	2	4	9	6	9	7	15	2	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	3	0	0	0

Ob. =Observed, Gn. = Synthetically generated

Table 6
Sum of frequencies of the elements of the row for observed and generated wind speed data of second order Markov model for different sets of current and preceding states

Preceding State	Current State																							
	1		2		3		4		5		6		7		8		9		10		11		12	
	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.
1	2108	2103	2393	2388	1022	1023	210	226	50	40	11	19	5	9	3	3	1	2	0	2	0	0	0	0
2	2452	2443	6602	6501	4627	4629	867	842	180	162	61	28	5	41	8	4	1	6	1	1	0	1	0	0
3	980	1010	4658	4610	9656	9529	3122	3081	539	569	154	119	40	46	13	27	6	9	2	6	0	1	0	0
4	171	166	845	877	3100	3029	3985	4114	1636	1671	360	380	80	37	22	33	3	14	4	7	0	7	0	0
5	60	61	197	173	565	595	1586	1606	2181	2294	902	921	177	194	39	20	7	20	3	1	1	1	0	1
6	18	16	66	59	134	113	337	349	917	938	1069	1071	456	439	94	76	15	11	7	6	1	3	0	0
7	7	8	25	24	41	49	72	81	168	158	460	449	495	540	216	225	32	26	6	8	3	6	0	6
8	4	4	10	11	19	31	21	27	35	32	81	72	232	242	152	151	67	55	14	7	1	2	0	0
9	2	3	4	6	3	6	4	4	9	15	14	18	30	27	70	69	58	63	17	19	3	2	1	2
10	1	1	4	5	4	2	1	3	2	6	2	4	3	2	15	16	21	19	12	18	6	7	2	0
11	0	1	0	3	0	1	1	2	0	2	0	0	2	1	3	6	4	6	6	6	7	9	2	2
12	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	3	0	4	1	2	3	0	0	0

Ob. =Observed, Gn. = Synthetically generated

Table 7
General statistical parameters of observed and synthetically generated wind speed time series

Station Name	Type of Wind Data	Mean	Std. Dev.	Max.	Min.	Percentiles						
						1	10	25	50	75	90	99
Mersing	Observed	2.69	1.55	11.60	0.00	0.00	1.00	1.60	2.50	3.50	4.80	7.40
	Generated (First order)	2.76	1.57	11.20	0.00	0.11	1.02	1.65	2.53	3.61	4.89	7.43
	Generated (Second order)	2.77	1.59	11.90	0.00	0.10	1.02	1.65	2.54	3.64	4.92	7.51
Kuantan	Observed	1.95	1.64	15.20	0.00	0.0	0.00	0.40	1.80	3.00	4.20	6.20
	Generated (First order)	2.13	1.56	15.46	0.00	0.00	0.32	0.79	1.92	3.15	4.34	6.32
	Generated (Second order)	2.13	1.59	15.55	0.00	0.00	0.31	0.78	1.90	3.14	4.33	6.37

Table 8
Weibull parameters of observed and synthetically generated wind speed time series

Station	Observed		Generated (First order)		Generated (Second order)	
	K	C	K	C	C	K
Mersing	1.916	3.11	1.777	3.090	1.778	3.101
Kuantan	1.820	2.824	1.279	2.295	1.269	2.283

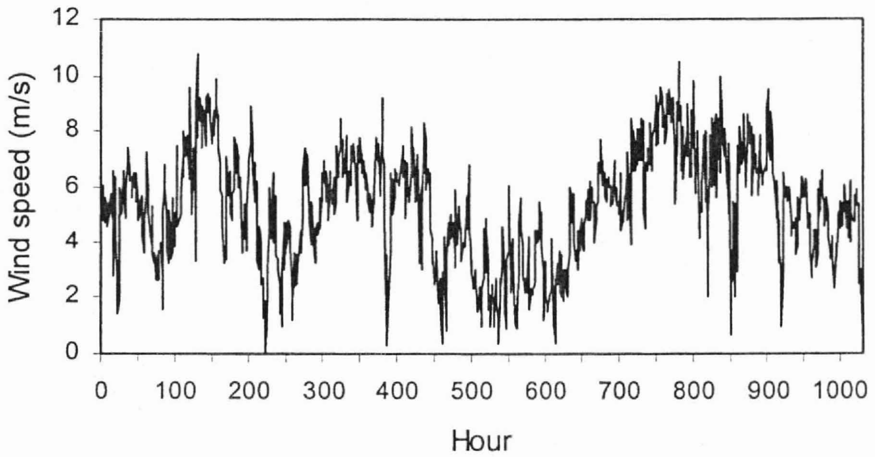

Fig. 1. Observed wind speed at Mersing (initial 1000 values only)

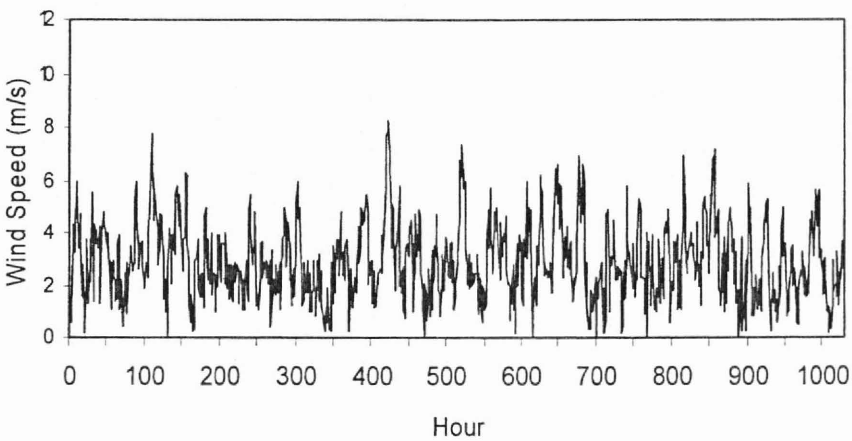

Fig. 2. Synthetically generated wind speed by first order Markov model at Mersing (initial 1000 values only).

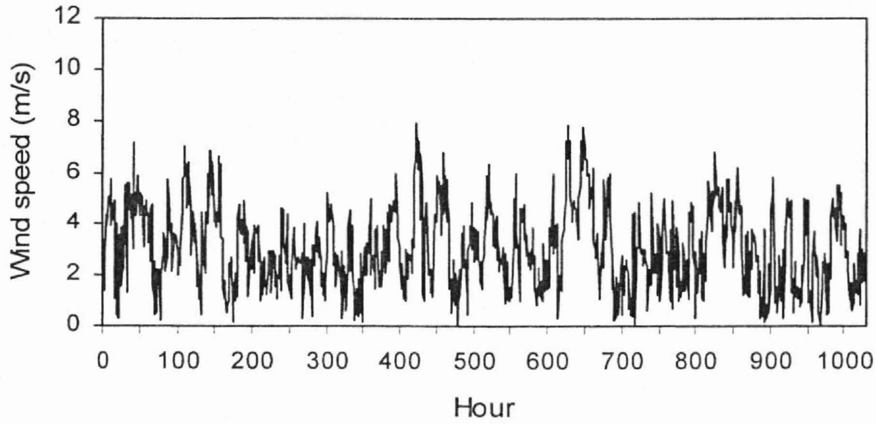

Fig. 3. Synthetically generated wind speed by second order Markov model at Mersing (initial 1000 values only).

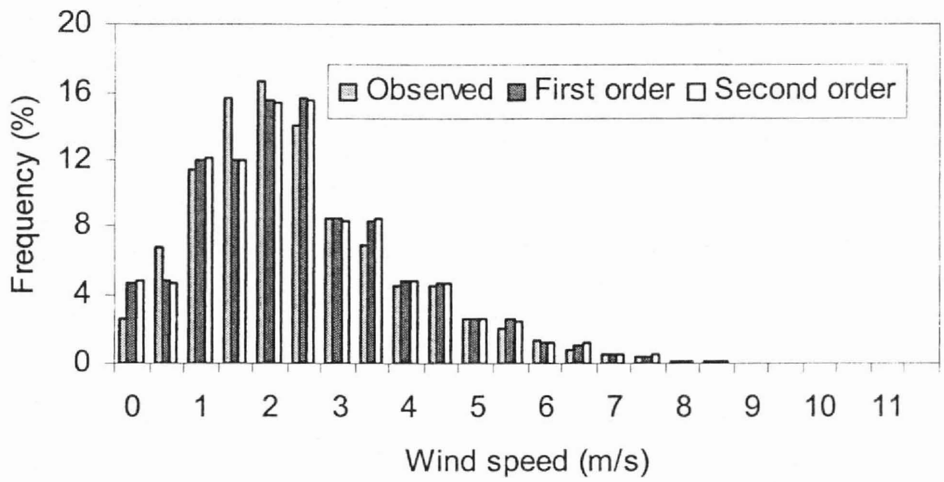

Fig. 4. Probability distribution of observed and synthetically generated wind speed at Mersing.

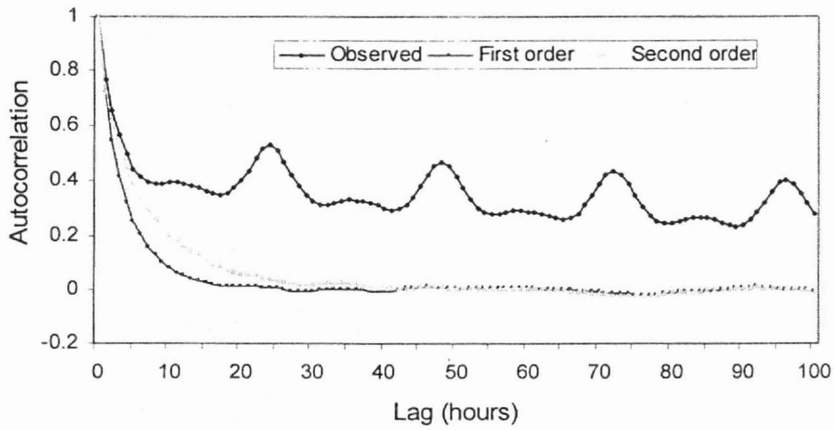

Fig. 5. Autocorrelation functions of observed and synthetically generated wind speed at Mersing.