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STOCHASTIC GENERATION OF HOURLY WIND SPEED TIME SERIES

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ABSTRACT

In the present study hourly wind speed data of Kuala Terengganu in Peninsular Malaysia are simulated by using transition matrix approach of Markovian process. The wind speed time series is divided into various states based on certain criteria. The next wind speed states are selected based on the previous states. The cumulative probability transition matrix has been formed in which each row ends with 1. Using the uniform random numbers between 0 and 1, a series of future states is generated. These states have been converted to the corresponding wind speed values using another uniform random number generator. The accuracy of the model has been determined by comparing the statistical characteristics such as average, standard deviation, root mean square error, probability density function and autocorrelation function of the generated data to those of the original data. The generated wind speed time series data is capable to preserve the wind speed characteristics of the observed data.

Keywords: Markov chain, transition matrix, synthetic generation of wind speed, autocorrelation, Weibull parameters.

INTRODUCTION

Owing to the present day's energy crisis, growing environmental concern and rapidly depleting reserves of fossils fuel, the planners and policy makers all over the world are making their best efforts to supplement the energy base with renewable energy sources. Wind is one of the potential renewable energy sources and has emerged out 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 Station. For properly designing a wind energy system, there is requirement of the prediction of wind speed statistical parameters. These parameters are also important for designing of wind sensitive structures and for air pollution studies. Wind energy is now economically viable, the cost of wind energy plant has fallen substantially and this trend is continuing (Rehman et al., 1994). Wind is the fastest growing source of energy world wide. It already supplies power to some of the developed and developing countries. Wind energy prices have fallen even faster, due to lower wind turbine prices, higher efficiency and availability, and lower operation and maintenance costs.

There are uniform periodic changes in the wind flow pattern of Malaysia. The country experiences four seasons, namely, the south-west monsoon, north-east monsoon and two shorter inter-monsoon seasons. The south-west monsoon usually starts in the later half of May or early June and ends in September. The prevailing wind flow is generally south-westerly and the speed is below 7.5 m/s. The north-east monsoon usually commences in early November and ends in March. During this season, steady easterly or north-easterly wind of 5 to 10 m/s prevails. In the east coast states of Peninsular Malaysia the wind speed reaches to 15 m/s or more during period of intense surges of cold air from the north. The wind during the two inter-monsoon seasons is generally light and variable. It is worth noting that during the months of April to November, when typhoons frequently develop over the west Pacific and move westwards across Philippines, south-westerly winds over the north-west coast of Sabah and Sarawak region may strengthen reaching a speed of 10 m/s or more. The seasonal wind flow patterns coupled with the local topographic features determine the rainfall distribution pattern over the country. During the north-east monsoon season, the exposed areas like the east coast of Peninsular Malaysia, western part of Sarawak and the north-east coast of Sabah experience heavy rainfall spells (Malaysia Meteorological Services, 2002).

Malaysia offers good opportunities for harnessing the power of wind to rural locations which are not properly connected to the electrical power grid. In order to predict the output of a wind generator and for efficient utilization of wind energy, the information regarding the statistical characteristics, persistence, seasonal and diurnal variation and prediction of wind speed are very important. These wind characteristics and prediction are important for site selection, performance prediction, and planning of windmill farming.

In the present study the hourly wind speed data from 1995 to 2001 at the meteorological station at Kuala Terengganu, Malaysia (latitude 5^0 23' N and longitude 103^0 06' E) at a height of 14 m above the ground level have been used to synthetically generate the wind speed time series by the first order Markov chain approach. Several tests have been conducted to check that the statistical characteristics of the wind speed data are satisfactorily preserved.

LITERATURE REVIEW

A lot of work has been done on the determination of wind characteristics and wind power potential. The wind characteristics and the available wind energy in Behrain were studied by Alnaser (1989). The power density and long term average wind speed and its variation at a height of 10 m above ground level were estimated. Rehman et al. (1994) calculated the shape and scale parameters of a Weibull speed density function for 10 locations in Saudi Arabia. The mean daily wind speed data from 1970 to 1990 was used in this study. The values of C were found to vary from 1.7 to 2.7 m/s, whereas the values of scale parameter, K, varied between 3 and 6. It was concluded that the data was well represented by the Weibull distribution function. Sopian (1995) carried out analysis of wind speed data at several locations in Malaysia in order to determine the wind energy potential and he suggested the use of medium size wind turbines for generating electricity in Malaysia. Mayhoub and Azzam (1997) used wind speed data from 15 meteorological stations in Egypt to assess the monthly and annual wind power. The study covered a period ranging from 1973 to 1884. The Weibull distribution parameters were estimated and used to calculate the wind power density.

There are a few studies on modelling and simulation of wind speed data using different stochastic approaches. Rehman and Halawani (1994) carried out wind persistence and stochastic time series analysis of wind speed data of a few stations of Saudi Arabia. They concluded that the stochastic time series analysis is suitable for description of autoregressive models involving time lags of 1 and 24 hours. Mohandes et al. (1998) compared the neural networks and the autoregressive approaches for modelling wind speed data and found that the neural networks approach performed better. Kaminsky et al. (1991) compared alternative approaches including Markov chain models for the synthetic generation of wind speed time series using wind speed data for a short period of eight hours sampled at a rate of 3.5 hertz. Recently, Sahin et al. (2000) used first order Markov chain model for the synthetic generation of hourly wind speed time series. He used the mean and standard deviation to examine whether the statistical characteristics of the observed wind speed data have been preserved by wind speed data generated using the first order Markov chain model.

WIND SPEED DATA

The wind speed data are generally available in time series format, in which each data represents an instantaneous sample wind speed or an average of wind speed taken at short intervals of time. The wind data at Kuala Terengganu belongs to the second category. The data used in this study is the hourly wind speed data measured from January 1995 to December 2001. Figure 1 shows the variation of daily mean speed from January 1995 to December 2001. It is clear from the diagram that the wind data has the seasonal effects. The diurnal variations of the overall hourly mean wind speed of all the years in Figure 2 show only one peculiar feature for all the months. There is a clear bell shaped trend which is evident throughout the year and this is due to the effect of solar heating balance. The wind speeds are usually reduced during the night but increased during the day (Zubair, 2002). From the point of view of wind energy generation, it is an advantage that most of the wind energy is produced during the day since electricity consumption is higher than at night.

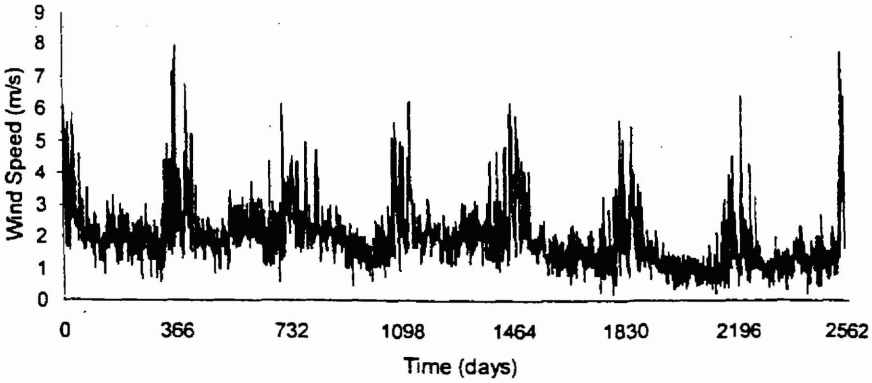

FIGURE 1 Mean daily wind speed from January 1995 to December 2001.

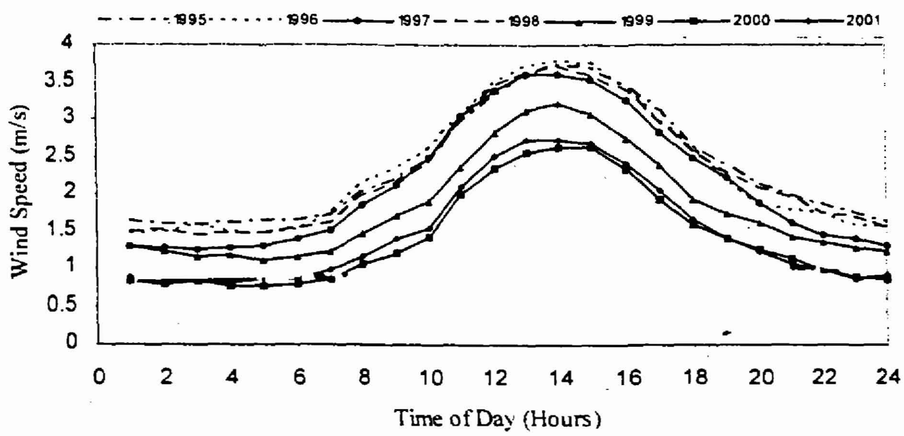

FIGURE 2 Diurnal speed variation for all the individual years.

FORMATION OF TRANSITION MATRIX

If there are n possible states, the Markov chain will be a series of events X_k, where $k=1, 2, 3, \ldots n$.

Let $$P_{ij} = Prob\ \{X_k = j | X_k = i\} \qquad (1)$$

If $X_k = i$, then the process is said to be in state i at time k. It is supposed that whenever the process is in state i, a fixed probability called P_{ij} exists and it will next be in the state j. The conditional distribution of any future state X_{k-1} is independent of the past states but on the present state X_k. only. So, the value P_{ij}

represents the probability that the process will, when in state i, next make a transition into state j.

The wind speed states have been adopted based on the visual examination of the histogram of the wind speed data. It was realized that 11 states each of size 1 m/s will be sufficient to define the probability distribution of the time series. The wind speed transition probability matrix (11 x 11) for wind speed time series at Kuala Terengganu for first order Markov chain model has been shown in Table 1. Each element of the matrix shows the probability of next wind speed state based on the current wind speed state. It is seen that the highest probability occurs on the diagonal of the matrix. Hence if the current wind speeds are known, it is most probable that the next wind speed will be in the same category. Furthermore, all the transition probabilities are around the diagonal; this means that the transitions from one state to another long distant state are less.

TABLE 1 Probability transition matrix

0.687	0.226	0.063	0.015	0.005	0.002	0.001	0.000	0.000	0.000	0.000
0.311	0.424	0.205	0.048	0.009	0.002	0.001	0.000	0.000	0.000	0.000
0.101	0.262	0.413	0.191	0.026	0.005	0.001	0.000	0.000	0.000	0.000
0.026	0.073	0.265	0.458	0.155	0.017	0.004	0.001	0.000	0.000	0.000
0.014	0.025	0.073	0.307	0.428	0.129	0.019	0.003	0.002	0.000	0.000
0.013	0.018	0.038	0.082	0.334	0.371	0.120	0.019	0.003	0.001	0.000
0.033	0.018	0.026	0.041	0.104	0.311	0.347	0.101	0.014	0.005	0.000
0.019	0.008	0.023	0.038	0.046	0.123	0.304	0.323	0.108	0.008	0.000
0.000	0.038	0.063	0.051	0.038	0.063	0.165	0.342	0.177	0.051	0.013
0.000	0.063	0.063	0.125	0.063	0.000	0.063	0.125	0.375	0.063	0.063
0.000	0.000	0.250	0.000	0.000	0.000	0.000	0.250	0.250	0.000	0.250

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. For a fixed present state i, the sum of the future state should be equal to 1 given as:

$$\sum_{j=1}^{n} P_{ij} = 1 \tag{2}$$

Based on this, the cumulative probability transition matrix, P_c, for the first order Markov chain model has been formed (Table 2) in which each row ends with 1. For generating the sequences of wind speed states, the initial state, say state i, is selected randomly. Then random values (0,1) are produced by using a uniform random number generator. For the next wind speed state, 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 preceding state but less than or equal to the cumulative probability of the next state, the next state is adopted. Once the states are known these are then converted to the actual wind speed using another uniform random number. Depending upon the requirement, the wind speed time series of any length can be generated. A time series of wind speed data equals to the number of wind speed data was generated. The frequency of each element of the probability transition matrix of the generated is compared in Table 3 with the frequency of the corresponding element of transition probability matrix of the observed data. The Markov chain approach has been able to maintain the frequencies of the generated data.

TABLE 2 Cumulative probability transition matrix

0.687	0.913	0.976	0.992	0.997	0.998	0.999	1.000	1.000	1.000	1.000
0.311	0.735	0.940	0.988	0.997	0.999	1.000	1.000	1.000	1.000	1.000
0.101	0.363	0.776	0.967	0.993	0.998	0.999	1.000	1.000	1.000	1.000
0.026	0.099	0.364	0.822	0.978	0.994	0.999	1.000	1.000	1.000	1.000
0.014	0.039	0.112	0.419	0.847	0.976	0.995	0.998	1.000	1.000	1.000
0.013	0.031	0.069	0.151	0.486	0.857	0.977	0.996	0.999	1.000	1.000
0.033	0.051	0.077	0.117	0.221	0.533	0.880	0.981	0.995	1.000	1.000
0.019	0.027	0.050	0.088	0.135	0.258	0.562	0.885	0.992	1.000	1.000
0.000	0.038	0.101	0.152	0.190	0.253	0.418	0.759	0.937	0.987	1.000
0.000	0.063	0.125	0.250	0.312	0.312	0.375	0.500	0.875	0.938	1.000
0.000	0.000	0.250	0.250	0.250	0.250	0.250	0.500	0.750	0.750	1.000

Besides the above acceptance procedures, the generated wind speed time series have been examined to determine their ability to retain the statistical properties in order to assess the applicability of Markov chain models for wind speed generation. For this purpose, the important statistical properties used are the general parameters such as mean, standard deviation, the probability Weibull distribution and the persistence structure of the time series.

GENERAL STATISTICAL PARAMETERS

To validate the first order Markov modelling approach, the general statistical parameters such as mean, standard deviation, minimum and maximum values of the synthesized values are presented together with the observed ones in Table 4. It is observed by the comparison of the corresponding observed and generated parameters that the first order Markov chain model has preserved most of the parameters satisfactorily.

TABLE 3 Frequencies of the elements of transition matrix for observed and generated wind speed data

1		2		3		4		5		6		7		8		9		10		11	
Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.	Ob.	Gn.
13067	12691	4308	4304	1203	1255	288	293	95	88	34	35	20	13	8	7	2	3	1	1	1	0
4430	4428	6044	5901	2922	2869	681	712	133	133	27	27	8	9	5	6	0	0	1	1	0	0
1184	1229	3085	3054	4863	4993	2248	2215	309	306	61	44	17	17	5	5	1	2	1	0	0	0
228	232	651	671	2352	2322	4064	4249	1379	1474	150	172	39	43	7	5	3	3	0	0	0	0
66	63	112	106	333	327	1399	1503	1953	1948	589	599	86	100	13	9	8	6	1	1	0	0
24	25	32	30	68	64	147	158	599	630	665	691	215	224	34	34	6	7	1	1	0	0
24	17	13	16	19	25	30	26	76	72	228	250	254	219	74	67	10	8	4	3	0	0
5	4	2	0	6	4	10	11	12	8	32	38	79	69	84	78	28	29	2	1	0	0
0	0	3	3	5	5	4	4	3	3	5	8	13	8	27	27	14	11	4	2	1	0
0	0	1	1	1	1	2	1	1	0	0	0	1	1	2	3	6	2	1	2	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0

TABLE 4 General statistical parameters of observed and synthetically generated wind speed data

Type of Wind Data	Mean	Median	Min.	Max.	Std. Dev.	Skewness
Observed	1.96	1.70	0.00	10.80	1.60	0.79
Generated	2.12	1.85	0.00	10.06	1.56	0.82

PERSISTENCE STRUCTURE

To determine the persistence structure in the observed and the generated wind speed data, the autocorrelation function (Shamshad, 2001) has been used. The autocorrelations for the observed and generated wind speed data were computed and presented in Figure 3. The comparison shows that the observed wind speed is correlated over a long period of time than the wind speed generated by Markov chain model. Hence, the observed wind possesses long period information than the first order synthetic Markov chain. It is expected that the algorithm for data generation can be improved if the second or higher order Markov chain models are used.

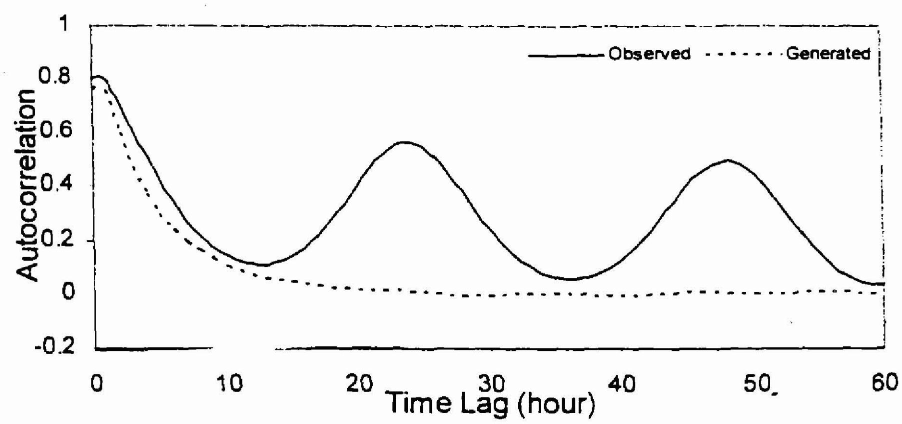

FIGURE 3 Autocorrelation functions of observed and generated wind speed.

WEIBULL DISTRIBUTION

The frequency distribution of wind speeds in general can be conveniently and adequately represented by the Weibull distribution function (Sopian et al., 1995; Seguro et al., 2000; Bawadi and Wan Hussin, 2001). For this function, the probability of the wind speed having a value V is given by the equation:

$$p(V) = \frac{K}{V}\left(\frac{V}{C}\right)^{k-1} \exp\left\{-\left(\frac{V}{C}\right)\right\}^{k} \tag{3}$$

The Weibull distribution is controlled by two parameters namely, the shape parameter (K) and the scale parameter (C). The Weibull distribution tends to get more peaked as k becomes larger with the peak moving in the direction of higher wind speeds. The parameter C scales the X-axis (wind speed) to fit different wind regimes. When the value of K equals 2, then the Weibull distribution is called Rayleigh distribution.

For K greater than 1, it can be seen that the Weibull distribution gives a zero probability of having wind speed zero. This is not true since there will always be period of calm. However, this is not a problem because the turbine will not be running at very low wind speeds and so this inaccuracy will not affect the estimation of the annual energy capture. The Weibull distribution tends to zero at high wind speeds. This means that there will be non-zero probability of obtaining all wind speeds up to infinity. This inaccuracy at high wind speeds is not a problem because this speed, the wind turbine is shut down.

The synthetically generated data 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 have been examined. The frequency distribution of data is shown in Figure 4. The visual examination of this figure shows that the probability at different bins have almost the same values. The probability distribution of the observed and the generated wind speed is characterized by Weibull distribution. The Weibull parameters for the observed and the generated wind speed time series are presented in Table 5 for comparison. It appears that the first order Markov chain model has preserved the Weibull parameters.

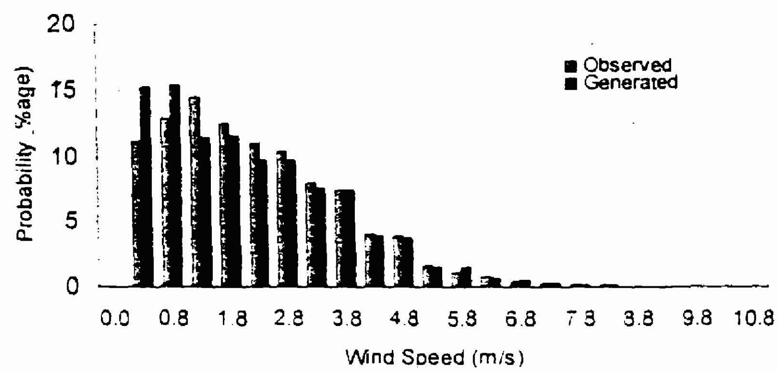

FIGURE 4 Probability distributions for observed and generated wind speed.

TABLE 5 Weibull parameters of observed and synthetically generated wind speed data

Observed		Generated	
K	C	K	C
1.595	2.578	1.286	2.286

CONCLUSION

The time series of hourly wind speed measured at the Kuala Terengganu meteorological station in Malaysia are analysed statistically using the first order Markov modelling approach. The manner in which Markov chain method is used to generate wind speed data is described. The synthetic wind speed time series are generated using the transition probability matrix. The limiting behaviour of Markov chain approach has been examined by carrying out several statistical tests. The comparison between the observed wind speed and the synthetically generated one indicates that the statistical characteristics of the wind speed are faithfully reproduced. It is recommended that in future research, the second or higher order Markov chain models should be used to improve the behavior of the autocorrelation function. The synthetic wind speed data can be utilized as input for any wind energy system.

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