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Markov Chain model for the stochastic behaviors of wind-direction data

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Analyzing the behaviors of wind direction can complement knowledge concerning wind speed and help researchers draw conclusions regarding wind energy potential. Knowledge of the wind's direction enables the wind turbine to be positioned in such a way as to maximize the total amount of captured energy and optimize the wind farm's performance. In this paper, first-order and higher-order Markov chain models are proposed to describe the probabilistic behaviors of wind-direction data. A case study is conducted using data from Mersing, Malaysia. The wind-direction data are classified according to an eight-state Markov chain based on natural geographical directions. The model's parameters are estimated using the maximum likelihood method and the linear programming formulation. Several theoretical arguments regarding the model are also discussed. Finally, limiting probabilities are used to determine a long-run proportion of the wind directions generated. The results explain the dominant direction for Mersing's wind in terms of probability metrics.

1. Introduction

Wind energy is counted among the most promising green energy options due to its characteristics of being abundant everywhere, renewable, widely distributed and minimally polluting [1]. In fact, critical issues, such as the global decline in fossil fuel reserves, the damaging effects of global warming, and rising demand due to increasing population, have necessitated the development of alternative energy resources, such as wind power [2]. Moreover, wind energy does not suffer from transportation problems, and its utilization does not require advanced technology [3]. Thus, wind energy has been growing rapidly worldwide and has become a top contributor to the renewable energy mix due to its high capacity and its generation costs, which are becoming competitive with those of conventional energy sources [4]. As reported by the Global Wind Energy Council (GWEC) [5], the total global cumulative installed wind power capacity has increased tremendously from 1996 to 2013. Fig. 1 shows the increasing trajectory of global cumulative wind capacity over the period from 1996 to 2014.

To investigate the potential of wind energy, wind speed and wind direction are important variables that contribute significant information. The variable of wind speed has been copiously studied by many researchers around the world, particularly in terms of mathematical and statistical analyses; for example, see [6–22]. Among such studies, the Markov chain is one of the most popular and powerful models to have been investigated by many researchers, particularly to analyze the stochastic behaviors of the fluctuating nature of the wind source. In fact, the Markov chain model has been determined to be a good model for synthetically generating wind-speed data. For example, Sahin and Zen [11] used a first-order Markov chain to model and simulate/generate synthetic wind-speed time-series data. Those researchers determined various states of the Markov chain based on the arithmetic average and standard deviation. They found that, for short periods of time, the Markov chain model is able to exhibit strong congruency between measured values and synthetic values. They also found that more than 90% of the statistical parameters in the synthetic wind speed could be account for by the Markov chain model. Nfaoui et al. [12] analyzed hourly wind-speed time-series data using a Markov chain model. Their analysis was performed by defining 12 categories of wind speed. They found that the 12×12 transition probability matrix is quite useful for generating synthetic wind-speed time-series data. In fact, they also described the limiting behavior of wind-speed data based on the Markov chain model. Shamshad et al. [13] compared the first and second orders of the Markov chain model's performance in generating synthetic wind-speed time-series data. Twelve wind-speed states at 1-m/s intervals were defined in order to capture the shape of the probability density function. Shamshad et al. found that the second order of

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the Markov chain would slightly improve the results of synthetically generated data. In addition, based on the observed wind-speed data and statistical properties such as the mean, standard deviation, percentiles, and autocorrelations, they concluded that the synthetic data from Markov chain model are able to satisfactorily preserve the statistical characteristic of wind-speed data. Kantz et al. [14] used a continuous-state Markov chain model to approximate the dynamics of turbulent wind-speed data. The *m*-th continuous state was defined by vectors of real numbers, and the transition probabilities were obtained separately from online data for every given actual state. Katz et al.'s results showed that the predicted probabilities derived from the Markov chain model are able to meaningfully forecast turbulent gusts.

Beyond the aforementioned observations, there have also been several interesting studies of wind modeling that have involved modification of the original Markov chain model. For example, Hocaoglu et al. [15] proposed a hidden Markov model (HMM) in which atmospheric pressure was defined as a dependent process when modeling the wind-speed data. In their model, they assigned the wind-speed variable as a hidden process behind the pressure observations. Thus, synthetic generation data for wind speed were produced using the information on the atmospheric pressure. Their results showed that the HMM can achieve high accuracy in generating wind speed estimates. Ailliot and Monbet [16] proposed the application of a non-homogeneous Markov-Switching Autoregressive (MS-AR) model to describe wind-speed time-series data. The time evolution of wind speed was explained by several autoregressive models, with switching between autoregressive models being controlled by the hidden Markov chain. They found that the MS-AR was able to provide good descriptions of important properties of the wind data, such as the marginal distribution, length of storms, and calm periods. However, the MS-AR model had some limitations, such as its potential to simulate negative wind-speed data and its failure to reproduce observed inter-annual variability that was available in the data. D'Amico et al. [17] proposed first- and second-order semi-Markov chains to model wind-speed data. They found that the wind-speed fluctuation could be described in a semi-Markovian nature. The synthetic data generated by the semi-Markov model were found to have statistical properties similar to those of real data.

There are still many more research studies that have used the Markov chain approach to evaluate and model the stochastic behaviors of wind-speed data. Unfortunately, studies of the wind-direction variable have not been common. As mentioned by Masseran et al. [18], the wind-direction variable has been recognized as an important one in the evaluation of wind energy because information about wind direction can complement information about wind speed to aid in drawing conclusions about energy potential. However, some researchers have dealt with Markov chain models with respect to wind direction. For example, Ettoumi et al. [19] used a first-order Markov chain model with nine states of wind direction representing the 9 directions of the compass card. Three-hour wind data were used in their study. They found that the first-order Markov chain model could be fitted well to the wind-direction data. In addition, they provided a combination of a first-order, nine-state Markov chain model for the wind direction with a first-order, three-state Markov chain model for the wind speed, and their final results were found to yield a good representation of the observed wind data. Hagen et al. [20] proposed a multivariate Markov chain model (MMM) to describe the wind energy at offshore wind parks. The MMM model was used to generate a sea state, which represented by the wind speed, wind direction, wave height, wave period and wave direction. The transition probability for the MMM model was estimated separately for each month and also for monthly transformations of the data. In addition, they evaluated the quality of the MMM model by comparing its statistical properties to the statistical properties of the observed data. Their final results indicated that the MMM model is able to provide a reasonable approximation of the observed data. Scholz et al. [4] proposed the application of a cyclic time-dependent model (CTDM) with a three-dimensional state space: namely, the wind-power, wind-speed and wind-direction variables. The transition probability for this model was expressed by a Bernstein polynomial. They also provided an objective function to ensure that the CTDM model would provide an accurate representation of the long-term behavior of the wind data. Based on the CTDM model, they simulated synthetic data, which were compared with the original data. Their results showed that the CTDM model was able to reproduce the diurnal pattern in the data. Moreover, the persistence of power production could also be estimated for the CTDM model.

This study has taken the initiative to promote the importance of wind-direction analysis, particularly with the application of Markov chain modeling, to provide information regarding behaviors of the wind regime, toward aiding the process of energy assessment.

2. Study area and data

Mersing is situated in the state of Johor, Malaysia. Its geographical coordinates are 2°26′North and 103°50′East, as shown in Fig. 2. Throughout the year, the Mersing region, as well as the whole of Peninsular Malaysia, generally experiences wet and humid conditions, with daily temperatures ranging from 25.5 °C to 35 °C. The wind that blows across Peninsular Malaysia is influenced by the southwest monsoon, the northeast monsoon and two short inter-monsoon periods. Generally, the southwest monsoon occurs from May to September, whereas the northeast monsoon occurs from November to March. In addition, because Peninsular Malaysia is surrounded by the sea, it is also influenced by the effect of sea breezes and land breezes, especially when the sky is not cloudy. During most afternoons, sea breezes occur at speeds of 10–15 kn. However, at night, the reverse process occurs. Weak land breezes occur in coastal areas [23].

The 020C Wind Direction Sensor, provided by Met One Instruments, has been used by Malaysia's Department of Environment to collect hourly wind-direction data. The 020C Wind Direction

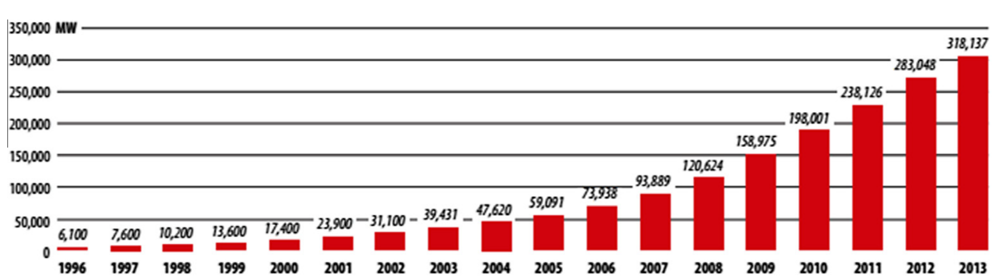

Fig. 1. Global cumulative installed wind capacity over the period 1996–2013 [5].