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A meteorological information mining-based wind speed model for adequacy assessment of power systems with wind power

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A B S T R A C T

Accurate wind speed simulation is an essential prerequisite to analyze the power systems with wind power. A wind speed model considering meteorological conditions and seasonal variations is proposed in this paper. Firstly, using the path analysis method, the influence weights of meteorological factors are calculated. Secondly, the meteorological data are classified into several states using an improved Fuzzy C-means (FCM) algorithm. Then the Markov chain is used to model the chronological characteristics of meteorological states and wind speed. The proposed model was proved to be more accurate in capturing the characteristics of probability distribution, auto-correlation and seasonal variations of wind speed compared with the traditional Markov chain Monte Carlo (MCMC) and autoregressive moving average (ARMA) model. Furthermore, the proposed model was applied to adequacy assessment of generation systems with wind power. The assessment results of the modified IEEE-RTS79 and IEEE-RTS96 demonstrated the effectiveness and accuracy of the proposed model.

1. Introduction

Energy consumption has been heavily dependent on fossil fuels for a long time, which causes problems such as resource depletion, climate change and environmental pollution. Wind power is considered as an alternative to fossil fuels in order to alleviate these problems. However, the stochastic nature of wind power poses challenges to power systems. Incorporating wind power into reliability assessment requires accurate modeling. The effect of wind power on reliability assessment is highly dependent on the characteristics of wind such as statistical characteristics (probability distribution) and time evolution characteristics (auto-correlation) [1]. Therefore, it is important to utilize an appropriate wind speed model to represent wind power variation characteristics in order to obtain accurate results in reliability assessment.

There are two main types of wind speed models: probabilistic models [2–4] and time series models [5–14]. Weibull distribution [2,3] and Rayleigh distribution [4] are most widely used in probabilistic models which can reflect the statistical characteristics of wind speed. However, the time evolution characteristics of wind speed are neglected in these probabilistic models. At present, the time series models are more widely used in reliability assessment studies. The stochastic process theory based models are mainly divided into two types: autoregressive moving average (ARMA) models [5,6] and Markov Chain Monte Carlo (MCMC) models [7–9]. The temporal auto-correlation of wind speed can be modelled in the ARMA models. However, these models cannot guarantee a good fit of the statistical characteristics. The probability distribution of the wind speed samples generated by ARMA models may be a normal distribution and negative wind speed samples are generated. And in the ARMA models, the wind speed data should be stationary and invertible. MCMC models represent the wind speed with a finite number of states. The probabilities in each state are assumed to be uniformly distributed, which can cause errors. The MCMC models represent time evolution characteristics using a transition matrix. Improved models such as the semi-Markov model [10] and Bayesian Markov model [11] show better accuracy in capturing time evolution characteristics. A two-tier reliability model is proposed in [12], in which the weather types and wind power fluctuations are modelled by Markov chains, respectively. Besides, models such as the two-dimensional wind speed statistical model [13] and time-dependent clustering model [14] are developed for reliability assessment.

The wind speed models proposed in the literatures are based on measured wind speed data with specific resolutions such as 10 min, 15 min or 1 h. They can describe the wind speed characteristics of the specific time resolutions. However, the wind speed

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characteristics for longer time scales cannot be captured. Moreover, the seasonal variations were not taken into consideration in these models. However, the seasonal factors should be considered to obtain an accurate results in long-term reliability assessment [9]. Thus, a meteorological information mining-based wind speed model for reliability assessment is proposed in this paper. The meteorological conditions and seasonal variations are considered in this model. Consequently, the characteristics of wind speed can be accurately modelled for longer time scales and the seasonal characteristics can be represented. Firstly, the influence weights of meteorological factors on wind power output is calculated using the path analysis method. Secondly, using an improved Fuzzy C-means (FCM) clustering algorithm, the daily meteorological states are obtained. Then, a two-step MCMC model is developed to model the meteorological conditions and wind speed: the first step is the meteorological state time series simulation considering the seasonal variations; and the second step is the wind speed time series simulation within a specific meteorological state. The empirical distribution function of wind speed is used in the second step to improve the probabilistic accuracy of each state in the model. The proposed model is validated from the probability distribution and auto-correlation. The modified IEEE RTS79 and IEEE-RTS96 with wind power were used to demonstrate the effectiveness of proposed model for reliability assessment.

The rest of the paper is organized as follows. The classification method is presented in Section 2. The two-step MCMC model is proposed in Section 3. The parameters of the traditional MCMC model and ARMA model which are used for comparison are presented in Section 4. In Section 5, the proposed model is verified by comparing with the traditional MCMC model and ARMA model. The effectiveness of the proposed model for reliability assessment is demonstrated in Section 6, followed by conclusions.

2. Classification methodology of meteorological states

The meteorological factors have significant effects on the wind power output. In this paper, the meteorological factors such as wind speed, wind direction, temperature, atmospheric pressure and precipitation are represented by an n-dimensional vector $\boldsymbol{X} = [x_1, x_2, \ldots, x_n]$. The characteristics of wind power output are represented by the daily power generation y. The overall process of classification is illustrated in Fig. 1. The meteorological data and daily power generation data are normalized firstly. Then, the influence weights of the meteorological factors are calculated using the path analysis method. A clustering technique is used to classify the multi-dimensional vectors.

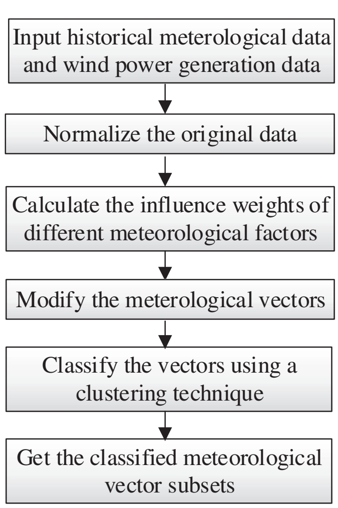

Fig. 1. Flow chart of classification methodology of meteorological states.

2.1. Data normalization

The daily meteorological dataset and power generation dataset of a wind farm can be denoted as a matrix:

$$\boldsymbol{Z} = [\boldsymbol{X}, \boldsymbol{Y}] = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} & y_1 \\ x_{21} & x_{22} & \ldots & x_{2n} & y_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{N1} & x_{N2} & \ldots & x_{Nn} & y_N \end{bmatrix} \quad (1)$$

where x and y are the meteorological data and power generation data, respectively; n is the number of meteorological factors; N is the total number of days.

The original data have different units. In order to eliminate the effects of the units on the classification results, the original data should be normalized to the values in the interval [0,1] by,

$$z_{ij}^* = \frac{z_{ij} - z_j^{\min}}{z_j^{\max} - z_j^{\min}} \quad (2)$$

where z_{ij} and z_{ij}^* are the original and normalized elements of matrix $\boldsymbol{Z}$, $z_j^{\min}$ and $z_j^{\max}$ are the minimum and maximum elements of jth column of matrix $\boldsymbol{Z}$, respectively.

2.2. Calculation of influence weights

Since the effects of meteorological factors on wind power output are quite different, the differences should be considered and represented by influence weights.

The path analysis method is widely used to identify the correlation between multiple variables, which is an extension of the multiple linear regression analysis [15]. The path coefficients are used to represent the links between independent and dependent variables. The conventional multiple linear regression model is shown as,

$$y^* = b_0 + b_1 x_1^* + b_2 x_2^* + \ldots + b_n x_n^* \quad (3)$$

where b_i ($i = 1,2,\ldots,n$) are the partial regression coefficients; x^* and y^* are the normalized meteorological data and daily power generation, respectively.

The direct path coefficients are considered in this paper, which are defined as,

$$E_{x_i^* \to y^*} = b_i \sqrt{\sum_{j=1}^{N} (x_{ji}^* - \overline{x_i^*}) \Big/ \sum_{j=1}^{N} (y_j^* - \overline{y^*})}, \quad i = 1,2,\ldots,n \quad (4)$$

Then, the influence weights of meteorological factors can be calculated by [16],

$$\omega_i = \frac{|E_{x_i^* \to y^*}|}{\sum_{j=1}^{n} |E_{x_j^* \to y^*}|} \quad (5)$$

Thus, the normalized meteorological vector modified by the influence weights is,

$$\boldsymbol{X}_\omega^* = [\omega_1 x_1^*, \omega_2 x_2^*, \ldots, \omega_n x_n^*] \quad (6)$$

2.3. Classification of meteorological states

To recognize typical meteorological states, the modified meteorological vectors are divided into C sets using the clustering technique. Clustering algorithms can be categorized by the principle (objective function, graph-theoretical, hierarchical) or the model