Journal of Wind Engineering & Industrial Aerodynamics 172 (2018) 453–465

Contents lists available at ScienceDirect

Journal of Wind Engineering & Industrial Aerodynamics

journal homepage: www.elsevier.com/locate/jweia

Wind speed scenario generation based on dependency structure analysis

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ARTICLE INFO

Keywords:
Scenario generation
Wind speed
Dependence structure
Tail dependence coefficients
Copula

ABSTRACT

Scenario generation is of great significance to scenario-based stochastic programming. The higher the accuracy of the scenarios, the closer the solutions of the problem are to real optimal values. One uncertain variable which is significant in planning microgrids and wind farms is wind speed. Complex dynamic behavior, being non-stationary, and the different type of tail dependence of wind speed data complicate its modeling. Tail dependence is an important feature in modeling accuracy and conventional wind speed scenario generation methods such as autoregressive integrated moving average (ARIMA) and multivariate distribution functions are not capable of modeling tail dependence. The current study uses copula functions with the ability to model tail dependence for the generation of wind speed scenarios. First, the structure of the dependence of wind speed data has been investigated using correlation matrix and tail dependence coefficients. Then, according to the dependence structure of the data, the appropriate copula function has been selected. The results show that the scenarios made by the student-T copula function are more accurate than conventional methods such as ARIMA and the normal multivariate distribution function.

1. Introduction

One problem with sustainable energy is its uncertainty. Such uncertainty can cause inaccurate estimation of project profitability and decreased reliability of the application of sustainable energy resources (Baringo and Conejo, 2013). One method of coping with uncertainty is stochastic programming. In this method, uncertainty is defined as a set of scenarios that should be able to accurately model the behavior of uncertainty, because the accuracy of the modeling influences the solutions to the problem (Álvarez-Miranda et al., 2015). Stochastic programing is employed for problems of planning and operating grids that include those for renewable energy resources. Wind speed, solar radiation, loads, prices, etc. are uncertain variables in microgrid planning and should be considered (Fu et al., 2016; Bornapour and Hooshmand, 2015). Jiao et al. considered wind speed, solar radiation and load as uncertain variables in an autonomous microgrid to design a power storage system. The use of stochastic programing has increased the reliability of the microgrid (Jiao et al., 2014). Wang et al. have considered wind speed and load as uncertain variables in a microgrid and have tried to increase the reliability and optimize the cost of microgrid planning (Wang et al., 2014).

The complexity of the dynamic behavior of wind speed complicates the modeling of the data. Accordingly, various studies focused on understanding the dynamics of the behavior of wind speed and its modeling. In most studies, wind speed is considered to be a stochastic time series; hence, statistical methods have been used to model it (Bigdeli et al., 2013; Bigdeli and Sadegh Lafmejani, 2016). A straightforward method of modeling is that based on the probability density function (PDF). In this method, the probability density function of wind speed is estimated first using the available data (generally for one year). Next, using the PDF, further samples are generated. It is useful when states that did not occur in the training data, but may possibly exist over time, are also seen and considered in decision-making. As the number of these scenarios is large and increases the size of computation, the number of generated scenarios can be decreased using scenario reduction methods (Tabar et al., 2017; Mohammadi and Mohammadi, 2014; Azaza and Wallin, 2017; Sadeghi and Kalantar, 2014). For non-Gaussian PDFs, methods such as maximum entropy, Hermite moment and spectral correction simulation have been used to increase the accuracy of wind speed modeling (Gurley and Kareem, 1997; Kareem, 2008). In the PDF method, it is assumed that wind speed in different hours is independent, although this is not true, because wind data has serial linear dependence. To solve this problem, another method considered for modeling wind speed is the autoregressive integrated moving average (ARIMA) method (Lowery and OMalley, 2013; Chen and Rabiti, 2017). A complete description of this method can be found in Conejo et al. (Conejo et al., 2010). ARIMA is able to model stochastic processes with a Gaussian

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https://doi.org/10.1016/j.jweia.2017.11.023
Received 7 July 2017; Received in revised form 16 October 2017; Accepted 23 November 2017

0167-6105/

distribution by first presenting a Weibull-to-Gaussian distribution conversion which enables its use for wind speed data with a Weibull distribution. Another method based on power spectral density and lower-order moments allows the ARIMA model to be used directly for non-Gaussian data (Li and Li, 2011). Furthermore, for modeling of non-stationary data, the ARIMA and generalized autoregressive conditional heteroscedasticity (GARCH) combined model can be used (Taylor et al., 2009; Ambach, 2016).

Another method that is suitable for modeling dependent stochastic variables is the multivariate distribution function. In previous studies, the normal multivariate distribution function has been used to generate wind speed scenarios. In this method, each hour of wind speed data is considered to be a variable (for a total of 24 variables). Then, based on the mean value of every variable and the covariance matrix of the variables the normal multivariate distribution function is used to generate a large number of wind speed scenarios (Pinson et al., 2007, 2009; Ma et al., 2013).

Various multivariate distribution functions based on univariate distribution functions have been developed; however, the selection and application of these multivariate distribution functions are dependent on marginal functions (the PDF of the variables). In other words, the family of multivariate distribution functions should be chosen considering the PDF of the stochastic variables. This restricts selection and makes it impossible to select a suitable multivariate distribution function considering the dependence structures (Frees and Valdez, 1998).

Dependence structure is measuring the correlation between variables and examines the tail dependence of the data. Assume that we have stochastic variables X and Y. If variable X falls below a certain threshold and, similarly, variable Y also falls below that threshold, the data can be said to have lower tail dependence. If variable X goes above a certain threshold and likewise variable Y also rises above that threshold, the data shows upper tail dependence. Symmetrical tail dependence is the concurrent existence of lower and upper tail dependence (Ané and Kharoubi, 2003). Fig. 1 shows the different types of tail dependence of data.

Fig. 1 represents the significance of tail dependence. In all four states, variables X and Y are dependent, but it can be observed that the scattering of data is very different; therefore, considering the type of tail dependence increases modeling accuracy. In previous studies, only the value of dependence of the wind speed data has been considered and the type of tail dependence has been neglected. On the other hand, the normal multivariate distribution function employed for wind speed modeling is not able to model tail dependence.

Copula-based multivariate distribution functions can be used to model different types of dependence structures. Copula functions are suitable for generation of multivariate distribution functions using marginal distribution functions. Copulas can be employed for a variety of marginal distribution functions. Furthermore, different copulas allow generation of multivariate distribution functions with different properties, which can be applied in the modeling of different types of dependent data (Embrechts et al., 2003). Valizade-Haghi et al. used the copula function to generate wind scenarios. They applied a Gaussian copula to generate wind scenarios, but did not investigate tail dependence; thus, the dependence structure is not considered in the selection of copula function for wind speed modulation (Valizadeh-Haghi et al., 2013).

As stated above, the dependence structure of wind speed data, especially tail dependence is very important in data modeling. Conventional wind scenario generation methods such as ARIMA and multivariate distribution functions are not capable of modeling tail dependence; hence, the current study used copula functions to generate wind speed scenarios. To select the proper copula function, it was necessary to investigate the wind speed data dependence structure using the correlation matrix and tail dependence coefficients. The results show that the two issues presented in this paper, namely, the study of tail dependence of wind speed data and the selection of the appropriate joint function with the ability to model tail dependence increased the accuracy of wind speed scenario generation over that of previous methods. The main contributions of this paper can be summarized as follows:

- Study of the tail dependence structure of wind speed data
- Selection of an appropriate copula function based on the dependence structure
- Improvement in accuracy of scenarios for generating wind speed

This paper is sectioned as follows: Section 2 introduces the data and

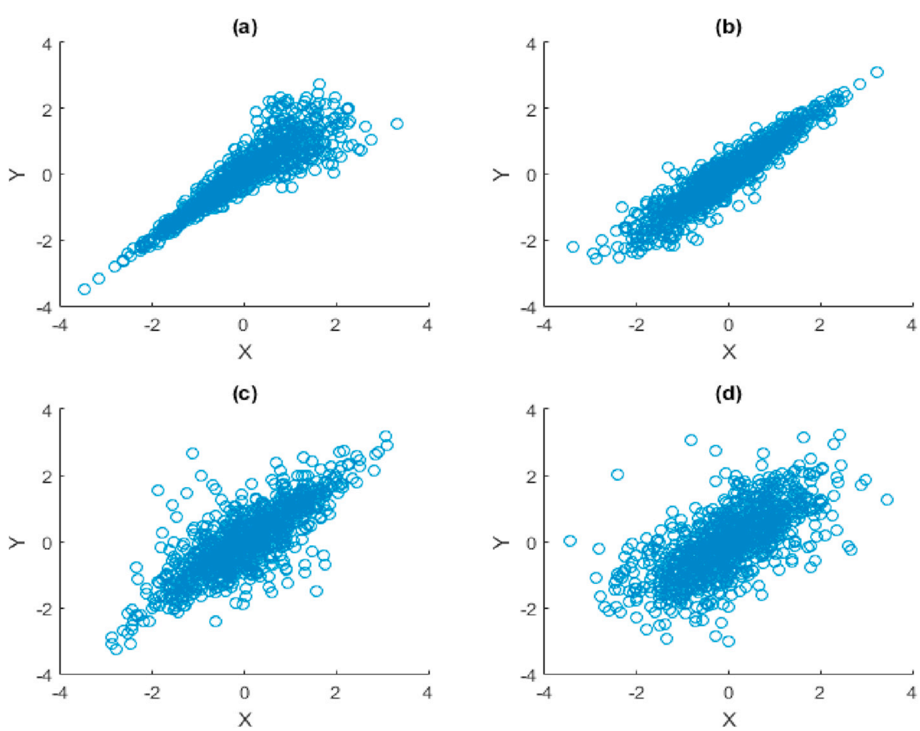

Fig. 1. a) Lower tail dependence b) Upper tail dependence c) symmetrical tail dependence d) no tail dependence.