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Modeling the temporal correlation of hourly day-ahead short-term wind power forecast error for optimal sizing energy storage system

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ABSTRACT

Due to the inherent stochastic and intermittent nature of wind generation, it is very difficult to sharply improve the wind power forecasting accuracy. The sizing of energy storage system (ESS) for wind farm can effectively reduce the uncertainty caused by the inevitable forecast error of wind power. However, optimal sizing of ESS is a multi-period decision-making problem and it is the key point that exactly captures the variation magnitude and speed of forecast error. This paper proposes a method to establish the multivariate joint cumulative distribution function (JCDF) of hourly day-ahead short-term multi-period forecast errors using Normal/t copula. Based on the proposed JCDF and multiple scenarios technique, a model of optimal sizing of ESS is proposed in which the temporal correlation relationship between different time period forecast errors and probability distribution of each time period forecast error are both considered. The simulation results verify the effectiveness of the proposed methods and show that if the temporal correlation of wind power short-term forecast error is ignored, the rated energy and power capacity of sizing of ESS will be significantly misestimated.

1. Introduction

Wind power is becoming one of the fastest growing renewable energy resources worldwide due to its advantages of environmental friendliness and reproducibility as well as the rapidly developing wind power generation technology. The installed capacity of wind generators and the contribution of wind power to grids continue to increase. However, the inherent stochastic and intermittent nature of wind generation results in both variability and uncertainty in availability of wind power [1–3].To guarantee the quality and reliability of the electricity supply, the fossil fuel-plants are forced to frequently adjust to cope with the unbalanced power caused by the rapid fluctuations as well as the limited predictability of wind power. An amount of reserves are required to ensure the system security and stability [4,5].

With the improvement of energy storage technology, an energy storage system (ESS) is considered as alternative approach to alleviate the negative impacts of the variability and uncertainty from wind generation [6]. In addition, it can also be used to improve the predictability of wind power [7] and reduce the system operation cost [8,9]. Since the ESS is expected to mitigate the uncertainty of wind power integration caused by the forecast error in recent years, extensive efforts have been devoted to optimal sizing of ESS considering system investment, operation and penalty cost [10–12]. Optimal sizing of ESS used to offset the forecast error and track the scheduling instruction is significantly affected by the wind power forecast error [13,14]. And the methods of optimal sizing of ESS are mainly classified into the following three categories according to the characteristics of forecast error.

(1) The methods based on probability distributions of forecast error have been studied in [15–20]. Ref. [15] assumed the wind power forecast error as a Normal distribution and proposed an operation method of optimizing the capacity of the battery energy storage system (BESS) to compensate the wind power forecast error. In [16], the wind speed forecast error was assumed as a Normal distribution and the probability distribution of wind power forecast error was obtained by turbine power curve. In this paper, the energy capacity of BESS was determined to realize wind farm generation dispatchability based on the trade-off between battery lifetime and the cost.

However, many studies indicate that the wind power forecast error does not follow a Normal distribution, but presents a certain sharp peak and fat-tailed distribution [17]. Ref. [17] proposed an indirect method based on the Beta distributions to obtain a probability density function

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Nomenclature

Sets

P	set of wind power scenarios
S	set of random samples
s	set of wind power reduced scenarios

Parameters

k	degrees of freedom
I	identity matrix
p_i	probability of the ith scenario
$\mathbf{P}_i$	the ith wind power scenario
T	dimension of a wind power scenario
τ	wind power prediction
Δt	length of time interval
$\boldsymbol{\rho}$	covariance/correlation matrix
$\boldsymbol{\rho}^{-1}$	inverse of covariance/correlation matrix
η_c	charge efficiency of ESS
η_d	discharge efficiency of ESS
Φ^{-1}	inverse of CDF of a standard normal distribution
Φ_ρ	CDF for a multivariate normal distribution with covariance/correlation matrix $\boldsymbol{\rho}$
t_k^{-1}	inverse of CDF of one dimensional t_k distribution with k degrees of freedom
$t_{\rho,k}$	CDF of multivariate t distribution with k degrees of freedom and covariance/correlation matrix $\boldsymbol{\rho}$
$[u_{i1},u_{i2},...,u_{iT}]$	the ith T-dimensional random sample
$\Gamma(\cdot)$	gamma function

Variables

E_i	rated energy of ESS of the ith scenario
E	final rated energy of the sized ESS
$P_{i,out}(t)$	expected power output of the ith scenario
P_{rcESS}	final charge power capacity of the sized ESS
P_{rdESS}	final discharge power capacity of the sized ESS
$P_{bu}(t)$	wind spill power at time t
$P_{ws}(t)$	back-up power at time t,
$P_{i,cESS}(t)$	charge power at time t of the ith scenario
$P_{i,dESS}(t)$	discharge power at time t of the ith scenario
$P_i(t)$	wind farm output at time t of the ith scenario
$[\underline{P(t)},\overline{P(t)}]$	domain of the expected wind power output at time t
$SoC_i(t)$	state of charge at time t of the ith scenario
$X_1,X_2,...,X_T$	random variables of Copula function
$\lambda_{i,c}(t)$	flags of charge power of ESS at time t of the ith scenario
$\lambda_{i,d}(t)$	flags of discharge power of ESS at time t of the ith scenario

(PDF) of wind power forecast error. With this PDF, Ref. [18] presented a probabilistic method for ESS sizing to quantify the remaining uncertainty as a function of the power and energy capacity of ESS. Moreover, Ref. [19] proposed a coordinated operational dispatch scheme for BESS-wind farm where the optimal BESS energy capacity is chosen by maximizing net present value. In [20], a mixed distribution based on Laplace and Normal distribution was proposed to model forecast errors for a single wind farm over multiple timescales, and a probabilistic optimization model was proposed to determine optimal size of ESS for wind farm in electricity markets, considering the economic profits and cost of the ESS installed.

(2) The methods based on the data pre-processing technique, such as discrete Fourier transform (DFT) and discrete wavelet transform have been proposed to optimize the sizing of hybrid energy storage system (HESS). In [21], a method used to size the sodium sulfur (NaS) batteries, compressed air energy storage (CAES), and conventional generators was proposed to mitigate different time-varying periodic components of wind forecast error obtained by DFT and discrete wavelet transform methods. Ref. [22] proposed a DFT-based method for the coordinated sizing of ESS and diesel generators in an isolated microgrid, and the generation-demand imbalance at different time scales obtained by DFT was complementarily compensated by ESS and diesel generators.

(3) The methods considering the correlation relationship of forecast error have been proposed in recent studies. For example, in [23], based on the probabilistic prediction of wind power, a methodology was presented for the dynamic sizing assessment of the EES for hedging wind power forecast uncertainty, in which the correlation pattern of short-term prediction errors was used as a basis. In [24], the correlation of day-ahead forecast errors was captured by a data-fitted autoregressive (AR) model to quantify the impact of correlation on energy storage sizing. However, due to the classical limitations of the AR model, the statistical characteristics of forecast error cannot be presented, e.g., its non-Gaussianity.

Since the optimal sizing of ESS used to compensate day-ahead forecast error and track the scheduling instruction is a multi-period decision-making problem, the charge and discharge power and state of

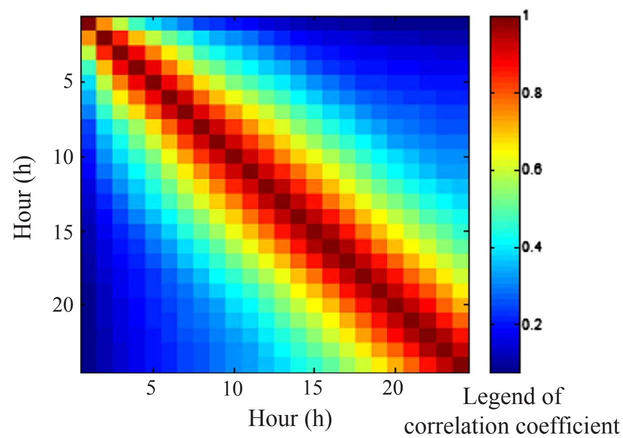

Fig. 1. Linear correlation coefficients of 24 time periods forecast errors.

charge (SOC) of ESS are all significantly affected by the variation magnitude and speed of forecast error. Refs. [23,24] have made significant contributions on optimal sizing of ESS taking into account the correlation relationship of forecast error. However, most of the wind farms currently have the capacity of point forecast skill of wind power and it is overwhelmingly crucial to further study (1) how to build the multivariate joint cumulative distribution function (JCDF) of forecast error directly using the historical multi-period forecast error data and (2) how to build an optimal sizing of ESS model to mitigate the day-ahead forecast error. Especially, the research has not mentioned whether the temporal correlation of forecast error affects the power capacity of sizing of ESS.

To solve the problems mentioned above, this paper proposes a novel method of building the multivariate JCDF of forecast error using copula theory and then proposes a novel method for sizing of energy storage based on multiple scenarios technique. The advantages of this study are as follows.

(1) A novel method is proposed to construct a multivariate JCDF of forecast error using copula function. It only needs the historical point forecast error data and improved forecasting skills are not