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An analysis-forecast system for uncertainty modeling of wind speed: A case study of large-scale wind farms

Jianzhou Wang[a], Tong Niu[a,*], Haiyan Lu[b], Zhenhai Guo[c], Wendong Yang[a], Pei Du[a]

[a] School of Statistics, Dongbei University of Finance and Economics, Dalian 116025, China
[b] Department of Software Engineering, University of Technology, Sydney, Australia
[c] State Key Laboratory of Numerical Modelling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China

HIGHLIGHTS

- An analysis-forecast system for wind speed uncertainty modeling is proposed.
- Recurrence analysis is developed to study the characteristics of wind speed.
- Feature selection is developed to determine optimal system input.
- An improved multi-objective optimizer is first proposed to optimize the system further.
- The proposed system shows a greater advantage over benchmark models considered.

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ABSTRACT

The uncertainty analysis and modeling of wind speed, which has an essential influence on wind power systems, is consistently considered a challenging task. However, most investigations thus far were focused mainly on point forecasts, which in reality cannot facilitate quantitative characterization of the endogenous uncertainty involved. An analysis-forecast system that includes an analysis module and a forecast module and can provide appropriate scenarios for the dispatching and scheduling of a power system is devised in this study; this system superior to those presented in previous studies. In order to qualitatively and quantitatively investigate the uncertainty of wind speed, recurrence analysis techniques are effectively developed for application in the analysis module. Furthermore, in order to quantify the uncertainty accurately, a novel architecture aimed at uncertainty mining is devised for the forecast module, where a non-parametric model optimized by an improved multi-objective water cycle algorithm is considered a predictor for producing intervals for each mode component after feature selection. The results of extensive in-depth experiments show that the devised system is not only superior to the considered benchmark models, but also has good potential practical applications in wind power systems.

1. Introduction

In recent years, given its advantages, such as renewability and cleanness, the comprehensive exploitation and utilization of wind energy has made it extensively socially and economically effective. More importantly, it is self-evident in a comparison of wind energy and conventional energy, which is a significant cause of global warming and atmospheric contamination, that wind power is one of the most promising energy sources available worldwide. Thus, wind energy is a greatly preferred energy resource in many parts of the world [1]. For example, wind power may become the second largest resource for generating electricity in China by 2050 [2]. However, in practice, the efficient and comprehensive development of wind power systems is considerably restricted because of the intrinsic randomness and intermittency of wind speed, which presents a significant challenge in terms of electrical network operation and management, in particular wind power integration (WPI). Accordingly, the effective analysis and accurate forecasting of wind speed not only constitute a challenging task, but are also an emphatic concern for those who make decisions-related to wind farms. It is crucial both to design more appropriate and efficient wind farms and to further determine the nonlinear dynamic pattern of wind speed in order to better manage and minimize the operational risks.

The analysis and investigation of the dynamic characteristics, in

* Corresponding author at: School of Statistics, Dongbei University of Finance and Economics, Shahekou district, Dalian 116025, Liaoning Province, China.
E-mail address: niuchenren621@126.com (T. Niu).

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Nomenclature

WPI	wind power integration
WSFM	wind speed forecast model
WSF	wind speed forecast
AR	autoregressive model
ARIMA	autoregressive integrated moving average model
ARCH	autoregressive conditional heteroskedasticity model
ANNs	artificial neural networks
PSO	particle swarm optimization
GA	genetic algorithm
LUBE	lower upper bound estimation
ELM	extreme learning machine
LLFNN	local linear fuzzy neural network
RBFNN	radial basis function neural network
WNN	wavelet neural network
MIMO-LSSVM	multi-input multi-output least squares support vector machine
WCA	water cycle algorithm
IMOWCA	improved multi-objective water cycle algorithm
EMD	empirical mode decomposition
EEMD	ensemble empirical mode decomposition
CEEMD	complete ensemble empirical mode decomposition
CEEMDAN	complete ensemble empirical mode decomposition with adaptive noise
IMFs	intrinsic mode functions
MIMO-LSSVM	multi-input multi-output least squares support vector machine
WCA	water cycle algorithm
RR	recurrence rate
DET	determinism
ENTR	entropy
L	average diagonal line length
$\overrightarrow{\mathbf{X}}^{i}_{River}$	the position of river
$\overrightarrow{\mathbf{X}}^{i}_{Sea}$	the position of sea
RR	recurrence rate
DET	determinism
ENTR	entropy
$\overrightarrow{\mathbf{X}}^{i}_{Stream}$	the position of stream
Randn	an uniformly distributed random numbers in [1,1]
C	a constant in Eqs. (13)–(15) and (21)
z_i	actual observed value of wind speed
τ	delay time
m	embedding dimension
ϖ	time window
$\lVert\cdot\rVert$	a norm
diag	diagonal matrix
LB	lower bound of variables
UB	upper bound of variables
max_iteration	maximum iteration number
ω	adaptive inertia weight
GD	generational distance
SP	spacing
CP	coverage probability
AW	average width
AWD	accumulated width deviation
$\boldsymbol{L}_i$	lower bound of *i-th* prediction interval
$\boldsymbol{U}_i$	upper bound of *i-th* prediction interval
c_i	a Boolean value
ς	predefined threshold in recurrence analysis
$P(l)$	the probability to find a diagonal line of length l in the recurrence plot
$\Phi(\cdot)/\boldsymbol{\phi}(\cdot)$	the nonlinear mapping
$\boldsymbol{\alpha}$	interval width coefficient
$\boldsymbol{I}_i$	the *i*-th prediction interval
rand	a uniformly distributed random number in [0,1]
Nsr	the number of streams
Npop	the number of raindrops
d_{max}	a small number close to zero
$\boldsymbol{\Theta}(\cdot)$	heavisible function
Costn	the fitness value of the *n*-th raindrop
T	training dataset
MLYE	maximum lyapunov exponent
d_{max}	the tolerance in IMOWCA
Std.	standard deviation
$S(t)_{mean}$	a statistic shown in Eq. (7)
$\Delta S(t)_{mean}$	a statistic shown in Eq. (8)
$Scor(t)$	a statistic shown in Eq. (9)
$\mathscr{R}^p$	input space with the dimension of p
MLYE	maximum lyapunov exponent

particular the predictability, of nonlinear systems are important for forecast modeling. However, most of the studies in the literature placed emphasis mainly on certain basic statistics, such as the maximum, minimum, average, and standard deviation [3,4]. Further, the Lyapunov exponent, complexity, skewness, kurtosis, and emergence of wind speed were investigated in Ref. [5]. Effective studies on the statistical distribution of wind speed, which is usually assumed to be a Weibull distribution function, in order to further determine wind speed patterns were reported in Refs. [6–8]. Evidently, these statistics do not suffice to reveal the profound characteristics of complex nonlinear systems, in particular highly volatile wind speed series. The recurrence plot and recurrence quantification analysis, which is essentially based on chaos theory, as an effective technique for studying complicated nonlinear systems, were developed in the field of wind speed forecasting. In the study reported in Ref. [9], wind speed series were analyzed using recurrence plots. However, this analysis was limited to recurrence plots, and is still not sufficient to quantitatively investigate the system behaviors of wind speed series. In order to further remedy the defect of recurrence plots that they lack quantitative analyses, a recurrence quantification analysis of recurrence plots, which can also be used to visualize the trajectories in phase space, was effectively developed in this study in order to investigate in greater depth the dynamic characteristics and predictability of wind speed series and the corresponding mode components.

Accurate modeling of wind speed has important practical significance for wind energy development and utilization in many forms, such as wind turbines that convert wind power into kinetic energy and mean flow acoustic engines that convert the mean flow power into acoustic power [10–12]. However, given the complex dynamic pattern of wind speed, the design of an effective and scientific wind speed forecast model (WSFM) is consistently attracting considerable research attention. In general, the mainstream studies of WSFMs can be systematically categorized into those using physics and statistical approaches [13] and artificial intelligence methods. Rich physics models involving wind speed forecasts (WSFs) were systematically introduced in Refs. [14–18]. Technically, these models in general involve computational fluid dynamics in order to simulate the atmosphere based on different grid designs [13]. In contrast to physics models, the alternative WSFMs are based on statistical modeling and machine learning theories, which are convenient for implementing the modeling and simulation of wind speed forecasting because of their accessibility and excellent local prediction ability. In earlier research on WSFMs, the traditional statistical models, which usually consist of an autoregressive model (AR) [19], autoregressive integrated moving average model