Energy Conversion and Management 156 (2018) 597–617

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Uncertainty modeling for chaotic time series based on optimal multi-input multi-output architecture: Application to offshore wind speed

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ARTICLE INFO

Keywords:
Interval prediction
Wind speed
Feature selection
Multiobjective optimization
Chaotic time series

ABSTRACT

Wind energy is attracting more attention with the growing demand for energy. However, the efficient development and utilization of wind energy are restricted due to the intermittency and randomness of wind speed. Although abundant investigations concerning wind speed forecasting have been conducted by numerous researchers, most of the studies merely attach importance to point forecasts, which cannot quantitatively characterize the uncertainties as developing intervals. In this study, a novel interval prediction architecture has been designed, aiming at constructing effective prediction intervals for a wind speed series, composed of a preprocessing module, a feature selection module, an optimization module, a forecast module and an evaluation module. The feature selection module, in cooperation with the preprocessing module, is developed to determine the optimal model input. Furthermore, the forecast module optimized by the optimization module is considered a predictor for giving prediction intervals. The experimental results shed light on the architecture that not only outperforms the benchmark models considered, but also has great potential for application to wind power systems.

1. Introduction

With the gradual depletion of fossil fuels, the world is not only curtailing the proportion of traditional energy in the industrial economy, but also seeking an alternative clean energy, such as wind, solar and wave energy. Being not only clean and renewable but also sustainable and widespread, wind energy has become urgently desired in recent years. The high penetration of wind generation, however, is expected to result in complex operational challenges [1] due to its inherently high uncertainty and intermittent nature, which creates great challenges for the dispatch planning and optimal management of the electric system on a wind farm. However, secure and reliable power dispatch and economical scheduling require high efficiency and accurate wind speed forecasts, which is conducive to mitigating the undesirable effects caused by the instability of an electric system.

Given the significant need, numerous researchers have investigated wind speed forecasting in both theory and practice. A variety of models are utilized to implement wind speed forecasting, which can be classified into two major categories [2], namely, numerical weather prediction (NWP) and prediction models using machine learning theory and the methods based on a historical time series.

With the improvement of the accuracy and efficiency of NWP models, the forecasting model based on NWP, including single-point-NWP and ensemble NWP, is becoming a research direction. A comprehensive reviews of the NWP models can be read in the literature [3]. However, it is noteworthy that the factors, including uncertain meteorological conditions, model initialization and heavy computation cost, restrict the application of NWP models in practice.

Currently, the forecasting models based on machine learning are becoming a mainstream research direction due to the excellent ability for self-learning and generalization, especially time-saving. In the literature [4], a forecasting model combining a support vector machine optimized by a genetic algorithm and feature selection based on phase space reconstruction was presented to perform the short term wind speed forecasting. This forecasting model exhibits excellence in wind speed forecasting compared to the benchmark models considered. Decomposition technique based on data usually plays a significant part in wind speed forecasting. In [5], a novel hybrid model based on wind speed forecasting was developed, combining variational mode decomposition and an extreme learning machine optimized by the hybrid backtracking search algorithm, which has become an effective forecasting model to characterize the nonlinear patterns in wind speed.

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https://doi.org/10.1016/j.enconman.2017.11.071
Received 29 May 2017; Received in revised form 16 October 2017; Accepted 23 November 2017

Nomenclature

CEEMDAN	complete ensemble empirical mode decomposition with adaptive noise
EEMD	ensemble empirical mode decomposition
EMD	empirical mode decomposition
WT	wavelet transfer
VMD	variational mode decomposition
IMF	intrinsic mode function
SVM	support vector machine
RBF	radial basic function
γ	regularization parameter
δ	squared kernel bandwidth parameter
MOGWO	multiobjective grey wolf optimizer
MOOA	multiobjective optimization algorithm
PSR	phase space reconstruction
ϖ	time window
τ	time delay
CP	coverage probability
AW	average width
AWD	accumulated width deviation
AGA	adaptive grid algorithm
RWSS	roulette wheel selection strategy
MIMOLSSVM	multi-input multi-output least square support vector machine
g_i	the *i*-th inequality constraints
h_i	the *i*-th equality constraints
L_i	the lower bound
U_i	the upper bound
I_i	the *i*-th prediction interval
$\boldsymbol{\alpha}$	the interval width coefficient
α (X_α)	the fittest solution in MOGWO algorithm
β (X_β)	the second best solution in MOGWO algorithm
δ (X_δ)	the third best solution in MOGWO algorithm
A	the coefficient vectors
C	the coefficient vectors
$\boldsymbol{t}$	the current iteration
archive	the reservoirs of optimal solutions
Max_iteration	the maximum iteration
r_1	the random vectors within [0, 1]
r_2	the random vectors within [0, 1]
P_i	wind power
ρ	air density
v_i	wind speed
NS	neighborhood structure
NWP	numerical weather prediction
LSSVM	least square support vector machnie
MOALO	multiobjective ant lion optimizer
MOPSO	multiobjective particle swarm optimization
NSGA-II	non-dominated sorting genetic algorithm II
MOIA	multiobjective immune algorithm
MODA	multiobjective dragonfly algorithm
MOWCA	multiobjective water cycle algorithm

Furthermore, complete ensemble empirical mode decomposition adaptive noise was applied to wind speed forecasting in [6], making a great contribution to the accurate wind speed forecasting. Additionally, wavelet packet decomposition and an artificial neural network optimized by a crisscross optimization algorithm were combined to establish the forecasting model for wind speed series in [7]. The modeling methods based on chaotic time series received important attention because of its excellent ability to map the nonlinear relationship in wind speed series. In [8], a hybrid forecasting model based on *k*-means clustering and an apriori algorithm was developed to perform short-term wind speed forecasting. The raw wind speed series was clustered by *k*-means clustering. Furthermore, the forecasting error was corrected via an association rules algorithm. The experiments indicate that the hybrid model can yield satisfactory forecasting results.

Many researchers made significant contributions to the wind speed forecasting model. However, most of these models merely yield point or time-average forecast results without mirroring the uncertainty of the forecasts, which hardly fulfills the need for risk management of a wind power system. Inevitable forecast bias exists in the process of deterministic point forecasts, which brings heavy risk to the power system scheduling, maintenance and operations. The main reason for the forecast biases is the previously mentioned uncertainty, which is unavoidably associated with the forecast variables [9] and model parameters. The uncertainty in forecast process is a concomitant factor, which exerts a significant influence on the decision-making process in electrical power systems. Accordingly, quantifying the uncertainty associated with forecasts through statistical metrics and prediction models will produce great realistic significance for electrical systems, especially for wind power integration.

Summarizing most of the existing literature, interval prediction models can be divided into three methods, namely, a single-point-based prediction error method, quantile regression, and a bootstrap-based method. However, the hypothesis in single-point-based prediction error method that prediction errors obey a certain known parametric type of distribution will unavoidably result in biases to uncertainty modelling, which is the biggest drawback of the error analysis method based on a distribution assumption. As for method based on quantile regression, a specific training sample set needs to be established for the process of forecasting modeling, which is the shortcoming of quantile regression method. Although bootstrap-based method has the excellent ability to address small sample sizes, its application will be restricted in practice when addressing a large-scale sample set. Additionally, the model based on bootstrap depends strongly on the restrictive assumptions concerning the statistical probability distribution and will produce a vast computing load in practical application when developing prediction intervals. The results of literature investigations indicated that there was no one best method for interval prediction, model performance under specific conditions needs further investigation and additional improvements should be continually made based on current knowledge obtained [10].

Superior to the majority of the aforementioned interval prediction models based on statistical distributions, a novel interval prediction architecture based on the optimal multi-input multi-output machine learning architecture that outperforms traditional techniques is developed in this study, where no assumption is made concerning the statistical distribution and wind speed patterns in the process of conducting interval prediction. Accordingly, the designed prediction interval architecture has a strong compatibility and anti-jamming for the abnormal points in the data studied when developing intervals.

The study aims to put forward an effective interval prediction architecture. Five efficient modules have been developed to strengthen the performance of the forecast architecture, which consists of a preprocessing module based on complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), a feature selection module using the C-C method based on chaotic theory, an optimization module applying a multiobjective grey wolf optimizer (MOGWO) and forecast module based on a multi-input multi-output (MIMO) least squares support vector machine (MIMOLSSVM). CEEMDAN, as a newly proposed signal processing technique, was developed to extract a meaningful information component from the wind speed series from Penglai, China. The C-C method, as a popular feature selection method, was applied to determine the optimal input form of the proposed