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Ultra-short-term forecast of wind speed and wind power based on morphological high frequency filter and double similarity search algorithm☆

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ABSTRACT

This paper proposes a forecast model for ultra-short-term prediction of wind speed and wind power, which is based on a morphological high-frequency filter (MHF) and a double similarity search (DSS) algorithm. The MHF is proposed to decompose the time series into two components: the mean trend, which reveals the non-stationary tendency of the time series, and the high frequency component, which depicts the fluctuations. The same strategy is employed to forecast the mean trend and the high frequency component, respectively. The two components are reconstructed in the phase space, respectively, where a non-uniform embedding strategy is proposed to better reveal their information. To select similar segments to be used for local forecast, the novel DSS algorithm is proposed for high frequency component, while the Euclidean distance is used for the mean trend. Finally, the least squares-support vector machine (LS-SVM) model is applied to forecast each component, respectively, and their sum composes the final prediction. Simulation studies are carried out using wind speed and wind power data obtained from four databases, and the results demonstrate that the MHF/DSS model provides more accurate and stable forecast compared to the other methods.

1. Introduction

As a type of renewable energy, wind energy has been vigorously developed in the past decades all around the world [1]. The global wind industry underwent a record year through 2015, closing with annual installations of 63 GW and total installed capacity of some 433 GW, exhibiting 17 percent increase over the previous year. On a national level, China leads the wind industry, with cumulative wind power installations of 145 GW at the end of 2015, with an astonishing rate over 30% [2]. Nowadays, wind power producers are allowed to bid in several electricity markets, such as NYISO, MISO, PJM, and ERCOT [3]. Since April 1, 2015, wind generators in Alberta and Canada gain the option to submit offers to the market as well [4]. Therefore, wind speed and wind power forecast are very important to the healthy operation of power systems and electricity markets owing to the following three reasons. Firstly, the electricity price is strongly influenced by wind power generation [5]. Secondly, with more accurate forecast, it will be easier for the transmission system operator (TSO) to make real-time scheduling [6]. Finally, an accurate forecast will be a guidance for investment [7]. The basic role of wind speed and wind power forecasting is to provide information about the wind speed and power that can be expected in the next few minutes, hours or days. Based on power system operation requirements, the forecast can be divided into four different horizons [8]: ultra short-term (a few seconds to 4 h), short-term (4 h to 24 h), medium-term (1 to 7 days), and long-term (more than 7 days). Ultra short-term forecasts are used for turbine control and load tracking, short-term forecasts are used for power system management and energy trading, and medium-term forecasts and long-term forecast are utilized for maintenance scheduling of the wind turbines [9]. Different models are used for different horizon forecasts. This paper focuses on the improvement of ultra short-term forecast.

However, both wind speed and wind power have the nature of high randomness and rapid fluctuation, thus it is difficult to forecast the original time series directly. Therefore, researchers have proposed to decompose the time series into a set of constitutive series by wavelet transformation (WT) [10,11], empirical mode decomposition (EMD) [12,13] or *k*-OCCO (opening-closing and closing-opening) filter based on mathematical morphology [14]. For the wavelet transformation, the choice of wavelet base function and decomposition scale relies greatly on experience, meaning that the decomposition can not adaptively extract the intrinsic characteristics of the time series [15]. As for EMD, the most serious problem is mode mixing, which not only causes serious

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Nomenclature

MHF	morphological high-frequency filter
DSS	double similarity search
LS-SVM	least squares-support vector machine
NYISO	New York Independent System Operator
MISO	Mid-continent Independent System Operator
PJM	Pennsylvania-New Jersey-Maryland
ERCOT	Electric Reliability Council of Texas
TSO	transmission system operator
WT	wavelet transformation
EMD	empirical mode decomposition
OCCO	opening-closing and closing-opening
IMF	intrinsic mode function
SE	structuring element
GA	genetic algorithm
AIMS	Australian Institute of Marine Science
AESO	Alberta Electric System Operator
NMAE	normalized mean absolute error
NRMSE	normalized root-mean-squared error
Per.	persistence model
SSMM	similar segments and mathematical morphology model
MTD-MMLP	mean trend detector and mathematical morphology-based local predictor model

Parameters

f	time series
g	structuring element
F	mean trend component
S	high frequency component
J	the number of segments divided from the time series f
d	the length of segment
δ	embedding dimension
τ	time delay
X_{tra}	training input
Y_{tra}	training output
X_{t}	testing input
p	look-ahead step
$\hat{y}_i$	forecast value
y_i	actual value
Y	installed capacity of wind farm or the maximum of historical speed data

aliasing in the time–frequency distribution, but also results in the individual intrinsic mode function (IMF) losing its clear physical meaning [16]. Similarly, the above two methods decompose the original time series into several parts. Even though each part can be predicted more accurately, the integration of tiny errors would lead to unsatisfactory prediction results. In [14], a k-OCCO filter based on mathematical morphology with a triangle structuring element (SE) is employed to reveal the tendency of wind power data, and treats the residual as noise. The filtering result is satisfactory but relies on the shape of SE. In [17], the mean trend is defined as a curve going through barycenters of the elementary oscillations. However, the calculation burden is heavy. In this paper, based on a novel SE and the OCCO filter, MHF filter is proposed to decompose the time series.

To explore the intrinsic characteristics of the time series, a widely accepted approach is to use the embedding theorem to transfer the time series into a phase space of a higher dimension [18]. To construct the phase space, we also need to determine the time delay, and it is common practice to use uniform embedding, where the time delay is a constant. However, Judd et al. consider that uniform embedding performs perfectly in classical systems, such as Hénon map and Lorenz map, but fails for time series with multiple periodicity [19]. Thus, non-uniform embedding is suggested. Unlike uniform embedding, non-uniform embedding allows different time delays to be used for different dimensions. In this paper, non-uniform embedding will be introduced to apply in wind speed and wind power prediction for the first time. However, the selection of time delays in the traditional non-uniform embedding brings the problem that the solution space grows exponentially with the increase in the embedding dimension [19]. To find the optimal time delays, a number of approaches have been proposed, including ant colony optimization approach [20], genetic algorithm (GA) [21], artificial neural network [22], etc. In order to reduce the computational load, the correlation dimension method which is used in uniform embedding is also used to calculate the embedding dimension of non-uniform embedding, and a novel parameter optimization method is proposed to calculate the time delays, which will be solved by GA.

Efforts have been made to improve the accuracy of wind speed and wind power forecast, and the technologies can be classified as two categories – global prediction and local prediction [23]. In global prediction, only one function is engaged for all available data, while local prediction uses more than one function to fit the data. According to the works [24–28,14], local prediction methods can normally perform better than global methods for time series prediction. The reason is that local prediction methods consider that each predicting point has its own model [25]. Two methods are usually used to find the models. The first one considers that the model is constructed by its nearest neighbors which are commonly found in the neighborhood from the time series, Thus the key point is to find out the best neighbours [26]. The second one approves that the model can be constructed using the similar segments of the forecast segment. Traditionally, similar segments are selected according to Euclidean distance criterion: a segment is considered as a similar segment to the forecast segment if its Euclidean distance is short enough. Euclidean distance criterion highlights the close numerical values of the time series, but neglects their tendencies, which causes false neighbors especially for complex time series. To filter false neighbors, exponential separation rate is added as the second criterion in the base of Euclidean distance criterion in [26]. Unfortunately, the improvement is slight. Hence, a “double similar” method is designed for the high frequency component of time series in this paper, which considers not only the numerical values of the time series, but also their tendencies.

In this paper, an SE, which is derived from the time series, is specially designed and used in the MHF filter, which is developed to decompose the time series of wind data into two components – the mean trend and the high frequency component. The forecast work will be carried out for the two parts, respectively. Firstly, the time series of each component is reconstructed into a higher dimension space by non-uniform embedding theorem to extract the intrinsic features. The non-uniform embedding theorem is realized by minimizing the forecast error of the reconstructed series from the persistence model using GA. After that, in order to conduct local forecast, similar segments are selected, where Euclidean distance criterion is adopted for the mean trend and the proposed DSS algorithm is applied for the high frequency component. Subsequently, for each component in the phase space, an LS-SVM model is trained with the corresponding similar segments. The LS-SVM model is selected because it is a powerful machine-learning tool and has been successfully used for time series forecast with satisfactory results in various fields [29]. Finally, predicting the mean trend component and high frequency component with the two LS-SVM models, respectively, and their sum is the forecast result.