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A new wind power prediction method based on ridgelet transforms, hybrid feature selection and closed-loop forecasting

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ABSTRACT

To reduce network integration and boost energy trading, wind power forecasting can play an important role in power systems. Furthermore, the uncertain and nonconvex behavior of wind signals make its prediction complex. For this purpose, accurate prediction tools are needed. In this paper, a ridgelet transform is applied to a wind signal to decompose it into sub-signals. The output of ridgelet transform is considered as input of new feature selection to identify the best candidates to be used as the forecast engine input. Finally, a new hybrid closed loop forecast engine is proposed based on a neural network and an intelligent algorithm to predict the wind signal. The effectiveness of the proposed forecast model is extensively evaluated on a real-world electricity market through a comparison with well-known forecasting methods. The obtained numerical results demonstrate the validity of proposed method.

1. Introduction

1.1. Problem definition

Fast growing clean energies such as wind power have become a major source of energy in power grids. However, the uncertain and nonconvex behavior of wind signals increase the negative effects of this energy source in operating power systems [1]. The generation of wind power is different to conventional power plants in terms of its characteristics and its output variability. These impose several drawbacks and problems to an independent system operator (ISO), whose role is to deal with the balance and security of the grid. Up to the end of 2006, the worldwide total cumulative installed electricity generation capacity from wind power had surpassed 74,200 MW, which implies an increase of 26% in only a single year [1]. It is predicted that by 2020, approximately 12% of the world's energy usage will be provided by wind power. Although the integration of wind power carries important economic and environmental profits, the intermittent and stochastic behavior of wind energy also presents challenges in power system operating and planning. As a power system must maintain instantaneous balancing among the gathered generation and consumers request at all times, fluctuations in wind farm output will increase the guideline requirements and decrease the operational efficiency of some generating units. To help address this, an accurate forecast of wind power can play a critical role in power system operations [2]. However, forecasting wind power generation is very difficult, because one cannot ensure its availability when needed [3]. For this purpose, an accurate prediction model for wind power has been sought by researchers in recent years.

1.2. Literature review

Different prediction methods have been proposed by researchers in recent years. In [3], the authors used the persistence method (PM) to predict wind power. In [4], the auto-regressive and moving average (ARMA) model was used, while the auto-regressive integrated moving average (ARIMA) was used by the researchers who authored [5]. In [6], the Gaussian process (GP) was used to predict wind power, while Kalman filtering (KF) was used by [7]. All the aforementioned methods are time-series methods which cannot forecast the complex, nonlinear wind signal, and they are often prone to biases [8]. For this purpose, some intelligent methods have been proposed to solve the prediction problem, as presented in the following paragraph.

A neural network (NN)-based forecast engine was proposed by [9] to predict wind power. The use of a support vector machine (SVM) was proposed by [10], while a combination of a SVM and an evolutionary algorithm (EA) was presented by [11] to solve the forecast problem, and a combination of SVM with a wavelet transform (WT) was presented by [12]. A fuzzy model-based wind speed and power forecast

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was presented by [13], which was applied to wind parks using a spatial correlation method. A combined enhanced particle swarm optimization (EPSO) with a hybrid forecast engine was proposed by [14]. In [15], a combination of WTs with PSO and an ANFIS-based forecast engine was presented. This method was applied for short-term wind power forecasting in a test case based in Portugal. In [16], a data-mining approach was applied to forecast wind power ramp rates. Classified wind power prediction was proposed by [17], which was based on an SVM model. Finally, various types of NN based forecast engines were presented by [18–20], such as the recurrent NN (ReNN) [18], the Ridgelet NN (RNN) [19] and the Elman NN (ENN) [20]. Additional reviews of wind power forecast methods can be found in [21–24].

Relative to linear methods, nonlinear methods are independent in terms of time series data; so, NN- and SVM-based methods are more noteworthy in wind power forecasting. However, they all require a large quantity of historic data as well as an accurate training model. Accordingly, the proposed methods cannot guarantee a reliable prediction for complex signal such as wind power. For this purpose, we propose a new hybrid prediction model that includes a ridgelet transform (RT), feature selection and a closed loop forecast engine. The contributions of this work can be summarized in the following subsection.

1.3. Contributions

According to our review of the available prediction methods, an accurate prediction model is needed. The contribution of our prediction model can be summarized as follows:

(a) Application of a RT to get wind power sub-signals. In this manner, the wind power signal is divided into sub-signals for easy prediction. This is the first time that this prediction method has been applied to wind power.
(b) Presentation of a new feature selection method to select the best candidates. With this model, the signal is filtered out to increase the accuracy and speed of the forecast engine.
(c) Application of a new forecast engine with a closed-loop model to increase the prediction accuracy. All free parameters of the mentioned forecast engine are optimized by an intelligent algorithm.

1.4. Paper organization

The remaining parts of the paper are organized as follows. In Section 2, the proposed RT is introduced. In Section 3, we proposed the feature selection model. The hybrid closed loop forecast engine is presented in Section 4. The numerical results and our analysis are presented in Section 5. Finally, Section 6 concludes the paper.

2. Proposed ridgelet transform

2.1. Review

Recently, a WT-based forecast method was presented as a way to predict wind power, along with other prediction problems. The basic concept in wavelet analysis begins with the selection of a proper wavelet function, called the mother wavelet ($\psi_{(t)}$). Then, an analysis is performed on its shifted and scaled versions which is summarized by the following general equation: $W(a,b;X,\varphi) = |a|^{\frac{-1}{2}} \int_{-\infty}^{\infty} X(t)\varphi^{*}\left(\frac{t-b}{a}\right)dt$. Where a is a dilation factor and b is a translation of the origin.

Although time and frequency do not appear explicitly in the transformed result, the variable $1/a$ gives the frequency scale, and b gives the temporal location of an event. Commonly, $\psi_{(.)}{}^{*}$ is not orthogonal for different values of a for continuous wavelets, although orthogonality is satisfied by selecting a discrete set of a. However, discrete wavelet analyses can miss any physical signals whose scale is different from the selected discrete set of a. A continuous or discrete wavelet analysis is basically a linear analysis, and it is non-adaptive in nature. A very interesting characteristic of the wavelet analysis is that it provides a uniform resolution for all scales. Limited by the size of the basic wavelet function, the downside of the uniform resolution is poor resolution.

As another technique, a Fourier spectrum defines uniform harmonic components globally; hence, it needs several additional harmonic components to simulate non-stationary data that are globally non-uniform. Moreover, a Fourier spectral analysis uses the linear superposition of trigonometric functions; thus, it requires additional harmonic components to simulate the deformed wave-profiles. In addition, the empirical model decomposition (EMD) has been previously used, which attempts to decompose nearly any signal into a finite set of functions called Intrinsic Mode Functions (IMFs). The algorithm utilizes an iterative sifting process, which successively subtracts the local mean from a signal. An IMF is a function that satisfies two conditions: (1) in the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one; and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero [14].

Due to the mentioned disadvantages of current models, we used a new transform tool in this paper called a ridgelet transform. For a summary of the ridgelet's construction, its model is based on the partition of unity in Fourier space, where, in [25], it is presented as a spherical symmetric wall through scaling and rotation as the transformations according to the various elements to each other. This model can be presented by a square partition frame as well, which is presented in Fig. 1(a) and (b). To make smooth transitions potential – the smoothness is the critical factor of the characteristics of the Galerkin matrix – one ridgelet has to be supported by neighboring shears and scales. The mentioned description is presented in Fig. 1(c) and (d). More information of this support is presented in [26].

2.2. Continuous ridgelet transform

A continuous ridgelet transform (CRT) can be presented as follows, based on an integratable bivariate function f(x):

$$CRTf(a,b,\theta) = \int_{R^2} \psi_{a,b,\theta}(x) f(x) dx \tag{1}$$

where ridgelets $x_1 \cos\theta + x_2 \sin\theta = const$, and for 2-D it is presented by a wavelet type function as:

$$\psi_{a,b,\theta}(x) = a^{-\frac{1}{2}} \psi((x_1\cos\theta + x_2\sin\theta - b)/a) \tag{2}$$

For the wavelets: ψ^{scale} point-position, while for the ridgelet: ψ^{scale} line-position.

A Ridgelet function is presented in Fig. 2, where both the wavelet and ridgelet are linked by a random transform which can be presented as:

$$Rf(\theta,t) = \int_{R^2} f(x)\delta(x_1\cos\theta + x_2\sin\theta - t)dx \tag{3}$$

The transform application in 1-D for the wavelet transform to the slices can be presented as:

$$CRTf(a,b,\theta) = \int_{R^2} \psi_{a,b}(t) Rf(\theta,t) dt \tag{4}$$

If the 1-D Fourier transform (FT) is replaced for the wavelet, we can write for 2-D:

$$F_f(\xi\cos\theta,\xi\sin\theta) = \int_{R} e^{-j\xi t} Rf(\theta,t) dt \tag{5}$$

In summary, the RT is an application of the 1-D wavelet transform to the slices of the radon transform, where the 2-D FT is the submission of the 1-D FT to those radon slices.