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Wind power forecasting based on principle component phase space reconstruction

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ABSTRACT

Forecasting of wind power is very important for both power grid and electricity market. Wind power forecasting based only on historical wind power data is carried out in this work. In a first treatment to the wind power data, Phase Space Reconstruction (PSR) is used to reconstruct the phase space of the wind dynamical system. Secondly, Principle Component Analysis (PCA) is used to minimize the influence from improper selection of the delay time and phase dimension. Finally, a prediction model, using Resource Allocating Network (RAN), is built for nonlinear mapping between the historical wind power data and the forecasting. Performance of the proposed method is compared with Persistence (PER), New-Reference (NR), and Adaptive Wavelet Neural Network (AWNN) models by using data from the US National Renewable Energy Laboratory (NREL). Analysis results indicate that the forecasting error of the proposed method is about 3% for 48 look-ahead hours, which is remarkably below the errors obtained with other forecast methods and has a probability close to 80% for 48 look-ahead hours forecasting within 12.5% error. The proposed method can also forecast wind power for turbines of different capacity and at different elevations below 10% error.

1. Introduction

Due to the environmental impact of fossil-fired power generation units, renewable energy, including wind, solar and wave energy, is highly regarded as a viable alternative for new installed electricity production capacity. However, wind energy is inherently intermittent, due to its high correlation with stochastic, non-stationary wind speed. Wind integrated to the electrical power grid brings many challenges to grid operators such as operational problems maintaining system frequency, power balance, voltage support, and quality of power, as well as planning and economical forecasting concerns (including uncertainty in wind power unit commitment, economic load scheduling, and spinning reserve calculations) [1–3]. An accurate wind power forecasting tool to mitigate the undesirable effects in the growing wind power scenario is of significant importance. There are two kinds of wind power forecasting techniques, namely physical methods and statistical methods. Depending on Numerical Weather Prediction (NWP) data, physical methods calculate power output by plugging the NWP data into the manufacturer power curves. These methods are too complex to implement and are site specific. Moreover, it usually takes several hours for an NWP calculation to provide forecasting result. Many large NWP centers update their prediction every few hours (e.g. 6 h) [1]. The NWP forecasting errors are also larger than those produced by other models for short prediction horizons (e.g. 3–6 h) [4]. Statistical methods, may or may not take NWP's inputs, they build relationships between inherent characteristics of a system and the measured data, such as the Autoregressive (AR) model [5], the Autoregressive Moving Average (ARMA) model [6], the Auto Regressive Integrated Moving average (ARIMA) model [7], PER (Persistence) [8] and NR (New-Reference) [9]. These statistical models can outperform physical methods for short term horizon forecasting [1,4]. To take advantage of the two kinds of methods, some hybrid models combining physical methods and statistical methods are studied and reviewed in Refs. [4,10,11]. More recently, due to the uncertainty of wind power, probabilistic forecasting method has drawn more attention [12]. This approach provides probabilistic information about future

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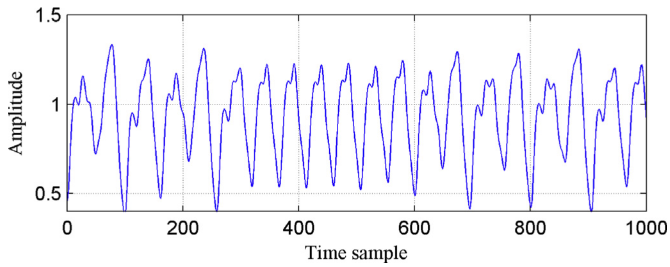

Fig. 1. M–G time series.

events when it is difficult to produce accurate forecast [13,14]. Nowadays, more researchers lay a lot of emphasis on forecasting methods based on statistical systems using artificial intelligence methods. Most of the new research work is based on building predictive models that are independent of the NWP data. Neural Network [15,16], Support Vector Machine (SVM) [17], Wavelet [15] and hybrid methods [18,19] are used to forecast wind power using historical data, exclusively. The mentioned artificial intelligence methods map nonlinear input signals (historical data) to target values (wind power forecast) [20,21]. The models accuracy depends on whether the historical data can reveal the real dynamical properties of the system, and how sensitive the chosen data are as input to the forecasting model. Otherwise, the prediction error becomes significantly large.

One method that can help provide more robust wind power forecasting is Phase Space Reconstruction (PSR). The PSR algorithm extends a one-dimensional time series to a high-dimensional phase space. Thus, the characteristics which cannot be identified in one dimensional space are transformed into different features of an attractor, which can be easily identified in a high-dimensional phase space. Theoretically speaking, a time series can sufficiently reconstruct an original dynamic system, but only if the embedding dimension and delay time is correctly chosen [22–26]. In this study, Principal Component Analysis (PCA) is used to reduce the influence of improperly choice of time delay and embedding dimension. Then a new forecasting model based on Resource Allocating Network (RAN) is proposed and applied for forecasting of M-G chaotic time series and actual wind power data. The accuracy of the proposed approach is tested with wind power data.

2. Phase space reconstruction

Phase space reconstruction is considered as a useful way to reconstruct the phase space of a dynamical system from observables. The phase space of system can be represented by a signal record of some observable $x(i)$, where $i = 1,2,\ldots,N$, according to Takens and Packard et al. [22,23]. From this procedure, the time series $x(i)$ can be reconstructed in a multi-dimensional phase space as follows:

$$X(t) = (x(t), x(t+\tau), \ldots, x(t+(m-1)\tau)) \tag{1}$$

Where, $t = 1, 2,\ldots, N-(m-1)\tau$. τ is the delay parameter. m is the embedding dimension. From Takens [22], in data reconstruction, if the dimension of the manifold containing the underlying attractor is d, the topological properties of the attractor can be preserved when embedding the data in a dimension $m \geq 2d+1$. It's very important that the delay time, τ and embedding dimension, m be chosen properly in the method.

Until now, there is still not a good way to choose τ and m. Researchers have proposed approaches to obtain the two parameters subjectively and empirically (e.g. the C–C method [26] and time window length methods [25]). Inappropriately selection of τ and m will result in a reconstruction error. According to Takens [22], for the condition of no-noise in a signal, the choice of τ has no influence on system reconstruction. However, it is impossible to achieve a signal without noise.

To illustrate the problematic outlined in the previous paragraphs, a chaotic time series, which is called the M-G time series, is introduced. The M-G time series is shown in Fig. 1 and a time series with a random noise is shown in Fig. 2 as well. From Figs. 1 and 2, it can be seen that if τ is larger, a lot of information included in the system will be ignored. That is not the case when a significant level of noise is maintained in the phase space. In Refs. [27], τ is advised to be selected larger than needed to prevent ignoring system information. Additionally, if m is larger than it actually should be, the dimension of the reconstructed system is redundant. And if m is smaller, the reconstructive system cannot reveal the true system.

Given the difficulty in choosing appropriate τ and m, PCA was chosen to minimize the influence from an unsuitable parametric selection.

3. Principle component analysis

After phase space reconstruction, a system, as shown in Eq. (2), can be achieved, where for the system, $X \in \boldsymbol{R}^{((N-(m-1)\tau-1)\times m)}$:

$$X = \begin{pmatrix} x_1, x_{1+\tau}, \ldots, x_{1+(m-1\tau)} \\ x_2, x_{2+\tau}, \ldots, x_{2+(m-1\tau)} \\ \ldots \\ x_{N-(m-1)\tau}, x_{N-m\tau}, \ldots, x_N \end{pmatrix} \tag{2}$$

In the PCA concept, X can be considered as a matrix of the original signal which has m dimensions and N-(m-1)τ samples. PCA can map the “original” signal to a new multi-dimension space and decrease the noise and redundance by finding the principle component of the signal. The process is as follows.

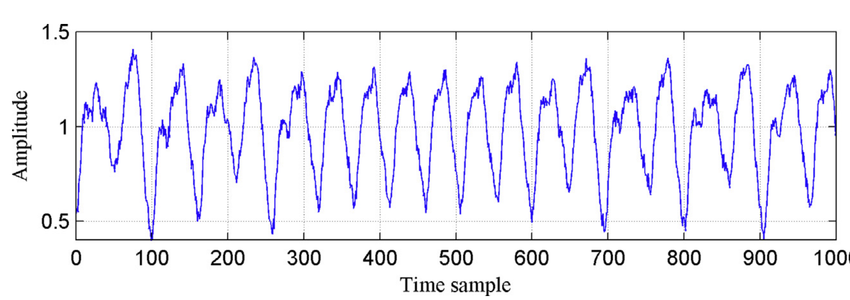

Fig. 2. M–G time series with noise.