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A new wind power prediction method based on chaotic theory and Bernstein Neural Network

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ABSTRACT

The accuracy of wind power prediction is important for assessing the security and economy of the system operation when wind power connects to the grids. However, multiple factors cause a long delay and large errors in wind power prediction. Hence, efficient wind power forecasting approaches are still required for practical applications. In this paper, a new wind power forecasting method based on Chaos Theory and Bernstein Neural Network (BNN) is proposed. Firstly, the largest Lyapunov exponent as a judgment for wind power system's chaotic behavior is made. Secondly, Phase Space Reconstruction (PSR) is used to reconstruct the wind power series' phase space. Thirdly, the prediction model is constructed using the Bernstein polynomial and neural network. Finally, the weights and thresholds of the model are optimized by Primal Dual State Transition Algorithm (PDSTA). The practical hourly data of wind power generation in Xinjiang is used to test this forecaster. The proposed forecaster is compared with several current prominent research findings. Analytical results indicate that the forecasting error of PDSTA + BNN is 3.893% for 24 look-ahead hours, and has lower errors obtained compared with the other forecast methods discussed in this paper. The results of all cases studying confirm the validity of the new forecast method.

1. Introduction

Wind power has been developing rapidly in recent years due to several advantages including environmental protection and renewability. Wind power has been recognized as an ideal energy source and has gotten significant worldwide attention [1–4]. Accuracy of wind power prediction is important for assessing the security and economy when wind power source connects to the grids. The extreme randomness and uncontrollability of the wind cause the output power of wind farms has the characteristics of volatility and indirectness, which resulting in difficulties in power grid pitch peak, reactive power and voltage control. These difficulties affect the security and stability of the power grid and limit the development of practical wind power systems [5]. Therefore, building a useful wind power prediction method has significant importance.

Many forecasting approaches have been proposed to increase wind power forecasting accuracy. There are mainly two kinds of wind power forecasting methods: physical methods and statistical methods. The physical method calculates actual output power by considering numerical weather prediction (NWP) data with historical power output [6]. NWP model exhibits more accurate forecasting performances when the environment remains stable. However, this method is complex and incurs high cost. Besides, some detailed weather data are not available to get and sometimes weather prediction data is updated after several hours delay. Conversely, statistical models, which are known as time-series-based models, only employ historical data [7]. The statistical method is primarily used for short-term wind power prediction. This method builds the relationship between the inherent characteristics of a system and the measured data with numerical weather prediction or historical inputs data. In this group, there included the simple Persistent model, the Autoregressive models (including the Auto Regressive (AR) model, the Auto Regressive Moving Average (ARMA), the Auto Regressive Integrated Moving Average Model (ARIMA)), and the artificial neural networks (ANN). The principle of the Persistent prediction method is derived from the inertia principle of the atmospheric system, which uses the latest true value as the predictive value for the next time step. This method has a

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simple structure. However, the result of the wind power prediction using this method is unstable and has high errors. And most of the autoregressive models exist multicollinearity problems.

Among these statistical forecasting methods, ANN is the most popular method for their higher accuracy, which has been used in many researches on wind speed or wind power forecasting. For instance, Bhaskar and Singh [8] presented a survey in which wind series' wavelet breakdown is fulfilled and Adaptive Wavelet Neural Network (AWNN) is used to regress upon each resolved signal, later a Feed-Forward Neural Network (FFNN) is used for nonlinear mapping between wind speed and wind power output. And the results reported that the forecast model has normalized RMSE value between 10% and 20% for 30 look-ahead hours. Liu, Wang and Jin [9] used BP for power prediction, and analyzed with numerical weather prediction data. The results showed that the precision of the BP method can meet the requirements. Ma and Zhang [10] proposed a method based on RBF neural network to directly forecast wind power for the future 24 h, and the forecasting error of RBF is about 8.71% for 24 look-ahead hours. The results indicate that the method to forecast wind power can improve the prediction accuracy. However, Catalao J P S suggested that it seems that the Artificial Neural Network (ANN) forecasted well with the training data of wind power, but it may encounter large forecasting error in the test phase [11]. Besides, neural network is difficult to determine the associated weights. For this reason, many other artificial intelligence methods as SVMs and fuzzy logic et al. are proposed. Kavousi-Fard [12] proposed a new fuzzy method, which used lower upper bound estimation (LUBE) method to construct the forecasting model, bat algorithm with a new modification is introduced to solve the problem. Zeng and Qiao [13] proposed a new wavelet kernel to improve the generalization ability of the support vector machine (WSVM). The normalized errors of most samples fall between 10% and 10%. More than 70% of the normalized errors are less than 5% in the case of 1-h-ahead. Liu et al. [14] proposed a short-term wind-power prediction methods based on the wavelet transform-support vector machine and statistic-characteristics analysis. In general, artificial intelligence models outperform the time-series models at almost all time scales because of the stronger nonlinear forecasting capacity of the artificial models. While building the models for these statistical methods, historical data is always used as direct input after signal denoising [15] and dimensional reduction [16,17].

Due to the complex characteristics of the original wind power series, individual model cannot represent the majority of the traits in the time series. To make use of the two types of approaches, a number of hybrid models that combine statistical and physical methods are studied in literature [18–20]. There are mainly three kinds of hybrid models. The first hybrid model combines several models to build a new model. The second can obtain forecasting results by combining the results from different models. The third is based on statistical systems with artificial intelligence methods, which combines intelligence algorithm or improved ANN to build predicting models. Among the three models, the third kind has become the most popular method and commonly used in forecasting wind powers. Osório and Matias [21] used new hybrid evolutionary-adaptive methodology, called HEA, using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization. The method was tested for short-term (3-h ahead with 15-min intervals) wind power predictions in the Portuguese system. The results showed that the average MAPE value was only 3.75% for an average error variance of 0.0013. Chen and Zheng [22] studied a combination of probabilistic and numeric models: A Gaussian Process (GP) combined with a NWP model is used to wind-power that forecasts up to one day ahead of time. The proposed model provides around 9%–14% improvement in forecasting accuracy compared to an artificial neural network (ANN) model, and nearly 17% improvement. Yan and Li [23] presented a hybrid deterministic–probabilistic method where a temporally local "moving window" technique is used in Gaussian process (GP) to examine estimated forecasting errors. The smallest mean RMSE is 10.9%, which is lower than many other methods. Therefore, to enhance the forecasting performance, the improvement methods need to be performed. Recently, several studies have carried on valuable attempts, such as Ahmed et al. [24] proposed a hybrid neuro-fuzzy wind power prediction system is proposed, Ouyang et al. [25] used a method based on regime of switching kernel functions. Dowell and Pinson [26] proposed a very short term probabilistic wind power forecasts by sparse vector autoregression.

In spite of improvements in wind power forecasting approaches, wind power forecasts even suffer from high errors. These errors typically range from 8% to 22% (in terms of normalized Mean Squared Error (nMSE)) depending upon several factors including predicting horizon, the types of forecasting models, scale of wind farm, and geographic positions [27,28]. Most of hybrid forecasting models are all basing on wind power series. Wind power models make use of time series through analyzing wind profiles to obtain the forecast values. In local power management's circumstance, the study of time series can be highly helpful with the help of predictability analysis.

In this paper, a new forecasting method is proposed based on analyzing wind power series to get more accurate wind power forecasting results. There are four steps.

First, the historical wind power data of a given wind farm are analyzed by calculating of the largest Lyapunov exponent and reconstructing the chaotic wind power series by phase space reconstruction [29]. The results of numerical simulations show that chaotic characteristics exist in the wind power series. This discovery inspires us to model the wind power as a complex non-linear dynamic system with chaotic behaviors. Chaotic time series is a regular and random series. Chaos theory is often used to scrutinize the behavior of the dynamical systems. The chaotic systems are extremely sensitive to initial conditions such as errors and noises [30,31]. All small changes in initial conditions of chaotic system can result in disproportionally large consequences. The input vector of the BNN model is the reconstructed chaotic wind power series based on the best delay time and the best embedding dimension. The best delay time is calculated by the autocorrelation method and the best embedding dimension is calculated by the Cao method.

Second, the new Bernstein Neural Network (BNN) is used to forecast the chaotic wind power series. Significant research interests have been attracted by chaotic time series forecasts for learning complex systems' characteristics over the past few years. Some chaotic prediction methods have been developed based on the dynamic reconstruction technique, such as Lyapunov exponents and ANN. In this paper, a neural network and Bernstein polynomial are combined to build a new BNN to forecast the chaotic wind power series. The random selection of hidden neurons may cause overfitting or underfitting problem in the Neural Networks. In this paper, a new intelligence algorithm is used to train the BNN model.

Third, a new swarm intelligence algorithm, inspired from state transition, is used to determine the optimum number of neurons in the hidden layer and obtain the best weight factors. The parameters of BNN optimized by PDSTA will increase its training efficiency and forecasting accuracy.

Last, the accuracy of the proposed method is tested. The output of a wind farm in Xinjiang, as an example, is simulated by this method and other methods for comparative studies. Fig. 1 presents the flowchart of the proposed model. In Fig. 1, it clearly shows the four steps about how to build the PDSTA + BNN forecasting model. And the details of phase space reconstruction and PDSTA are all shown in Fig. 1.