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One-day-ahead probabilistic wind speed forecast based on optimized numerical weather prediction data

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ABSTRACT

At present, wind forecast based on Numerical Weather Prediction is widely recognized and applied for a safer and more sufficient usage of wind sources. However, because of the unescapable inherent errors of numerical techniques, there are many negative cases of forecasts. Thus, aiming to quantize and evaluate the inherent errors of physical outcomes, this paper analyzes the characteristic of residuals between numerical results and actual measured data in statistical way, designs combined non-linear and non-parameter algorithms to correct original prediction values, and achieves probabilistic one-day-ahead 96-step wind speed forecasts. The concise process of the method can be described as followings. Firstly, this work utilizes autocorrelation analysis to verify the non-noise attribute of error sequences. Based on the characteristic, adaptive and structured error correction models of nonlinear autoregressive with exogenous inputs network are established to acquire deterministic optimized outcomes. Then, aiming to calculate conditional error boundaries of different confidence levels, mixture kernel density estimation is adopted step by step to estimate joint probability density of corrected values and revised errors. The results on test set show the correction considering inherent errors of numerical techniques can integrate the physical with statistical information effectively and enhance the forecast accuracy indeed.

1. Introduction

Nowadays, fossil fuels are running off and have caused numerous environmental problems such as greenhouse effect meanwhile. Thus to solve the fossil fuel depletion, wind power is generally considered as an effective alternative due to its clean and renewable nature [1]. Through its collaboration with other renewable sources of energy, the world energy crises can be solved in the future [2]. But the fluctuation, stochasticity and intermittence of wind always challenge the stability of power grid, especially on the condition of high penetration level [3]. The common method to cope with this situation is abandoning wind which results in tremendous energy waste. Hence, precise wind speed forecast (WSF) is considered as a feasible measure to abate this phenomenon and enhance the wind grid-tied ratio. However, the intense uncertainty of wind always restricts the accuracy of WSF so that relevant research is still a tough issue.

In terms of power system operation requirements, the forecast can be divided into four different horizons: very short-term (few seconds to 30 min), short-term (30 min–6 h), medium-term (6–24 h), and long-term (1 day and more) [4]. Among the various prediction horizons, one-day-ahead WSF plays an important role. In 2011, the National Energy Bureau (NEB) drafted a regulation requiring 24 h ahead wind forecast of 96 steps for dispatching preparation. And wind farms will be fined for exceeding the presupposed error threshold [5]. Thus to be well demand-orientated, this paper mainly focuses on one-day-ahead WSF to serve the power grid scheduling and improve the power plant economy.

As for a suitable approach for WSF up to 24 h, this section reviews the pertinent literature briefly. Currently, the mainstream methods are based on statistics and physics. In the study of statistical means, time series analysis and machine learning algorithms catch the fancy of researchers most. In [6], a day-ahead WSF method based on f-ARIMA models was proposed by Kavasseri et al.. Bivona et al. [7] introduced two methods including SARIMA and ANN to model the stationary component of stochastic theory. Results showed that both of them were effective to realize the WSF without a degradation during the 24 h forecast window. Maatallah et al. [8] utilized Hammerstein Auto-Regressive technology and built recursive WSF model for 1–24 h horizon. On the other hand, Zhang et al. [9]compared the Deep Boltzmann Machine (DBM) forecast ability with AR, ANFIS, SVR, and the improvement more than 10% of precision indicated the competitive capability of DBM to approximate nonlinear and non-smooth daily wind speed data. Wang et al. [10] combined seasonal index adjustment (SIA) and Elman recurrent neural network (ERNN) methods to construct the hybrid models for medium-term WSF which perform well in the dataset.

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Zhao et al. [11] put forward a method consisting of training stage along with the iterative forecasting and leave-one-day-out resampling correcting stage for 24 h WSF. The effectiveness of this model could be obviously observed in four case studies in China. Relative to the statistics, physical approach always refines the NWP data with downscaling method which could take into account the on-site conditions, such as local terrain and wind farm layout [4]. Depending on Weather Research and Forecasting (WRF) simulation, Zhao et al. [5,12] respectively proposed the CSFC-Apriori and CS-FS-E model to extract the information and characteristics of one-day-ahead WRF forecasting error. The methods significantly reduced the uncertainties of the WRF simulation and performed best among other compared models. Chu et al. [13] considered the deviation of estimated biases associated with the difference in weather type within each unit of the statistical sample to fulfil bias correction scheme. The 28–52 h predictions of forecasting system verified the optimization capacity of information contained in weather types.

It can be found both of statistical and physical methods have their merits in day ahead or longer term WSF, naturally it's feasible and advantageous to combine them to achieve more accurate prediction. On the other hand, most of aforementioned models are valuable for point prediction, but fail to convey enough uncertain characteristics of wind speed. Unlike deterministic WSF, probabilistic models can provide a reasonable range to further point forecast results and assist power system operation [14]. In this framework, some methods are broadly applied such as Gaussian process regression (GPR) and quantile regression (QR). In [15], a mixture localized copula GPR approach was proposed for long-term WSF. Zhang C etc. [16] utilized GPR based hybrid method to realize probabilistic prediction of wind speed. Lv et al. [17] and Wang et al. [18] designed WSF algorithms by combining Wavelet Analysis and Deep Belief Network with QR respectively. Besides them, non-parameter kernel density estimation (KDE) is also well recognized [19]. Its most attractive advantage is that there is no need to presuppose the data distribution [20]. The authors adopted K -nearest neighbors and a kernel density estimator for probabilistic wind forecast in [21]. In [22], Han et al. combined KDE and ARMA to develop non-parametric hybrid models for WSF, and the results outperform some other traditional algorithms. Zhang et al. [23] employed boundary kernel method to eliminate the density leak at the bounds of wind power distribution. The improvement of the proposed method over the standard kernel density estimator is demonstrated by short-term probabilistic forecasting results. Miao et al. [24] utilized mixture kernel density model for wind speed distribution estimation. This technology can estimate the distribution with relatively higher accuracy in comparison to existed methods.

Compared with most previous research aiming to improve the numerical models itself, this paper employs a new perspective to modify the original physical forecasts. It analyzes the inherent errors of NWP results in statistical way and proposes a novel method to realize the one-day-ahead probabilistic WSF. When applying the NARX models and probabilistic relationship acquired by mixture KDE in training set to test samples, the enhanced performances certify the generalization ability and reliability of proposed method. And this also indicates the combination of physical information and statistical technology based on nonlinear and non-parameter algorithm can benefit the prediction accuracy in probabilistic framework. The major contributions of this paper can be summarized as follows:

(1) This work is well demand-oriented. The models proposed can fulfill day-ahead WSF of 96 steps with the NWP data of 15 min temporal resolution, which conform the regulation enacted by National Energy Bureau.
(2) The non-noise attribute of NWP error sequences is proved through autocorrelation analysis. This result verifies the necessity of error correction, and provides important prior knowledge for subsequent research process.

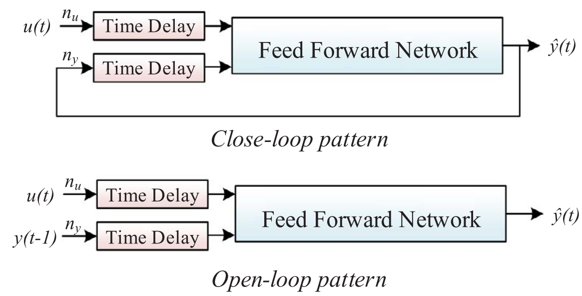

Fig. 1. Two operation patterns of NARX network.

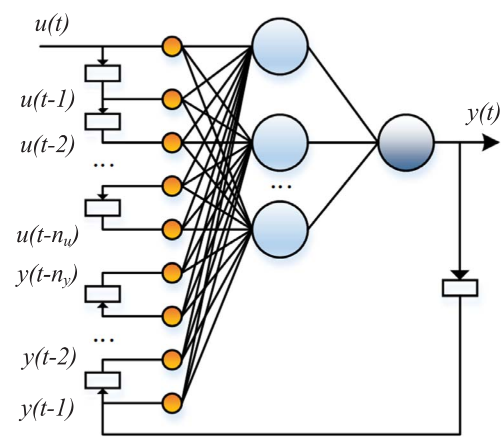

Fig. 2. Structure of close-loop NARX.

(3) This paper utilizes NARX network structured by 10-fold cross validation to realize the modification of NWP data. The enhanced performances on test set present the superior multi-step prediction and generalization abilities of established models.
(4) Based on mixture KDE, joint probability density (JPD) of optimized forecast values and revised errors on every step is obtained to calculate the conditional error boundaries. By this means, this research achieves probabilistic one-day-ahead WSF.

The rest of this paper is organized as: Section 2 introduces the principles of NARX network, cross-validation and mixture KDE briefly. The experimental results of case studies are presented in Section 3. Followed that Section 4 deploys the corresponding discussion and conclusion.

2. Methods

This section introduces the main methods employed in this paper briefly, including NARX network, cross-validation, kernel density estimate, and the integral technology process.

2.1. Nonlinear autoregressive with exogenous inputs network

As for the strongly dynamic and nonlinear object like wind, dynamically driven networks are more suitable for its data analysis [25]. Among the different kinds of dynamic networks, NARX network performs well. Through feedback and memory, it retains the data from previous moments and makes calculation for the next time so that the multi-step WSF correction can be achieved. Its dynamic behavior can be described as the following expression:

$$y(t) = F(y(t-1),y(t-2),\cdot,y(t-n_y),\quad u(t),u(t-1),u(t-2),\cdots,u(t-n_u)) \tag{1}$$

In the formula, nonlinear function F is approximated by NARX network. $y(t)$ and $u(t)$ represent the target variable and exogenous