Applied Energy 178 (2016) 886–901

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

One day ahead wind speed forecasting: A resampling-based approach

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HIGHLIGHTS

- Develop a novel resampling-based one-day-ahead wind speed forecasting approach.
- Optimize cross-validation errors by Fibonacci search method for model selection.
- Embed correction operation in the iterative forecasting process to improve accuracy.
- Propose the leave-one-day-out resampling method to estimate correction parameters.
- Design four case studies from two wind farms in China to verify the effectiveness.

ARTICLE INFO

Article history:
Received 18 February 2016
Received in revised form 11 May 2016
Accepted 18 June 2016

Keywords:
Wind speed forecasting
General regression neural network
Cross-validation
Fibonacci search method
Leave-one-day-out resampling
Forecast correction

ABSTRACT

Wind speed forecasting plays a vital role in dispatch planning and operational security for wind farms, however, its difficulty is commonly accepted. This paper develops a nonlinear autoregressive (exogenous) model for one-day-ahead mean hourly wind speed forecasting, where general regression neural network is employed to model nonlinearities of the system. Specifically, this model is a two-stage method consisting of the model selection and training stage along with the iterative forecasting and correcting stage. In the former stage, the model is in the series-parallel configuration, and its test error is estimated by the cross-validation (CV) method. With the help of ARIMA identification results, CV errors are minimized by the Fibonacci search method to select the best lag structure and the only adjustable parameter. In the latter stage, the model is in the parallel configuration, and the so-called leave-one-day-out resampling method is proposed to iteratively estimate correction parameters for horizons up to 24 h ahead, which holds out each full-day data segment from the sample of observations in turn to faithfully reproduce the entire process of training, iterative forecasting and correcting in the in-sample period. Finally, the out-of-sample corrected forecasts can be successively obtained by using the model selected and trained in the former stage and the correction parameters estimated in the latter stage. Furthermore, effectiveness of this model is verified with four real-world case studies of two wind farms in China.

1. Introduction

Over the past decades, the growing energy consumption is under threat from the reality that viable reserves of fossil fuels are being fast depleted, which is likely to plague us for a long time. Meanwhile, the greenhouse effect intensified by the burning of fossil fuels brings increasing global awareness. These lead to a global movement towards the production of renewable energy for sustainable development, where wind power plays an increasingly important role [1,2]. By the end of 2015, the worldwide total installed wind capacity has reached about 435 GW, out of which 63 GW were installed in 2015. This increase is substantially higher than in the same period in 2014 when 52 GW were added [3]. However, high penetration of wind power introduces great challenges in power system controlling and planning. In particular, the intermittent and stochastic nature of the wind results in the variation of wind power output, which makes it difficult to maintain the balance between the power supply and demand when wind power is integrated into the existing power grid [4,5]. Accurately forecasting wind speed is one of the possible solutions to

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http://dx.doi.org/10.1016/j.apenergy.2016.06.098
0306-2619/

this challenge since it saves adequate time to develop countermeasures in advance before a significant variation.

Depending on the required application, wind speed forecasting may be performed over one of these four different time horizons: very short-term (few seconds to 30 min ahead), short-term (30 min to 6 h ahead), medium-term (6 h to 1 day ahead) and long-term (1 day to 1 week or more ahead). Very short-term forecasts are useful to control the wind turbines in real time; short-term forecasts can be factored into the load dispatch planning; medium-term forecasts are helpful in operational security and power system management; long-term forecasts can guide the maintenance scheduling to optimize operating cost [4,6]. Unfortunately, it is very difficult to forecast wind speed because of complex interactions from various geographical and physical factors such as the rotation of the earth, local topographical properties, temperature and pressure difference [7,8]. In order to achieve more accurate and reliable wind speed forecast, a large number of approaches have been developed, where physical and statistical approaches are the mainstream.

Physical approaches generally downscale weather forecasts from numerical weather prediction (NWP) models on a coarse grid to specific locations, where the on-site conditions, such as the local terrain and wind farm layout, are taken into account [9]. Two examples are Prediktor and Previento which developed by Landberg [10] and the University of Oldenburg [11] respectively. The former one is implemented using the forecasts from the HIRLAM model as NWP input and employing the WAsP model along with PARK program to take local conditions and wake effects into account. The latter one is similar, however uses forecasts from a different NWP model, i.e. Lakelmodell. In addition, to improve forecast accuracy, the model output statistics (MOS) module may be set into physical approaches as well [4]. On the other hand, statistical approaches are aimed at fitting the relation between the required wind speed forecast and predictors such as online measured data and NWP forecasts, which can be achieved by training with historical measurement data according to forecast errors [6]. Time series based and neural network (NN) based models are two important subclassifications of these approaches. In the former ones, autoregressive integrated moving average (ARIMA) model family is the most popular to forecast wind speed, such as AR [12], ARMA [13,14], f-ARIMA [15] and Hammerstein AR (HAR) [16], while in the latter ones, the frequently used models include feed-forward neural networks (FFNNs) [7,17], recurrent neural networks (RNNs) [18], radial basis function (RBF) NNs [19] and more. In addition, Markov-switching model [20], Kalman filtering [5,21], the first-order and second-order adaptive coefficient methods [22], combining models [23], decomposition then forecasting models [7,24–26] and many hybrid models [27–32] report excellent forecast performance for wind speed as well.

In general, physical approaches are more applicable for longer time horizons than statistical approaches. However, they are weak in handling small scale phenomena and need large amount of computational resource and time, while statistical approaches are inexpensive, easy-to-use and time-saving [6,9]. As for the approaches suitable for one day ahead wind speed forecasting which is the focus in this paper, we have scanned the literature about both medium-term and long-term forecasting since one-day-ahead forecasting is a transition between them. This section reviews several related studies, and some methods for intra-day ahead and two (or three) days ahead forecasting are involved besides one day ahead forecasting. Torres et al. [13] predicted the mean hourly wind speed up to 10 h ahead by using the ARMA model with transforming and standardizing the original series, and reported this method behaves significantly better than the persistence model. Bivona et al. [33] obtained mean hourly wind speed forecasts for the horizons up to 24 h ahead using the seasonal ARIMA (SARIMA) model, and concluded that this model, based on only 1-month wind speed data, could provide similar forecasts to those acquired by a FFNN model that is trained on 2-year data. El-Fouly et al. [34] developed two linear models to predict mean hourly wind speed up to 12 h and 24 h ahead, which related the predicted interval of the current year to its corresponding interval(s) of previous one or two years. Experimental results showed the superiority of the proposed models compared with the persistence model. Maatallah et al. predicted wind speed up to 24 h ahead through adapting Hammerstein model to an autoregressive approach, and the results showed that the HAR model outperformed both the ARIMA model and ANN model [16]. To predict the wind speed up to 48 h ahead, Salcedo-Sanz et al. [35] and Hervás-Martínez et al. [36] proposed a hybrid system. That is, get hold of NWP forecasts in a smaller area in advance by downscaling the Global Forecast System (GFS) data using Fifth-Generation Penn State/NCAR Mesoscale Model (MM5) considering the local terrain and atmospheric soundings, then use a neural network to process these forecasts along with other related variables to acquire the final forecasts, where a common FFNN and an evolutionary product unit NN are respectively employed in these two works. Barbounis et al. [18,37] employed several local RNNs to predict wind speed up to 72 h ahead with feeding NWP forecasts from the atmospheric modeling system of SKIRON into networks' input, where a global recursive prediction error (GRPE) algorithm and its local version, i.e. the decoupled RPE (DRPE), were developed to update weights for on-line applications.

From the literature shown above, it can be found that NWP forecasts are generally needed in long-term forecasting, while forecasting up to intra-day or one day ahead can be performed based on historical data alone. In order to perform one-day-ahead wind speed forecasting, this paper proposes a two-stage nonlinear autoregressive (exogenous) model with the general regression neural network (GRNN) where NWP forecasts can be included in it as exogenous variables. This model consists of the model selection and training stage along with the iterative forecasting and correcting stage, where it is in the series-parallel and parallel configurations respectively. In the former stage, assisted by the ARIMA identification results, the best lag structure and the only adjustable parameter in GRNN are found out through optimizing the cross-validation (CV) errors by the Fibonacci search method. In the latter stage, let the network output be connected to appropriate input by feedback connections to perform iterative forecasting, and a correction operation is embedded in this process. Then the 24 out-of-sample corrected forecasts on the next day are successively obtained. By the way, a so-called leave-one-day-out resampling method is proposed to estimate correction parameters in this stage, which holds out each full-day data segment from the sample of observations in turn to faithfully reproduce the entire process of training, iterative forecasting and correcting stages in the in-sample period.

The main contribution of this paper is just this two-stage nonlinear autoregressive (exogenous) model for one-day-ahead wind speed forecasting, which integrates GRNN, cross-validation approach, Fibonacci search method, leave-one-day-out resampling method, iterative forecasting and correcting. There are two advantages for it: (1) As a fully data-driven approach, the proposed model makes full use of the precious data through resampling. It uses the historical observations not only to select the model by optimizing the cross-validation errors, but also to correct the forecasts by the leave-one-day-out resampling method. From this point of view, it is a cheap approach and especially suitable for small wind farms. (2) Since the leave-one-day-out resampling based correction operation is embedded in the iterative forecasting process, the phenomenon of forecast error propagation and amplification with forecast horizon is alleviated a lot. This improves the