Energy Conversion and Management 173 (2018) 197–209

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Research and application of a hybrid model based on Meta learning strategy for wind power deterministic and probabilistic forecasting

Jianming Hu[a], Jiani Heng[b,*], Jingwei Tang[a], Miaolin Guo[a]

[a] College of Economics and Statistics, Guangzhou University, Guangzhou, China
[b] School of Statistics, Dongbei University of Finance and Economics, Dalian, China

ARTICLE INFO

Keywords:
Dynamic combination
Wind power forecasting
Data pre-processing
Quantile regression-based model
Deterministic and probabilistic forecasting

ABSTRACT

Wind power forecasting is becoming an increasingly significant part in the operation and programming of electric force and power systems. However, highly precise wind power forecasting is still a difficult and challenging issue owing to the randomisation and transience of the wind series. In this paper, a novel Meta-learning strategy is proposed for adaptively combining heterogeneous forecasting models that were selected from a constructed candidate model bank. This study first implements the Box–Cox transformation to the wind speed and wind power sequence. Subsequently, the wind power as well as wind speed, which are decomposed by adopting the wind direction, are regarded as the inputs of the individual models. They are used to train a base-level forecasting learner to model the forecasting values of the wind power series. Finally, models with poor performances are dynamically trimmed and combining the remaining individual models are combined by adopting the random forest algorithm for the subsequent deterministic and probabilistic forecasting task. The wind power data from a wind farm located in northwestern of China are adopted to illustrate the forecasting effectiveness of the developed approach. The simulation in three experiments demonstrated the following: (a) the proposed Meta-learning based model is suitable for providing accurate wind power forecasting; (b) the proposed Meta-learning based hybrid model exhibits a more competitive forecasting performance than the individual models by extract advantage of each models; (c) the proposed model not only improves the accuracy of the deterministic forecasts but also provides more probabilistic information for wind power forecasting.

1. Introduction

With the deterioration of human living environment and exhaustion of traditional resources, renewable energy has shown its vital importance worldwide. In the last decades, wind energy has particularly rapidly grown in some areas. By the end of June 2017, the global cumulative installed wind capacity reached approximately 511,371 MW [1]. However, owing to the intermittency and instability of wind sources, the wholesale integration of wind energy in the grid system presents a tremendous challenge in power generation designing, turbine schedule maintenance, and power grid system operations. To alleviate the unfavourable impacts of wind power integration, it is necessary to provide more accurate information from wind power forecasts, including deterministic and probabilistic forecasts. This will decrease the reserve capacity, increase the wind power penetration, and achieve safe and efficient operation of wind farms.

Numerous models have been developed to enhance the accuracy of deterministic wind power forecasting. These models are commonly classified into four types: physical-based forecasting models, conventional statistical-based forecasting models, artificial intelligence (AI)-based forecasting models, and hybrid forecasting models.

Physical-based forecasting models which have advantages in long-term prediction generally use numerous physical considerations to reach the finest prediction precision. Various physical methods have been presented, and the most widely applied models are numerical weather prediction and weather research and forecasting (WRF) [2–3]. The conventional statistical forecasting models which mainly utilise historical data to determine whether the error of fitting is in accordance with the random-walk procedure, are very effective for short-term prediction. These type of models primarily refer to time-series techniques including auto-regressive moving average (ARMA) [4], auto-regressive integrated moving average (ARIMA) [5], fractional ARIMA (f-ARIMA) [6], and exponential smoothing, which are widely known as the scientific approaches used in the study of wind speed forecasting in the early times.

With the rapid development of information technology, the ability

* Corresponding author at: School of Statistics, Dongbei University of Finance and Economics, Dalian 116000, China.
E-mail address: hengjn13@lzu.edu.cn (J. Heng).

https://doi.org/10.1016/j.enconman.2018.07.052
Received 10 April 2018; Received in revised form 14 July 2018; Accepted 16 July 2018
0196-8904/

to perform complex calculation has significantly improved. AI forecasting models such as artificial neural network (ANN) [7], support vector machine (SVM) [8], and fuzzy logical system [9], which can produce nonlinear maps and perform parallel processing have been extensively applied for wind power forecasting with outstanding learning performance and good capabilities for generalisation. These forecasting models which learn from patterns and capture the hidden nonlinear relationships existing in the given historical data or map the relations between the input and output, with a good data error tolerance, are particularly suitable for complex and uncertain relationships.

Hybrid forecasting models are proposed based on the combinations of the above-mentioned different types of models, signal decomposition techniques, and intelligence optimisation algorithms. These models can be classified into two categories. The first type connect individual models by setting weight coefficients. The most commonly used combination methods are the weighted median and weighted average. The other type is regarded as “decomposition–ensemble”, which can achieve satisfactory results for not only capturing the intrinsic factors of a wind speed series but also for improving the forecasting accuracy. Some examples are wavelet decomposition (EWT) [10], empirical mode decomposition (EMD) [11], singular spectrum analysis (SSA) [12], ensemble EMD (EEMD) [13], and complete EMD with adaptive noise (CEEMDAN) [14], which realise a preliminary process on datasets. In addition, some pre-processing approaches such as Box-Cox [15] and some feature selections [16] are also implemented in hybrid forecasting models and obtained satisfactory forecasting performance. The forecasting models combine the advantages of each individual model and provide accurate and reliable wind speed prediction. Various studies have empirically demonstrated that hybrid forecasting models as the most effective approach for improving wind speed forecasting. Therefore, this study also attempts to employ the hybrid model framework for achieving a good forecasting performance for wind power forecasting.

The above-mentioned models focus on point or deterministic wind speed or power forecasts and offer point estimation of the wind speed when the input is appropriate. However, they fail to reveal the uncertain characteristics of wind speed. Therefore, the attention of some researchers has been drawn to the probabilistic forecasting of wind power [17–19], which has tremendous significance for utilities and system operators. With regard to the studies on probabilistic forecasting, quantile regression (QR) is one of the predominant methods for wind power forecasting. A QR model allows estimating various quantile functions of a conditional distribution. This model is extremely useful when the conditions are unevenly distributed and have non-standard shapes. [20]. However, most of the former applications of QR in forecasting primarily depended on linear or nonlinear models with simple parameters. To improve nonlinear time-series forecasting, a more flexible type of model called QRNN (quantile regression neural network) is proposed by Taylor in 2000 [21]. This neural network structure has the ability to deal with numerous complex forecasting problems in wind speed and with financial time-series [22].

Recently, Cerqueira et al. developed a novel ensemble method called Meta-learning strategy to manage time-series forecasting [23]. Different from most of the present ensemble method for time-series forecasting, Meta-learning strategy tracks the loss of the available models and adapts their weights accordingly. It possesses the ability to combine forecasting models that are distinct across the time-series adaptively. The Meta-learning strategy is based on the ensemble of heterogeneous forecasters, arbitrated by a Meta-learning model, designed to cope with the different dynamics of the time-series, and rapidly adapt the ensemble to regime changes. The empirical results show the competitiveness of the method in comparison with the state-of-the-art approaches for combining forecasters.

In addition, to further explore the data characteristics and improve the performance of the forecasting model, some researchers pay attention to feature selection which can eliminate invalid candidate features and reduce the size of the input sets, thereby shortening the operation time. Feature selection techniques can be classified into three categories: correlation and principle component analysis-based [24], optimisation algorithm-based [25] and information theory-based [26] feature selection. Other techniques focus on forecasting approaches, which have been proposed in recent years.

In this study, to achieve a more satisfactory wind power forecasting performance, the wind speed is decomposed with direction to obtain the angle information as the input of the forecasting engines (QRNN, QR, quantile regression support vector machine (QRSVM), and quantile random forest (QRF) models) which are combined with the autoregressive integrated moving average with other exogenous variables (ARIMAX), SVM, boosting regression model, bagging regression model, and other models. The motivation for our developed model is based on the fact that different learning models have different areas of expertise in the input space. The major contributions of this paper are as follows:

- With respect to the probabilistic forecasting of wind power series, various reports have discussed that the conditional predictive densities of wind power cannot be Gaussian and also that their higher order moments may be directly associated with their average values and some external signal potentially. Thus, this study adopts the Box–Cox transformation, missing value processing, signal decomposition and standardization for variance stabilization, and then works in the Gaussian framework for wind power data.
- Systematic evidence has been found that different learning models have different professional fields in the input space. Not all models perform well at any given prediction point. Some models have different performance results over time, and some models are good (or bad) throughout the time-series. This study addresses this problem with a novel group of models, where the poor performing models are dynamically trimmed from the combination rule for selecting the most effective combination mode. Compared with non-dynamic combination model, the selected model is dynamically entered into the combination model, and thus avoiding the subjectivity of static selection models.
- Complete consideration of the uncertainty of wind power may be beneficial for power system management to reduce the degree of risk. Therefore, QR based forecasting engine is adopted as the Meta-learning to construct confidence intervals for the prediction. The probabilistic forecast can deal with uncertainties induced by stochastic wind power.
- When using a group of models for leveraging individual learners with different inductive biases to better manage wind power series, the Meta-learning layer algorithm affects the final performance of the quantile wind power forecasting owing to its generalisation ability. Thus, this research pays particular attention to discuss the ability of the Meta lever algorithm, and empirically show that the QRF models are the most predictable, whereas the neural network (NNet) is the least predictable model for wind power forecasting.

The remainder of this paper is organised as follows: Section 2 describes the methodology adopted in this study and the strategy of the proposed model. A case study to illustrate the effectiveness of the proposed model and the related discussion are provided in Section 3. Finally, Section 4 presents the main conclusions of this work

2. Methodology

2.1. Box-Cox transformation

The Box–Cox transformation, which was proposed by Box and Cox in 1964, is an effective transformation for stabilising the variance of a time-series [27].

Definition 1. The definition of the method is as follows: