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A Gaussian process regression based hybrid approach for short-term wind speed prediction

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ABSTRACT

This paper proposes a hybrid model based on autoregressive (AR) model and Gaussian process regression (GPR) for probabilistic wind speed forecasting. In the proposed approach, the AR model is employed to capture the overall structure from wind speed series, and the GPR is adopted to extract the local structure. Additionally, automatic relevance determination (ARD) is used to take into account the relative importance of different inputs, and different types of covariance functions are combined to capture the characteristics of the data. The proposed hybrid model is compared with the persistence model, artificial neural network (ANN), and support vector machine (SVM) for one-step ahead forecasting, using wind speed data collected from three wind farms in China. The forecasting results indicate that the proposed method can not only improve point forecasts compared with other methods, but also generate satisfactory prediction intervals.

1. Introduction

Wind energy has become a promising energy source due to its clean and renewable nature. With the large-scale development of wind energy, several challenges emerge, such as limited dispatchability, limited predictability, high variability, and non-storability [1]. The intermittent and stochastic nature of wind speed increase the operating cost and reduce the reliability and stability of power systems. To alleviate the adverse effects of wind power integration, accurate wind speed and power forecasting are important and urgently needed [2]. Short-term wind forecasting is vital for operation planning when the penetration level of wind power is high [1]. Many methods for short-term wind speed prediction have been proposed in recent decades.

The majority of methods reported in the literature focus on point forecasting of wind speed. Generally, these approaches can be classified into four categories: (1) numerical weather prediction (NWP) based physical methods; (2) classical time series models; (3) modern machine learning methods; (4) hybrid (or combined) approaches. The NWP models generate forecasts for weather conditions through computations of thermodynamics and fluid dynamics equations [3]. The NWP-based methods utilize the output of NWP, taking into account the physical description of the wind farm, to predict the local wind speed [4,5]. Such methods usually require rich physical background knowledge and substantial computational resources. Contrary to the NWP models, the time series models are constructed based on historical wind speed data. Classical time series models, including the autoregressive (AR), the autoregressive moving average (ARMA) [6] and their variants, have been widely used in short-term wind speed prediction [7,8]. These models can explicitly reveal the linear relationship in the wind speed series, but the prediction results will be unsatisfactory if the non-linear characteristics in the series are prominent.

Recently, machine learning methods have been extensively studied and applied in the field of wind speed prediction. Two representative models, artificial neural networks (ANNs) and support vector machines (SVMs) are widely used. For example, Chen and Lai [9] used ANN to predict the hourly wind speed in a wind farm in Hubei province of China. The results showed that the ANN had better forecasting performance than the autoregressive integrated moving average (ARIMA) model. Cadenas and Rivera [10] applied ANN for short-term wind speed forecasting in the region of La Venta, Oaxaca, Mexico. Diverse configurations of ANN were considered and compared to guarantee the performance of the model. Noorollahi et al. [11] utilized ANN for wind speed forecasting in three wind observation stations in Iran. The average value of the histogram error obtained from the best model was about 2.6%. Ramasamy et al. [12] used an ANN model to predict wind speeds for 11 locations in the western Himalayan state of Himachal Pradesh, Indian. The mean absolute percentage error (MAPE) and correlation coefficient were found to be 4.55% and 98% respectively. Wang et al. [13] proposed a method based on correlation dimension, mutual information and support vector regression for

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short-term wind speed prediction. The results demonstrated that the accuracy of the proposed method was superior to ANN. Salcedo-Sanz et al. [14] presented two evolutionary algorithms, Evolutionary Programming and Particle Swarm Optimization, to tune the hyperparameters of SVM. They found that the evolutionary SVM model had a better performance than ANN in the wind speed forecast at a Spanish wind farm. Cheng and Guo [15] proposed an approach based on information granulating and SVM. The simulation results indicated that the variation trend and variation space of short-term wind speed could be predicted accurately. Zhu et al. [16] used a morphological filter and SVM for short-term wind speed prediction. The results demonstrated that the proposed method can achieve a better performance than ARMA and the traditional SVM. Besides ANN and SVM, other machine learning methods are also applied to the forecasting of wind speed. Yesilbudak et al. [17] presented a new approach based on k-nearest neighbor classification for short-term wind speed prediction. Troncoso et al. [18] comparatively evaluated the performance of different types of regression trees in a real problem of very short-term wind speed prediction.

Moreover, there has been a growing trend of combining various models together, forming a hybrid (or combined) model, to pursue more accurate predictions [19,20]. The hybrid model usually employs multi-component models to capture different patterns in wind speed series. Kani and Riahy [21] developed a hybrid method based on ANN and Markov chain. ANN was first used to predict short-term wind speed values and then the results were modified by Markov chain. A new hybrid algorithm was proposed for very short-term wind speed prediction using linear prediction and Markov chain [22]. The linear prediction model was used to capture short-term patterns and the Markov chain was utilized to consider long-term patterns. The results showed that the proposed method obtained a higher accuracy than the persistence model and the linear prediction model. Chen and Yu [23] proposed a hybrid modeling method to predict short-term wind speed, using unscented Kalman filter (UKF) and SVM. SVM was first employed to formulate a nonlinear state-space model and then UKF was adopted to perform dynamic state estimation recursively on wind sequence with stochastic uncertainty. The forecasting results indicated that the proposed method had much better performance than AR, AR-Kalman, ANN and SVM. Another type of hybrid models is composed of a signal decomposition module followed by a forecasting module [24,25]. The signal decomposition module first decompose the original wind speed series into several sub-series. Then, forecasting models are built to predict the sub-series. By aggregating the predictions of each sub-series, the final prediction of the original series is obtained. For example, Wang and Hu [26] proposed a combination model for probabilistic short-term wind speed forecasting. In their study, empirical wavelet transform (EWT) was first employed to extract meaningful information from wind speed series. Then GPR was utilized to combine independent forecasts generated by various forecasting engines (ARIMA, extreme learning machine (ELM), SVM, least square SVM) in a non-linear way. The results indicated that the proposed combination method could generate more reliable and accurate forecasts than the individual forecasting engines. Liu et al. [27] evaluated the performance of different signal decomposition algorithms combined with ELM. The results indicated that by utilizing the decomposition algorithms, all the proposed hybrid models had better performance than the single ELM. Meng et al. [28] developed a new hybrid model based on wavelet packet decomposition (WPD) and ANN, which was trained by crisscross optimization algorithm. They found that the proposed hybrid model obtained a better forecasting performance than ANN and WPD-ANN. Other hybrid models involve the ensemble of several individual statistical models. That is, first multiple plausible component models are employed to make predictions, and then they are combined based on some weighting strategy [29,30]. Since the hybrid models incorporate the advantages of individual models, usually they have better forecasting performance.

From the above literature review, it can be found that most of the latest methods are based on the combination of different forecasting models. These hybrid models usually have better forecasting performance than the single ones. In the hybrid framework, ANN and SVM are the most used models, whereas other machine learning models such as GPR, are under-explored in the field of wind speed forecasting. Moreover, most of the methods focus on generating point predictions for future wind speed and the uncertainty associated with the point predictions is usually neglected. From a practical point of view, it is risky to operate a wind farm just according to the point forecasts. Although in recent years, some studies for interval forecasting of wind speed have been published [31,32], they lack the analysis of how to generate good point predictions. In order to provide both point and interval predictions for future wind speed, a Gaussian process regression (GPR) based hybrid forecasting model is proposed in this paper. Gaussian processes (GPs) combine the Bayesian learning with kernel machines, providing a principled and probabilistic approach for regression [33]. GPs have been extensively applied to various kinds of modeling and forecasting tasks, such as robotics and control [34], prediction of daily global solar irradiation [35], and facial expression recognition [36]. Several studies of GPs in the field of wind speed forecasting have also been reported recently [26,37]. The hybrid method proposed in this paper uses the AR model to identify the overall structure of the wind speed series, and employs the GPR model to capture the local structure of the series. In the GPR model, different types of covariance functions are combined to extract the characteristics of the data. In addition, partial autocorrelation function (PACF) is used to identify the number of inputs (i.e., the AR order) and automatic relevance determination (ARD) is used to take into consideration the relative importance of different inputs. The proposed method is tested on three real data sets of hourly mean wind speed measurements. In order to evaluate the proposed model, we compare it with three benchmark wind speed forecasting models: the persistence model, ANN and SVM.

The reminder of the paper is organized as follows. Section 2 presents the proposed hybrid model for wind speed prediction. The experimental procedure and results are presented and discussed in Section 3. Finally, conclusions are drawn in Section 4.

2. Methodology

2.1. AR model

AR (autoregressive) is a parametric time series model, which assumes that the current value of the series y_t is a linear combination of the recent past values of itself. Mathematically, a pth-order AR model (AR(p)) can be formulated as

$$y_t = w_0 + \sum_{i=1}^{p} w_i y_{t-i} + e_t \tag{1}$$

where w_0 is a constant term; w_i is the ith AR coefficient, which reflects the influence of past observation y_{t-i} on current value; e_t is the error term at time t.

PACF (partial autocorrelation function) is used to determine the value of p, since for an AR(p) model, the PACF cuts off after the lag k exceeds the order p. To estimate the PACF at a variety of lags, the sample PACF can be calculated using the Yule-Walker equations:

$$r_j = \hat{\phi}_{k1} r_{j-1} + \hat{\phi}_{k2} r_{j-2} + \cdots + \hat{\phi}_{k(k-1)} r_{j-k+1} + \hat{\phi}_{kk} r_{j-k} \quad j = 1, 2, \ldots, k \tag{2}$$