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Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization

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ABSTRACT

As an essential issue in wind energy industry, wind speed forecasting plays a vital role in optimal scheduling and control of wind energy generation and conversion. In this paper, a novel method called EnsemLSTM is proposed by using nonlinear-learning ensemble of deep learning time series prediction based on LSTMs (Long Short Term Memory neural networks), SVRM (support vector regression machine) and EO (extremal optimization algorithm). First, in order to avert the drawback of weak generalization capability and robustness of a single deep learning approach when facing diversiform data, a cluster of LSTMs with diverse hidden layers and neurons are employed to explore and exploit the implicit information of wind speed time series. Then predictions of LSTMs are aggregated into a nonlinear-learning regression top-layer composed of SVRM and the EO is introduced to optimize the parameters of the top-layer. Lastly, the final ensemble prediction for wind speed is given by the fine-turning top-layer. The proposed EnsemLSTM is applied on two case studies data collected from a wind farm in Inner Mongolia, China, to perform ten-minute ahead utmost short term wind speed forecasting and one-hour ahead short term wind speed forecasting. Statistical tests of experimental results compared with other popular prediction models demonstrated the proposed EnsemLSTM can achieve a better forecasting performance.

1. Introduction

As a promising and practical solution to cut greenhouse gas emissions and build a renewable society, wind energy is becoming more and more popular in various countries. The global wind report, released by the Global Wind Energy Council (GWEC) in 2017, has stated that the 2016 world wind power market was more than 54.6 GW, causing the total global installed capacity to nearly 487 GW, which was still led by China, US, Germany and India [1]. And the capacity of wind energy will continue to grow vastly in next years. However, it can be a difficult task to perform a reliable and seasonable wind power management in electrical power systems due to the natural irregular characteristic of wind speed. The unstable and uncontrollable wind speed influences heavily the generation of wind power and subsequently this will impact wind turbines control, power systems and micro-grid scheduling, power quality and the balance of supply and load demand [2,3]. So, dependable and accurate wind speed forecasting can not only provide a security basis for wind energy generation and conversion, but also reduce the costs of power system operation.

The existing wind speed forecasting approaches can be classified into three groups as physical models, statistical models and artificial intelligence models. Physical models are plain methods, which take advantage of physical information like atmospheric pressure, temperature, obstacles and roughness [4]. Thereinto, NWP (numerical weather prediction) models employ a set of mathematics equations based on physical information to forecast. Moreover, a range of statistical models have been researched to perform wind speed forecasting in the recent decades. The widely used statistical models include autoregressive models (AR), moving average models (MA), autoregressive moving average models (ARMA), autoregressive integrated moving average models (ARIMA) and seasonal autoregressive integrated moving average (SARIMA). Liu [5] proposed a novel method based on recursive ARIMA and EMD (empirical mode decomposition) to perform short term wind speed forecasting for railway strong wind warning system. Kavasseri et al. [6] developed a fraction-ARIMA to predict one-day and two-day ahead wind speed in North Dakota. On the other hand, with the rapid development of soft-computing technologies, artificial intelligence models have been proposed successfully for time series prediction. Among them, ANN (artificial neural networks) such as back propagation neural networks [7], multi-layer perceptron neural networks [8], radial basis function neural networks [9], Bayesian neural networks [10] and extreme learning machine [11] have been applied to

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wind speed forecasting. Chang et al. [12] provided an improved neural network based approach with error feedback to predict short term wind speed and power. Noorollahi et al. [13] used ANN models to perform temporal and spatial wind speed forecasting in Iran with success. In [14], Ma et al. proposed a generalized dynamic fuzzy neural network optimized by BSO (brain storm optimization) to forecast short-term wind speed. Another popular group is SVM (support vector machine) with high generalization ability. Jiang et al. [15] presented a hybrid short term wind speed forecasting model using v-SVM optimized by cuckoo search algorithm. Chen et al. [16] developed a state-space based SVM with unscented Kalman filter for wind speed prediction. Additionally, to improve the forecasting performance of a single model, combination or hybrid models are investigated recently to solve this problem [17,18]. For combined methods, different individual models are used to predict and their predicted results are combined to give the final prediction with the corresponding weight coefficients. Xiao et al. [18] proposed a novel combined model based on no negative constraint theory and artificial intelligence algorithm, in which the chaos particle swarm optimization algorithm was used to find the optimal weight coefficients. To simultaneously obtain high accuracy and strong stability, Wang et al. [19] developed a combined forecasting model using multi-objective bat algorithm for wind speed forecasting. In [20], Wang et al. presented a robust combined model adopting ARIMA, SVM, ELM and LSSVM (least square support vector machine) for short term probabilistic wind speed prediction, in which GPR (Gaussian process regression) is utilized to combine the results of individual predictors. The recent researches have demonstrated that combined forecasting mechanism can achieve better prediction performance than single models. However, it should be noted that the commonly accepted combination strategy of weight coefficients is a linear approach, which could not find the non-linear relationship of individual models. Besides, more advanced prediction approaches need to be introduced to enhance the forecasting performance rather than conventional machine learning algorithms like ANN and SVM.

In recent years, the utilization of deep learning in time series modeling has aroused many people's great research interest [21]. Lv et al. [22] performed traffic flow prediction with big data in a deep learning approach. Qiu et al. [23] proposed an ensemble deep learning method for electrical load forecasting. Moreover, advanced deep learning methods have also been successfully applied into wind speed forecasting field. In [24], Hu et al. provided a deep auto-encoder based model using transfer learning for short term wind speed prediction. Khodayar [25] proposed a rough deep neural network architecture with auto-encoders to perform short-term wind speed forecasting. Wang [26] developed a new deterministic and probabilistic wind speed forecasting method using deep belief network models. Furthermore, ensemble learning has been acknowledged widely that the learning performance could be promoted by combing paralleling learning models intelligently [27]. Although the existing combined models for wind speed forecasting can be regarded as one type of ensemble prediction, almost of their forecasting results are a linear combination of individual predictors. From the perspective of general ensemble learning, ensemble prediction based on non-linear learning should be more explored and researched. Thus, in this study, a novel method using nonlinear-learning ensemble of deep learning time series prediction based on LSTMs (Long Short Term Memory neural networks), SVRM (support vector regression machine) and EO (extremal optimization algorithm) named EnsemLSTM is proposed for wind speed forecasting. LSTMs, as a breakthrough variant of RNNs (recurrent neural networks), can learn the temporal and long term dependencies from time series data deeply and solve the vanishing gradient problem effectively compared with traditional RNNs [31,32]. EO is a novel promising intelligent optimization algorithm from the statistical physics field and has been applied to a lot of combinatorial and continuous optimization problems, which shows its superiority over commonly used ones like GA and PSO [37–41]. Inspired by ensemble learning, a cluster of LSTMs with diverse hidden layers and neurons are firstly introduced to explore and exploit the hidden information of wind speed time series. To overcome the shortcomings of linear representation of traditional combined models, the predictions of LSTMs are aggregated into a nonlinear-learning regression top-layer to give the final ensemble prediction in this paper rather than a linear combination. ANN is a classic artificial intelligence method, but it is unstable and its performance depends on data vastly, which make it difficult to predefine the network construction. Additionally, due to limitations of training algorithms, ANN may easily fail into local minima [28]. On the contrary, SVRM has superiority in solving complex nonlinear regression and prediction problems and has achieved extensive application and remarkable success in forecasting field [29,30]. Accordingly, the nonlinear-learning top-layer used in this paper is composed of SVRM to get rid of the weakness of ANN and the EO will be introduced to search for the optimal parameters of this top-layer. Therefore, the main differences between the proposed EnsemLSTM and traditional combined models are summarized: (a): LSTMs, a kind of deep learning method is introduced as the forecasting engine in EnsemLSTM while predictors of traditional combined models are conventional machine learning algorithms like ANN and SVM; (b): To overcome the defects of liner representation of traditional combined models, a nonlinear-learning regression top-layer is adopted in EnsemLSTM to give the final ensemble prediction; (c): The application of a novel promising intelligent optimization algorithm i.e. EO is performed to find the optimal parameters of the top-layer in EnsemLSTM.

The principal contributions of this paper are as follows: (1) A deep learning time series prediction based on LSTMs is introduced to explore and exploit the implicit information of wind speed time series for wind speed forecasting; (2) To improve the generalization capability and robustness of a single deep learning approach, nonlinear-learning ensemble of deep learning time series prediction consisting of a cluster of LSTMs with diverse hidden layers and neurons and one nonlinear-learning regression top-layer composed of SVRM optimized by the EO is developed; (3) The performance of the proposed EnsemLSTM is successfully validated on two case studies data collected from a wind farm in Inner Mongolia, China, to perform ten-minute ahead utmost short term wind speed forecasting and one-hour ahead short term wind speed forecasting. Statistical tests of experimental results have demonstrated the proposed EnsemLSTM can achieve a better forecasting performance when compared with other prediction models.

The remainder of this article is arranged as follows. In Section 2, the optimization problem formulation of nonlinear-learning ensemble of deep learning time series prediction for wind speed forecasting is proposed and the related basic learning and optimization algorithms are introduced. Section 3 presents the proposed EnsemLSTM. Section 4 describes the evaluation indices of model forecasting performance. In Section 5, two case studies are performed and the discussion and comparison of forecasting models are also given in this section. Finally, conclusion and future work of this paper are given in Section 6.

2. Problem formulation

2.1. Deep learning time series prediction

As one distinctive class of RNNs, LSTMs utilize special units named memory blocks to take the place of the traditional neurons in the hidden layers [31,32]. Moreover, there exist three gates units called input gates, output gates and forget gates in memory blocks and hence LSTMs have the ability to update and control the information flow in the block through these gates. The schema of LSTMs is displayed in Fig. 1. And the implementation of updating the state of the cell and calculating the output of LSTMs can be followed below.