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Numerical Weather Prediction Correction Method Based on Online LSTM

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ABSTRACT

Due to serious wind power network security such as the randomness and suddenness of wind speed, and the current wind speed forecasting cannot meet the industrial demand, it is urgent to realize the influence of wind speed forecasting. In this article, the short-term forecast of wind speed is revised. The structure and prediction method, combined with historical NWP (numerical weather forecast) wind speed and historical measured wind speed and other related data, established an online modification model for short-term wind speed forecasting. The model uses historical NWP wind speed as model input data, and historical measured wind speed as output data. First, train the model in an offline environment to test the effect of the model; secondly, train the model in an online environment and modify the model dynamically; finally, get the optimal short-term NWP wind speed forecast modification model. Using the established modification model, the historical NWP data of a wind spot in North China was modified. Compared with the original NWP data, the accuracy was improved by 0.861 m/s, which proved the effectiveness of the NWP modification method. At the same time, it proves the effectiveness of the online model and reduces the model's dependence on historical data.

Keywords Short-term wind speed prediction, NWP wind speed correction, Deep neural network

1. INTRODUCTION

As the current low-cost and most mature form of renewable energy utilization, wind energy has the potential for large-scale development and commercial utilization [1]. How to solve the large-scale grid connection, operation and consumption of wind power has become an important topic in wind power research. High-precision wind speed prediction can not only provide valuable information for energy balance supply, assist the operation and management of the grid, and reduce the impact of wind power fluctuations on the energy system [2] to maintain the stability of the grid, but also promote the construction of wind farms [3]. Ultimately, increase the power grid's capacity to accommodate and consume wind power, increase the enthusiasm for wind power operation, and make it possible to connect wind power to the grid on a large scale.

The output power forecast of wind turbines is mainly based on the relevant weather forecast information obtained on the forecast day, which is provided by the results of Numerical Weather Prediction (NWP). The data quality of NWP wind speed determines the performance of the wind speed prediction model to a large extent. In the NWP wind speed forecast, wind speed is an important source of model errors and has a significant impact on the prediction results [4]. In terms of wind energy forecasting: In 2020, a multinational team composed of 5 units including the Technical University of Munich and the European Center for Medium-Range Weather Forecast (ECMWF) provided benchmark data and evaluation criteria for data-driven mid- and long-term weather forecasts, as well as linear regression models and depth Benchmark scores for learning models and physical forecasting models [6]. The German AWPT model uses machine learning to predict the wind speed in the next eight hours based on the NWP forecast, which is the most mature wind speed prediction system at present [7]. The wind

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farm power prediction system developed by Yan Jie [8] can provide information such as prediction and its uncertainty analysis, statistical analysis of historical data, and error analysis.

In addition to the accuracy of Numerical Weather Prediction, the wind speed forecasting model also has two problems: 1) The training samples used to train the prediction model are large in size, dimensional and not strictly cleaned, etc.; 2) The internal algorithm structure of the prediction model is too simple, mostly linearized, and the data layer and data depth of the prediction model are seriously insufficient. This project intends to study a numerical weather forecast correction model based on deep learning algorithms, which uses the measured wind speed in a short time to establish a Numerical Weather Prediction model and establishes a dynamic correction strategy to compensate for insufficient data feature extraction caused by a small amount of data and other issues, so that the model has higher accuracy and more universality. By comparing the impact of data length and model update frequency on the accuracy of the revised model, the optimal modeling plan is determined.

2. CORRECTION MODEL OF NUMBERICAL WEATHER PREDICTION BASED ON OFFLINE LSTM

2.1 LSTM deep neural network algorithm

2.1.1 LSTM network structure

Long and short-term memory neural network (LSTM) is an improved deep learning algorithm based on recurrent neural network (RNN). Its core idea is to change the gradient of decimal values from continuous multiplication to accumulation which allows LSTM to solve the problem of vanishing gradients when processing long-term timing information. This model is now widely used in various fields and has played an outstanding role in solving many problems.

2.1.2 LSTM network training algorithm

The training algorithm of LSTM neural network is a back-propagation algorithm that expands over time. The specific steps are as follows:

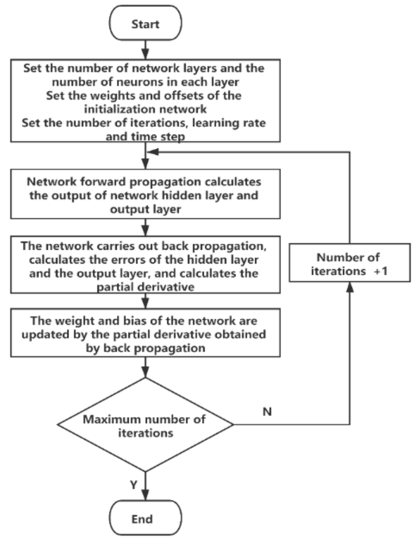

Fig. 1 The LSTM training flowchart

2.2 Correction of Numerical Weather Prediction Based on LSTM Deep Neural Network

2.2.1 Data normalization

When applying the LSTM deep neural network model for data correction, the input layer parameter range is required to be [0,1], so the data used for the model needs to be normalized, and the parameter range obtained by the output layer is also [0,1]. Finally, the parameters obtained from the model need to be reverse-normalized to obtain the corresponding wind speed value.

2.2.2 LSTM Deep Neural Network Correction Process

When building an NWP wind speed forecast correction model for a wind farm, the data set needs to be divided into training set and test set first. After the training set is used to train the LSTM deep neural network correction model, the NWP wind speed in the test set data is input into the model to obtain the corresponding correction wind speed. Finally, the corrected NWP wind speed and the uncorrected NWP wind speed are compared with the actual wind speed. Different error evaluation methods, such as Root Mean Square Error (RMSE), can be used to evaluate and calculate the wind speed prediction error before and after the correction model is used.

When applying NWP to the short-term wind speed forecast correction, this paper adopts the numerical weather forecast NWP wind speed information as the initial value calculation, and gives a set of NWP wind speed data every 15 minutes for the case wind field, a total of 11808 sets of NWP wind speed information forecasts data. Although the NWP wind speed itself is a quantitative and objective prediction, applying NWP wind speed data to wind turbines at different locations in a wind farm for short-term wind speed prediction of a single unit will produce different prediction errors. In order to reduce the error caused by the NWP wind speed, this paper uses a deep neural network to correct the NWP forecast wind speed, and has achieved certain results.

2.2.3 Error evaluation method

To evaluate the correction ability of a trained correction model, the root mean square error (RMSE) index is usually used internationally; for the correction accuracy of the short-term NWP wind speed forecast correction model, the RMSE calculation function in Python is selected for calculation.

RMSE is the standard deviation of the residual (prediction error), which represents the deviation of the regression. The smaller the value, the better the fitting effect. Residuals are used to measure how far away the data points are from the regression line. RMSE measures the degree of distribution of these residuals, which indicates how the data is concentrated in the most suitable range. RMSE is usually used in climate, prediction and regression analysis to verify experimental results.

2.3 Offline LSTM correction model

This chapter mainly uses the offline deep neural network correction model to correct the NWP wind speed data, and compares the obtained corrected NWP wind speed data, the uncorrected NWP wind speed data and the actual wind speed data. The RMSE obtained from different sets of values is analyzed to evaluate the quality of different parameter correction models, and finally the NWP wind speed forecast correction model with the best parameter settings (offline) is obtained. The data source of this article: NWP wind speed data and measured wind speed data of a wind farm in North China from May to August 2011, with a data resolution of 15 minutes, and a total of 11,808 sets of data.

2.3.1 Offline model parameter setting

According to the NWP wind speed correction model based on deep neural network, the normalized NWP wind speed is used as the input of the model, and the normalized actual wind speed is used as the model output. The data of a wind farm in North China is corrected and analyzed, and different parameters (data Length) The difference between the corrected NWP wind speed data and the measured wind speed data to determine the optimal data input and output length.

2.3.2 Offline model prediction and correction process

1) Obtain NWP forecasted wind speed and measured wind speed data: NWP wind speed data and measured wind speed data of a wind farm in the north from May to August 2011, with a data resolution of 15 minutes, a total of 11808 groups;

2) Divide the test set and training set: use the first 10,000 sets of data as the training set, and the last 1808 sets of data as the test set;

3) Establish a numerical weather forecast correction model based on the long and short-term memory deep neural network;

4) When training the model, the input data lengths are respectively: 1, 4, 8, 16, 32, 48, and the corresponding output data lengths are respectively: 1, 4, 8, 16, 32, 48;

5) During the model test, the first 1728 groups of data in the 1808 groups of data in the test set are equally divided into 6 groups, and each group represents data for three consecutive days in the future. Using the model, the NWP wind speed data in each group is used as input to obtain Compare the output result of the model with the corresponding measured data;

6) By comparing the magnitude of the RMSE of the forecast correction data obtained with different parameter settings, the influence of different input and output data lengths on the accuracy of the correction model is obtained, and the optimal modeling scheme is determined.

2.4 Analysis of offline model correction results

The following is the RMSE of the NWP corrected wind speed data obtained when the model uses different input and output lengths. The six different RMSEs in each set of data are averaged to represent the model correction effect corresponding to this set of parameters. The smaller the average value, the better the correction effect.

Table 1 RMSE of NWP corrected wind speed (m/s)

Length of Data	Day 1-3	Day 4-6	Day 7-9	Day 10-12	Day 13-15	Day 16-18	Average
Initial NWP wind speed	2.277	2.178	3.629	2.159	2.155	2.516	2.486
1	1.694	1.599	3.308	1.626	1.712	1.833	1.962
4	1.471	1.702	3.362	1.339	1.886	1.576	1.889
8	1.501	1.674	3.244	1.371	1.9	1.686	1.896
16	1.46	1.624	3.218	1.29	1.886	1.578	1.843
32	1.36	2.051	3.357	1.27	2.051	1.532	1.937
48	1.915	1.602	3.424	1.45	2.058	1.434	1.981

It can be seen from Table 1:

1) When the model is not used for correction, the maximum average RMSE is 2.486 m/s. After using the NWP wind speed correction model, the average RMSE corresponding to the 6 groups of parameters are all less than 2.000 m/s, which proves that the model has a significant correction effect.

2) For the absolute correction effect of the model, when Inputlen = Outputlen=1, Inputlen = Outputlen = 4, Inputlen = Outputlen = 8, Inputlen = Outputlen = 16, Inputlen = Outputlen = 32, Inputlen = Outputlen = 48, the average RMSE of the corrected data output by the model is reduced to: 1.962 m/s, 1.889 m/s, 1.896 m/s, 1.843 m/s, 1.937 m/s, 1.981 m/s. It can be seen that when the model input and output data length (Inputlen, Outputlen) is 16, the absolute correction effect of the model is the best, and the minimum average RMSE at this time is 1.843 m/s.

Overall analysis can draw conclusions:

1) When the selected model uses the above 6 groups of different input and output length parameters, compared with the uncorrected NWP wind speed, the corrected NWP wind speed is numerically closer to the actual wind speed;

2) Correcting the NWP wind speed has played a great role in improving the accuracy of multiple sets of forecast data. The absolute root mean square error is controlled within 2.000 m/s, and the effect is significantly better than using the uncorrected NWP wind speed forecast data directly;

3) For the offline model, the NWP wind speed is the input, the measured wind speed at the corresponding time is the output, and the input and output lengths are both 16 hours, the model correction effect is the best.

2.5 Analysis of the results of offline model calculation examples

When the length of data of model input and output is 16, the absolute correction effect of the model is the best, because the essence of model training is to learn the correspondence relationship of historical data. Model prediction is to find the historical data sequence that is the same or the most similar to the current data sequence, and extract the data in its historical correspondence as the prediction result of the current data. When training the model, the input and output data length of the model is 16, which means that any continuous 4-hour wind speed data is a set of data. The data sequence can learn the periodic changes of wind speed to make the prediction results more targeted and reduce the prediction error.

3. NUMERICAL WEATHER FORECAST CORRECTION MODEL BASED ON ONLINE LSTM

3.1 Correction process and data sources

This chapter mainly uses the online deep neural network correction model to correct the NWP wind speed data, and compares the obtained corrected NWP wind speed data, the uncorrected NWP wind speed data and the actual wind speed data. The RMSE obtained from different sets of values is analyzed to evaluate the quality of different parameter correction models, and finally the NWP wind speed forecast correction model with the best parameter settings (online) is obtained.

3.2 Online LSTM correction model

3.2.1 Online model parameter setting

According to the NWP wind speed correction model based on the LSTM neural network, the normalized NWP wind speed is used as the input of the model and the normalized actual wind speed is used as the model output. The data of a wind farm in North China is corrected and analyzed, and the model is compared with different updates. The difference between the frequency-corrected data and the uncorrected data determines the optimal model update frequency.

3.2.2 Online model prediction and correction process

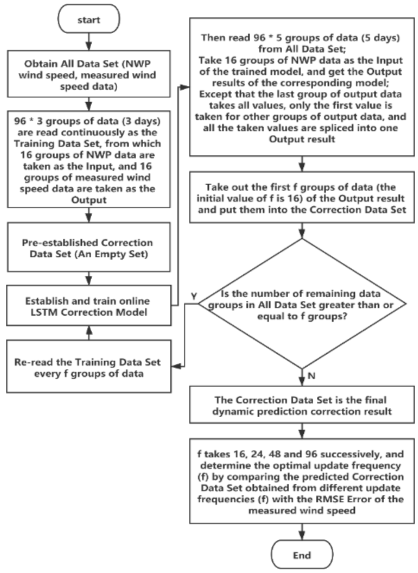

Fig. 2 Online LSTM correction mechanism

3.3 Analysis of online model correction results

The following is the RMSE of the NWP corrected wind speed data obtained when the model uses different update frequency parameters. The RMSE of the three different wind speed sections in each set of data is averaged to represent the model correction effect corresponding to this set of data. The smaller the average value, the better the correction effect.

Table 2 RMSE of NWP corrected wind speed (m/s)

Update frequency	Low wind speed section	Medium wind speed section	High wind speed section	Average
Initial NWP wind speed	2.434	2.152	3.194	2.593
4h	1.501	1.998	2.366	1.955
6h	1.525	1.824	2.137	1.829
12h	1.697	1.625	1.875	1.732
24h	1.826	1.600	1.948	1.791

It can be seen from Table 2: For the absolute correction effect of the model, when the update frequency of the model is 4 hours, 6 hours, 12 hours, and 24 hours, the average RMSE of the corrected data output by the model decreases to: 1.955 m/s, 1.829 m/ s, 1.732 m/s, 1.791 m/s. It can be seen that when the model update frequency is set to 12 hours, the absolute correction effect of the model is the best, and the minimum average RMSE at this time is 1.732 m/s.

Overall analysis can draw conclusions:

1) When the selected model uses the above four different update frequency parameters, compared to the uncorrected NWP wind speed, the corrected NWP wind speed is numerically closer to the actual wind speed.

2) Correcting the NWP wind speed has played a great role in improving the accuracy of multiple sets of forecast data. The absolute root mean square error is controlled within 2.000 m/s, and the effect is significantly better than using the uncorrected NWP wind speed forecast data directly.

3) For the online model, the NWP wind speed is the input, the measured wind speed at the corresponding time is the output, and the model update frequency is 12 hours, the model correction effect is the best.

3.4 Analysis of results of online model calculation examples

When the model update frequency is 12 hours, the absolute correction effect of the model is the best, because the essence of model training is to learn the correspondence of historical data. Model prediction is to find the historical data sequence that is the same or the most similar to the current data sequence, and extract the data in its historical correspondence as the prediction result of the current data. When the model is retrained, the model update frequency is 12 hours, which means that the model is updated every half day. The model can learn the different characteristic attributes of wind speed between day and night to make the prediction results more targeted, thereby reducing the prediction error.

3.5 Model comparative analysis and conclusion

1) Comparative analysis of online model and offline model: Offline models require a large amount of historical data to train the models. These models have poor applicability to new wind farms that lack sufficient historical data, and the natural wind speed is highly random. It is difficult to directly use long-term historical measured wind speed data to modify the forecast accuracy requirements. In contrast, the online model uses the measured wind speed in a short period of time to establish a numerical weather forecast correction model and establishes a dynamic correction strategy to compensate for the insufficient data feature extraction caused by the small amount

of data, so that the model has higher accuracy and more universal.

2) Analysis of online model and offline model conclusions: This article analyzes in detail the sample data, the construction ideas and correction results of the offline LSTM model, and the construction ideas and correction results of the online LSTM model, and a detailed comparison is made. By comparing the influence of model data input and output length and model update frequency on the accuracy of model revision, the optimal modeling scheme was determined. The numerical weather forecast correction model based on deep learning algorithm uses the measured wind speed in a short period of time to establish the NWP correction model, and establishes a dynamic correction strategy to make up for the insufficient data feature extraction caused by the small amount of data. Finally, the following experimental conclusions are obtained:(1) For the input and output data length parameters of the NWP wind speed correction model: when its value is 16, the absolute and relative correction effects of the model are the best, and the corrected wind speed accuracy, that is, the average RMSE obtains the minimum value as 1.843 m/s, which is 0.643 m/s lower than the original NWP data;(2) For the update frequency parameter of the NWP wind speed correction model: when the value is 12 hours, the absolute and relative correction effects of the model are the best, and the corrected wind speed accuracy, that is, the average RMSE obtains the minimum value of 1.732 m/s, which is 0.861 m/s lower than the original NWP data.

4. CONCLUSION

This paper proposes a method of correcting the NWP forecast wind speed based on the deep neural network, the algorithm principle and model construction process of using DNN to predict and correct NWP wind speed are given. Through the analysis of calculation examples, this paper has the following main conclusions:1) When the selected model uses 6 sets of different input and output wind speed data length parameters, the corrected NWP wind speed is closer to the actual wind speed than the uncorrected NWP wind speed;2) When the selected model uses 4 sets of different update frequency parameters, compared with the uncorrected NWP wind speed, the corrected NWP wind speed is basically closer to the actual wind speed. In summary, through the related research on the short-term correction of NWP wind speed, this paper proposes a method based on deep neural network correction that can significantly improve the prediction accuracy and proposes a feasible method for further research on wind speed prediction and wind power prediction in the future.

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