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A comprehensive wind speed forecast correction strategy with an artificial intelligence algorithm

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Wind speed forecasting is critical to renewable energy generation, agriculture, and disaster prevention. Due to the uncertainty and intermittence of wind, conventional forecasting methods with numerical weather prediction (NWP) models fall short of achieving satisfactorily high accuracy. Post-processing of the predicted results is necessary for enhancing the prediction accuracy. The industry generally employs time-series prediction (TSP) methods for error correction, yet it is time-consuming since repeated modeling is needed if the location changes. Aiming at addressing this problem, this paper discusses the application of a deep learning algorithm in the post-processing period of wind speed prediction. NWP results are utilized as the forecasting basis, and deep learning algorithms are used for minimizing errors. An experimental study is conducted with industrial data. The functionality and performance of TSP-based algorithms including rolling mean, exponential smoothing, and autoregressive integrated moving average algorithms are compared with deep learning-based algorithms, including long-short term memory and convolutional neural network. From the numerical results, both TSP and deep-learning error-correction methods can effectively increase the accuracy of day-level NWP model prediction results, while deep-learning methods are data-driven, and no modeling process is needed. This work also poses an insight into the future development of wind speed prediction in meteorology.

KEYWORDS

wind speed, numerical weather prediction, forecast correction, deep learning, artificial intelligence

1 Introduction

Weather forecasting plays a profound role in daily human life as well as in economic and social activities since it is pivotal to agriculture, disaster prevention and control, power generation, etc. (Barbounis et al., 2006). As a key indicator of the weather system, wind speed forecasting has particular value to a lot of engineering applications, e.g., meaningful for wind power generation. In particular, with the development of large-scale

wind farms, more and more wind power is integrated into the power grid (Yang et al., 2014), and the accuracy of wind speed directly affects the performance of wind power scheduling. However, due to the intermittence and uncertainty of wind, the high accuracy of wind speed forecasting is a challenge.

It is known that wind speed is pertinent to numerous factors, e.g., temperature, terrain, rainfall, pressure, etc., Hu et al. (2014). Inspired by this idea, the numerical weather prediction (NWP) system is a commonly used physical model for weather forecasting and wind speed forecasting (Alexiadis et al., 1998). However, this physical model is based on a meteorological system which is huge and complex, and with an experiment overhead, it is difficult to be constructed by individuals. With this drawback, the dominant proportion of existent forecast methodologies in the literature is generally data-driven models Al-Yahyai et al. (2010). As the performance of computing devices has increased dramatically in the past decades, more advanced artificial intelligence (AI) algorithms are being applied to these data-driven models for wind speed forecasting. However, conventional data-driven methods are statistical models which can achieve good accuracy in short-term prediction but have bad performance in long-term prediction due to the error accumulation problem. Physical models, e.g., NWP, could realize the large time-scale prediction, but the forecasting results are rough and low-accurate. Combining these two methods, a useful way of improving the long-term forecasting accuracy is correction modeling which utilizes statistical models to correct the results of physical models (Voyant et al., 2012). The mechanism of error correction methodologies is usually utilizing the current weather information as the input to further correct the predicted data (Wang et al., 2019). It aims to minimize the prediction errors brought by the meteorological models.

To realize a correct model with higher accuracy in wind speed forecasting, this article proposes a kind of comprehensive correction strategy based on a deep learning algorithm. Compared with the conventional models, deep learning algorithms have a better feature representation ability to improve prediction accuracy. It provides a comprehensive model, while the customized meteorological model of the local information is not needed. It can significantly reduce the workload. This article also compares the performance of NWP models with various conventional models and deep-learning models. Experimental results show that deep learning models can significantly simplify the workflow, while the prediction accuracy is satisfied.

The layouts of the other sections are organized in the following way: Section 2 demonstrates the related work of conventional methodologies in wind speed prediction. Section 3 shows the design process of the error correction for wind speed forecasting with deep learning. A case study is given to validate the functionality of the proposed method in Section 4. Section 5 concludes the whole paper and illustrates future work.

2 Related work

To increase the accuracy of wind speed forecasting, appreciable effort from academia and industry has been dedicated to the improvement of the models. Due to the intermittency and uncertainty of wind, as reported by Li (2022a), and the observation errors of the model, the prediction inevitably introduces errors, particularly under the hourly scale.

A straightforward way to reduce forecasting errors is by improving the accuracy of the prediction model. The extensively applied methods can be categorized into two types: physical models and statistical models. Similar to NWPs, a physical model requires numerous meteorological information and a physical mechanism which makes the application and modeling complicated (Maria Grazia De Giorgi et al., 2011). As mentioned earlier, multiple physical processes such as aerodynamics, thermodynamics, and hydromechanics are involved. Thus, the physical model of the meteorological system is generally complicated (Maria Grazia De Giorgi et al., 2011). Statistical models require historical data such as wind speed and time stamps to conduct the forecasting. A classical method is the persistence method which utilizes the latest measured wind speed value as the forecast basis of the next point (Buhan et al., 2016). Its major advantage is the straightforward working principle and low-computational overhead which enable it to be easy-implemented. Li (2022a) also built the model for the wind turbine generator for wind power generation forecast error correction. Various statistical learning algorithms are also applied in the wind speed forecasting industry, e.g., the autoregressive moving average (ARMA) model (Ergin Erdem, 2011) invented in the 1980s, the artificial neural network (ANN) (Li and Shi, 2010), support vector machine (SVM) (Ren et al., 2014), etc. Moreover, some hybrid methods combining several statistical learning algorithms are also proposed. Additionally, the physical model and data-driven model can also be blended to increase the accuracy of the prediction, as demonstrated in Nielsen et al. (2007).

Lima et al. (2020) compare the historical solar data with NWP model predicted results in Brazil, and they claim the predicted results have notable differences from the local data. Thus, due to prediction error existing in all forecasting methods, post-processing methods seem to be essential to correct the forecasting error. Vogelzang and Stoffelen (2011) proposed NWP model error structure functions with the scatterometer winds. Synthetic and model prediction methods are adopted. As a mighty tool for error correction, Kalman filtering has been employed in wind prediction (Wang et al., 2021; Vogelzang and Stoffelen, 2011). The machine learning technology has superiorities in regard to self-adaptive and data-driven features which enable it to be extensively applied for data post-processing of NWP. Li et al. (2021) utilized bilinear transformation and the ICEEMDAN framework for short-

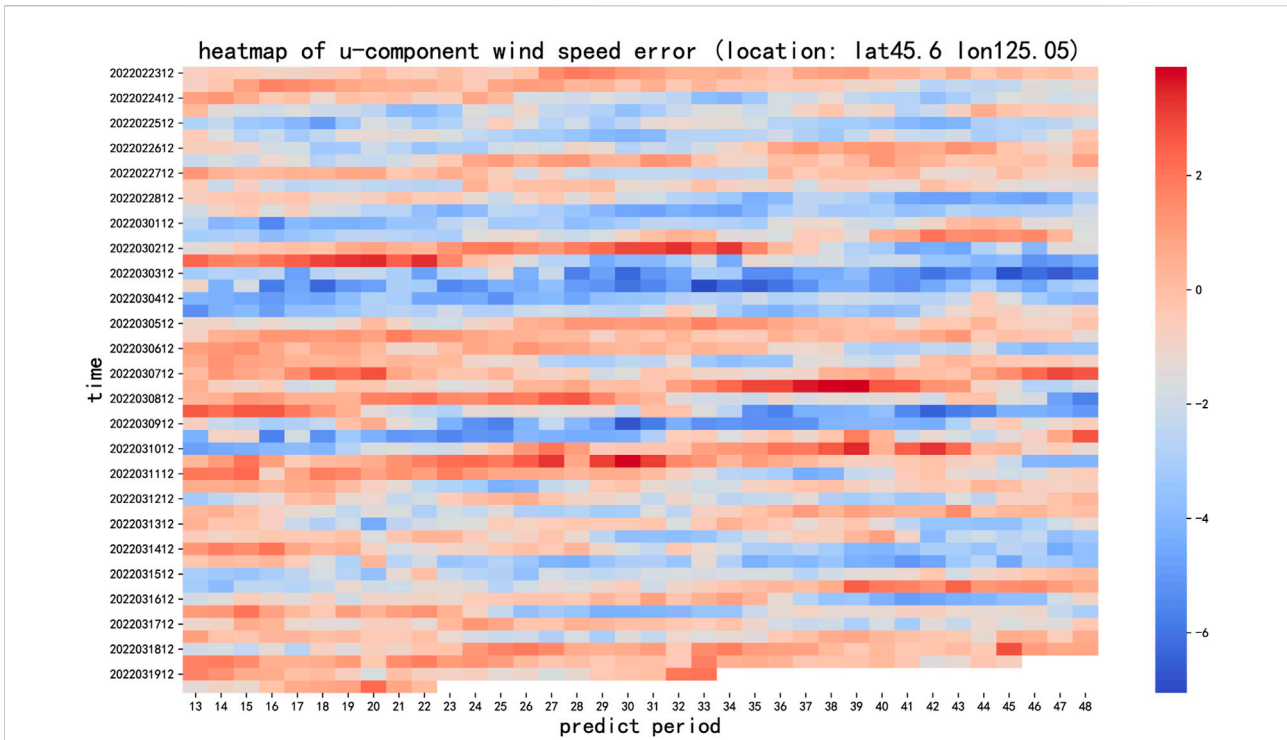


FIGURE 1
NWP prediction error of one location.

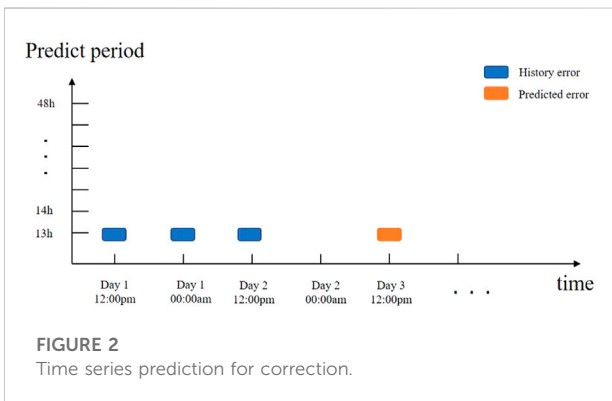


FIGURE 2
Time series prediction for correction.

term wind power prediction, while spatial-temporal analysis is applied in Li (2022b).

In Sweeney et al. (2013), different combined methods for wind speed forecasting were compared for error minimization. Zjavka (2015) proposed polynomial neural networks for on-line wind speed forecast correction. The multi-site model experimental study was conducted to validate the functionality of the proposed method. Jiang and Huang (2017) utilized hybrid methods of SVM and generalized the auto-regressive conditionally heteroscedastic model to correct the prediction error. Both the accuracy and

stability of the model were satisfied. Du (2019) employed an ensemble-based method that incorporates three machine learning algorithms for NWP prediction result correction. By combining the three predicted results, it can enhance the prediction accuracy. Hossain and Mahmood (2020) used a long short-term memory model for minute-level solar energy forecasting, while Yang et al. (2014) used deep learning methods for day-ahead hour-level forecasting. Tang et al. (2022) used two shallow machine learning algorithms for medium- and long-term weather forecasting. Intelligent techniques are also employed for the underground projects of the Rockburst Hazard in Ahmad et al. (2021b) and Ahmad et al. (2022) and shallow foundation on cohesion-less soils in Ahmad et al. (2021a).

3 Materials and methods

3.1 Forecasting setup

The prediction process is defined as $\bar{v} = f(\cdot)$, where \bar{v} is the predicted 10 m wind speed, and $f(\cdot)$ is the NWP model. The NWP models contain errors due in part to the quality of the data used to drive the model and in part to computational limitations. Some errors are systematic, and it is desired to be reduced by applying statistical post-processing methods.

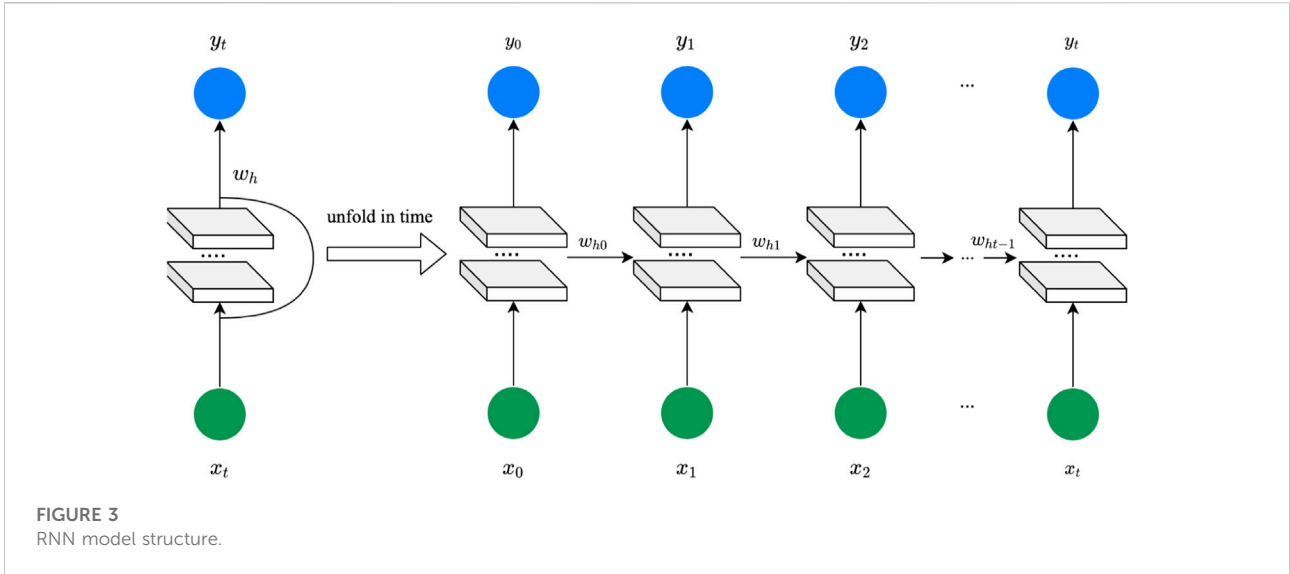


FIGURE 3 RNN model structure.

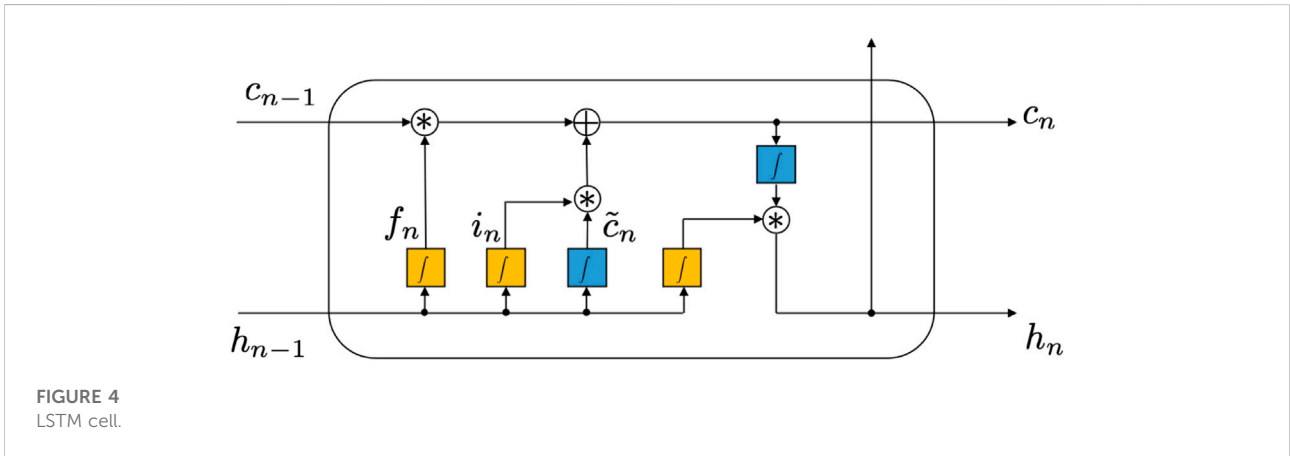


FIGURE 4 LSTM cell.

The current NWP model predicts 10 m wind speed data for every 12 h over a 13–48 h period. In addition, the real measurements are collected hourly; thus, the prediction error e_t can be calculated, as given in Eq. 1, when the real measurements are collected.

$$e_t = v_t - \bar{v}_t, \tag{1}$$

where \bar{v}_t is the NWP wind speed at time t ; v_t is the measured 10 min wind speed at time t . Figure 1 shows the heat map plot of prediction errors of one location.

3.2 Time series-based algorithms

Time-series prediction (TSP) algorithms predict the future value over a period of time by developing models based on previous data and applying them to conduct prediction. The future is estimated

based on what has already happened. Following the principle of TSP, the historical errors are learned and modeled to predict the future error, as shown in Figure 2. Once the error is predicted, the NWP wind speed can be corrected easily by just adding the predicted error. This process is expressed by Eq. 2 and Eq. 3:

$$\hat{e}_t = f_{tsp}(e_{t-1}, e_{t-2}, \dots), \tag{2}$$

$$\hat{v}_t = \bar{v}_t + \hat{e}_t, \tag{3}$$

where \hat{e}_t is the predicted error at time t and \hat{v}_t is the corrected NWP wind speed.

3.3 Deep learning-based algorithms

TSP-based algorithms only leverage historical error information, yet other features such as temperature and air pressure, are generally neglected. Moreover, for different

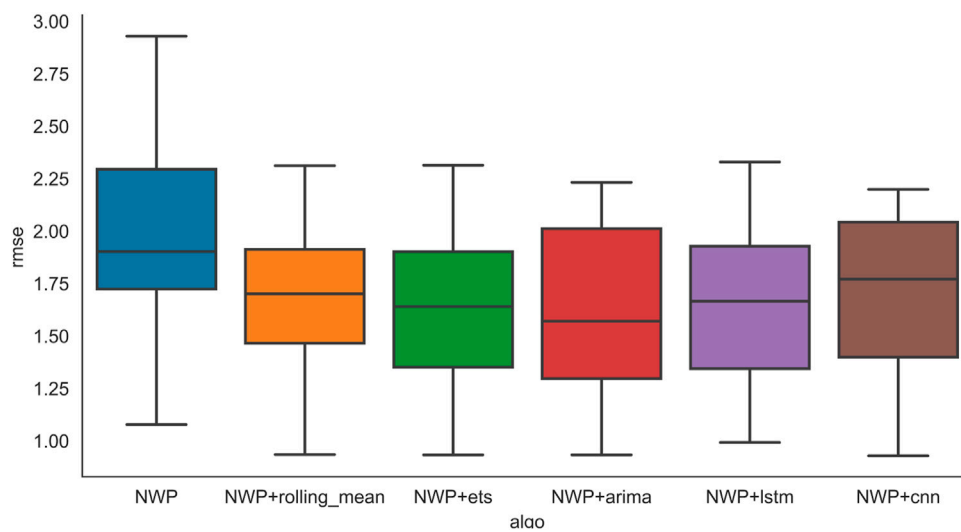


FIGURE 5
Overall rmse results based on the location.

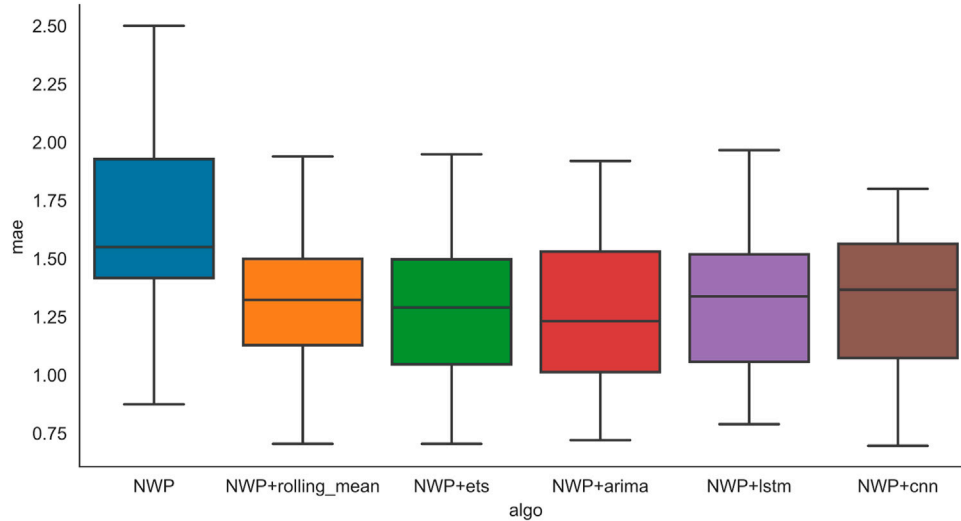


FIGURE 6
Overall mae results based on the location.

locations and predicted periods, TSP-based algorithms need to be modeled separately. In other words, for an NWP system monitoring 50 locations over 13–48 h periods, 1800 models are needed separately in terms of learning parameters and prediction. The modeling process is time-consuming.

To generalize the application scenarios of the forecasting model, in this paper, deep learning algorithms are utilized since they are able to automatically learn arbitrary complex

mappings from inputs to outputs, which have been widely used in time series prediction tasks recently. Deep learning-based time series prediction algorithms are able to take location patterns and prediction periods into consideration and thus can train a generalized model with location patterns and prediction periods as input features. For the sake of simplicity, deep learning-based TSP algorithms are verified to pose an optimal balance among multiple parallel prediction

tasks such as wind speed prediction for various locations and prediction periods.

3.3.1 Recurrent neural networks

Recurrent neural networks (RNNs) are appropriate for modeling time series data with the recurrent structure which uses neural networks to model the functional relationship between input features in the recent past to a target variable in the future. Figure 3 shows the structure of the RNN in which the transition of a hidden state from consecutive time slots is learnt from historical data. Specifically, the prediction of the output y_t depends not only on the input x_t but also on the hidden state w_{ht} , as shown in Eq. 4. w_{ht} plays the role of memorizing the previous information by weighting the previous output y_{t-1} . However, RNNs have the disadvantage of vanishing gradients due to the weight matrix multiplication at each time step. Thus, the RNN is not good at capturing non-stationary dependencies that occur over a long period of time.

$$y_t = f(x_t, w_{ht}). \tag{4}$$

3.3.2 Long short-term memory model

The long short-term memory (LSTM) model is a variant of the RNN first, as proposed by Zjavka (2015), to overcome the gradient vanishing problem in the vanilla RNN. Figure 4 shows the structure of an LSTM cell in which a cell state c and three gates are imported to enable the storage and access of information over long periods of time. Gates are composed of a sigmoid neural net layer and a point-wise multiplication operation which are able to optionally let information through. First, the input gate weighs the current input x_t and previous output h_{t-1} , as shown in the following:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{5}$$

where W_i and b_i are the weight matrix and the bias vector of the input gate, respectively. The output of the input gate controls the selection of information in the cell state.

$$\tilde{c}_t := \tanh(W_c \cdot [h_{t-1}, x_t] + b_c), \tag{6}$$

where W_c and b_c are the weight matrix and bias vector of the input layer, respectively. Therefore, the selected information can be represented by $c_t^i := i_t \odot \tilde{c}_t$.

Similarly, the forget gate controls the selection of information that should be dropped:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), c_t^f = f_t \odot c_{t-1}, \tag{7}$$

where W_f and b_f are the weight matrix and bias vector of the forget gate, respectively. Then, the new cell state is as follows:

$$c_t = c_t^i + c_t^f. \tag{8}$$

The output gate decides which part of information should be the output, i.e.,

$$o_n = \sigma(W_o \cdot [h_{n-1}, x_n] + b_o), h_n = o_n \odot \tanh(c_n), \tag{9}$$

where W_o and b_o are the weight matrix and bias vector of the forget gate, respectively.

4 Experimental study

In this section, the actual weather forecast data are utilized to evaluate the time series and deep learning-based strategies. The historical NWP output data are produced by Weather Research and Forecasting (WRF)-3.5 adopted by the Inner Mongolia Meteorology Bureau as one of their bases to deliver daily weather forecasts of that region. The WRF-out data are generated every 12 h (at 00:00 UTC and 12:00 UTC) from June 2019 to March 2022, containing predictions in advance of 12 h extending to 96 h with an interval of 1 h. The corresponding ground truth data are acquired from the China land surface data assimilation system, 2rd version (CLDAS-V2.0), which provide near-real-time reanalysis field data via integrating information from land surface stations, radars, and remote sensing of satellites.

The following experiments are implemented on a Linux PC with AMD Ryzen 5 3550H, 2.1 GHz CPU, 16 GB of RAM, and Python 3.8 with TensorFlow 2.8.0.

4.1 Empirical evaluation

To verify the superiority of the proposed correction strategy, the original NWP wind speed error and corrected wind speed error are compared. For the TSP-based algorithms, the training data are the past original NWP wind speed errors for a specific location and a specific prediction period. In contrast, for the deep-learning-based algorithms, the past original NWP wind speed errors for all locations and all predicted periods are used to train a general model. The input is features that are created from the historical NWP wind speed errors and additional related information.

4.1.1 Location-based evaluation

For the purpose of evaluating the correction and predicting the performance of the proposed strategy over all locations, the root mean square error (rmse) and the mean absolute error (mae) are used as the performance criteria. Obviously, the smaller the value, the better the performance of the proposed model is.

$$rmse_{loc} = \sqrt{\frac{\sum_T \sum_N (v_t^n - \hat{v}_t^n)^2}{T * N}}, \tag{10}$$

where $t \in \mathcal{N}^T$ is the time slot for making prediction, and $n \in \mathcal{N}^N$ is the prediction period. Thus, $rmse_{loc}$ evaluates the overall prediction performance for location **loc**. Similarly,

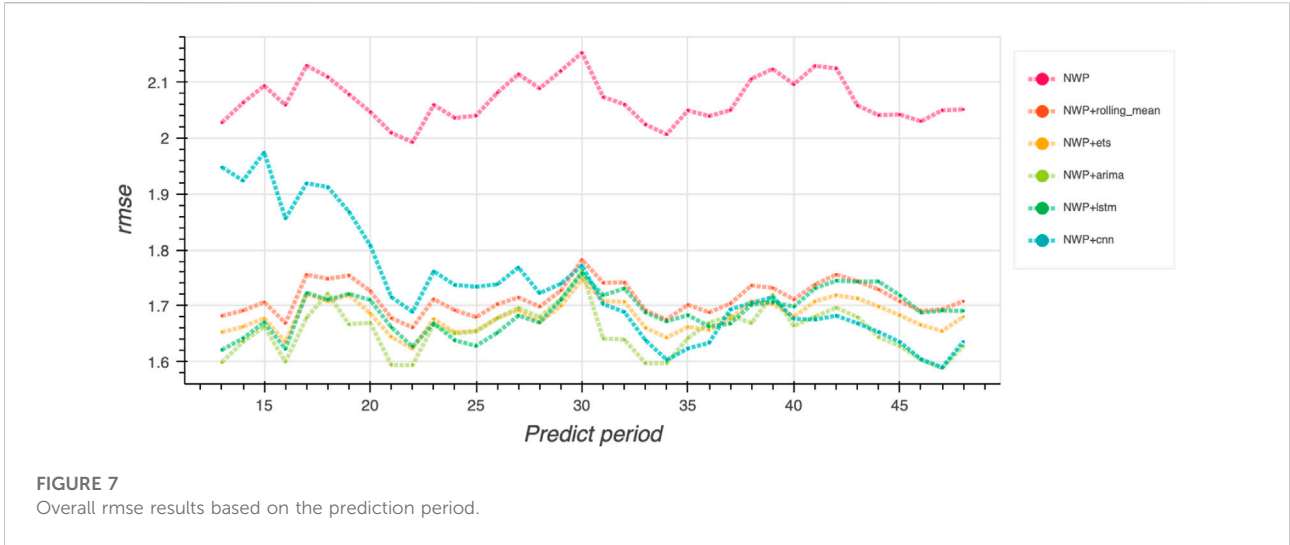


FIGURE 7
Overall rmse results based on the prediction period.

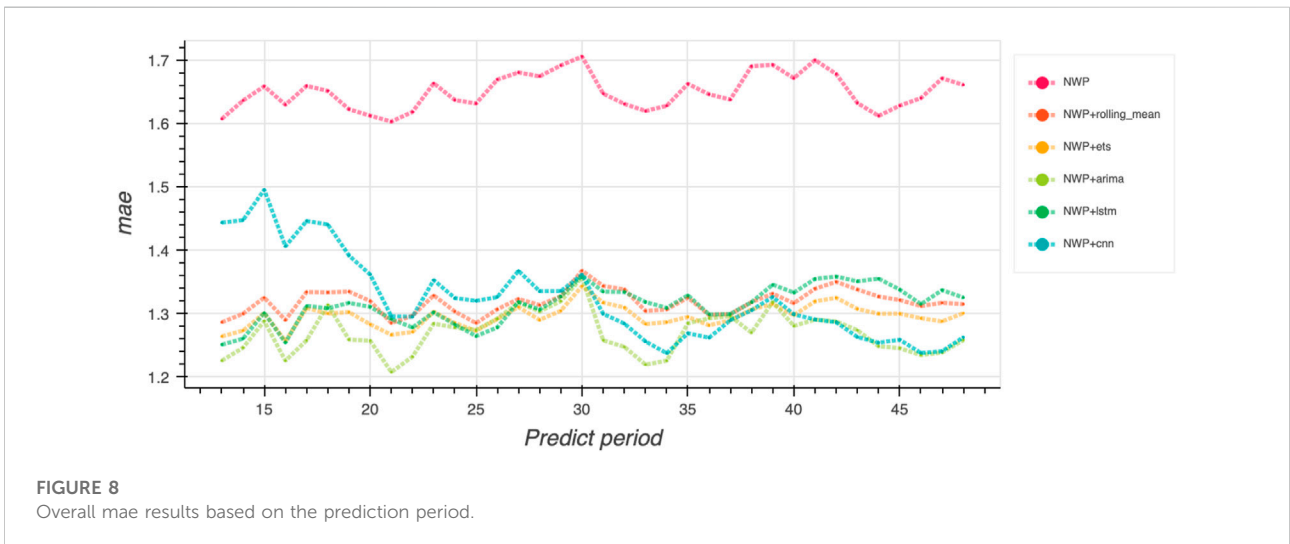
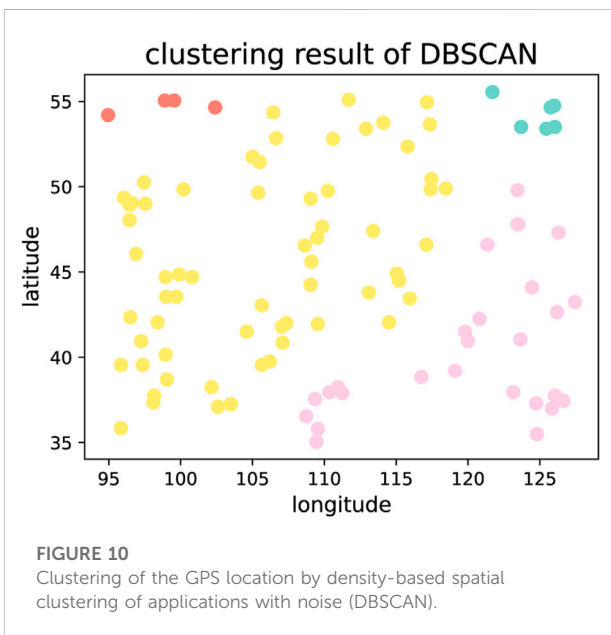
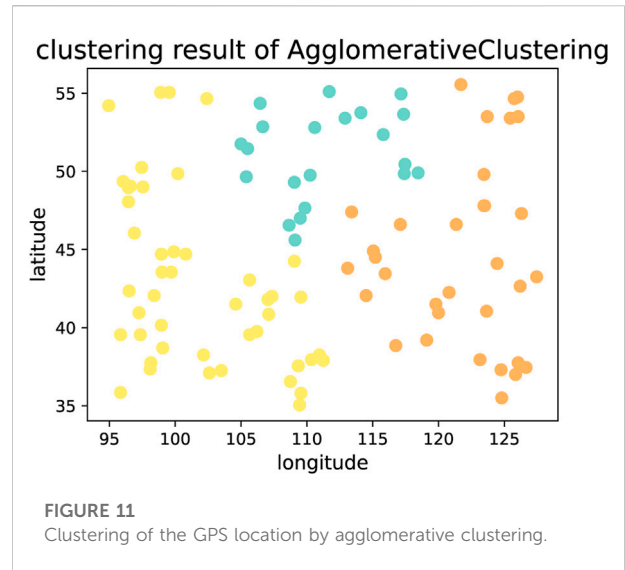
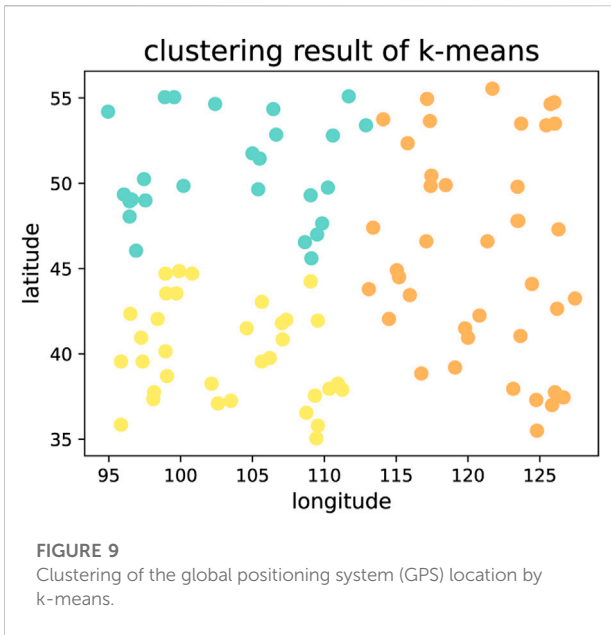


FIGURE 8
Overall mae results based on the prediction period.

$$\mathbf{mae}_{loc} = \frac{\sum_T \sum_N |v_t^N - \hat{v}_t^N|}{T * N} \quad (11)$$

The overall forecasting performance is evaluated in Figure 5 and Figure 6. The boxplot is used to compare the overall performance based on locations. The curve of NWP, i.e., the blue one on the left, shows the predicted results without correction. Rolling mean, ETS, and ARIMA denote the predicted results of the NWP model with conventional data correction models, while LSTM and CNN are the predicted results corrected with deep learning algorithms. From the result, without forecast correction, the rmse and mae are apparently higher than those with correction. Both TSP-based algorithms and deep-learning-based forecast correction

algorithms are able to reduce the prediction error. Specifically, rolling mean methods and LSTM show the best comprehensive performance. Thus, forecast correction is necessary since it can significantly increase the prediction accuracy. However, as demonstrated earlier, the rolling mean, exponential smoothing (ETS), and autoregressive integrated moving average (ARIMA) methods all need to build the local NWP model. This means the model is no longer applicable if the location changes. The deep learning model does not need to be trained repeatedly by location patterns and predicted period data which enables it to be more universal. Also, Figure 5 and Figure 6 show that the CNN algorithm has a reduced upper limit and lower limit of RMSE over the LSTM algorithm, but the



LSTM algorithm has a lower average RMSE. Reliability has the highest priority in terms of weather forecasting. Therefore, LSTM is still the most recommended algorithm for NWP forecast correction.

4.1.2 Prediction period-based evaluation

Similarly, rmse and mae for different prediction periods are also learnt to evaluate the correction and predicting the performance of the proposed strategies.

$$\text{rmse}_n = \sqrt{\frac{\sum_T \sum_L (v_{t,l} - \hat{v}_{t,l})^2}{T * L}}, \quad (12)$$

$$\text{rmse}_n = \frac{\sum_T \sum_L |v_{t,l} - \hat{v}_{t,l}|}{T * L}, \quad (13)$$

where $l \in \mathcal{N}^L$ is the location set. Thus, rmse_n and mae_n represent the overall predicting performance at the prediction period n .

To validate the application of the aforementioned algorithm in the short-term weather forecast, the predicted results over 48 h are plotted, as shown in Figures 7, 8. From the plots, without forecast correction, the rmse_n is 2.05 and the mae_n is 1.65. With forecast correction, the rmse_n is reduced to be lower than 1.7 and the mae_n is reduced to be lower than 1.4. It should be noted that the error of the CNN algorithm is high in the first 20 h and then falls down and stays stable in the following period. The NWP with the LSTM forecast correction model shows superior comprehensive performance over the other algorithms.

4.1.3 Clustering method-based evaluation

Different locations have different geographical features, i.e., some locations are on the highland, while some may be near the waters. Instead of treating them equally, clustering them into different groups may enhance the model representation ability. To verify this, three clustering methods based on the global position system (GPS) data are used to take advantage of the geographical information. The clustering results are further input to the LSTM model as additional features. Figure 9, Figure 10 and Figure 11 show the clustering of GPS data by different algorithms, where the locations are categorized into different groups.

The comparison results are shown in Figure 12 and Figure 13. From the plots, all the clustering methods can further reduce the rmse and mae. Among these clustering

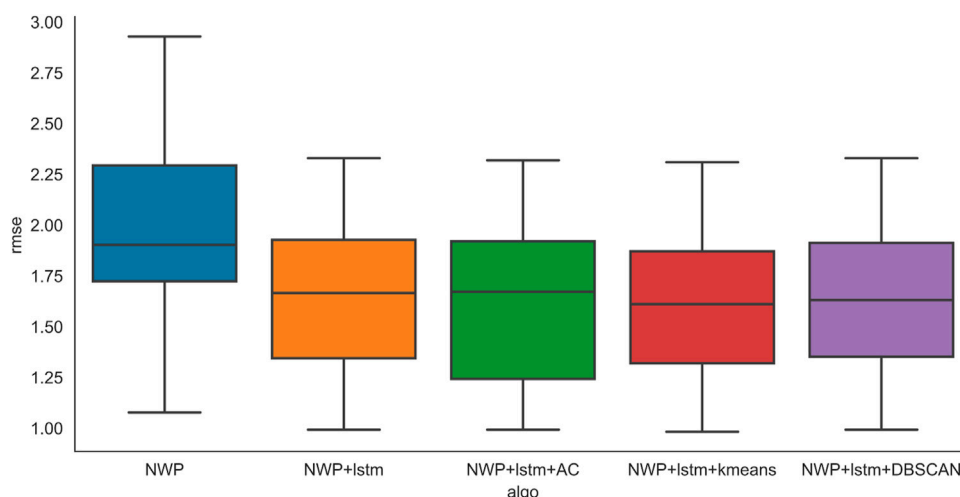


FIGURE 12
Overall rmse results for different clustering methods based on the location.

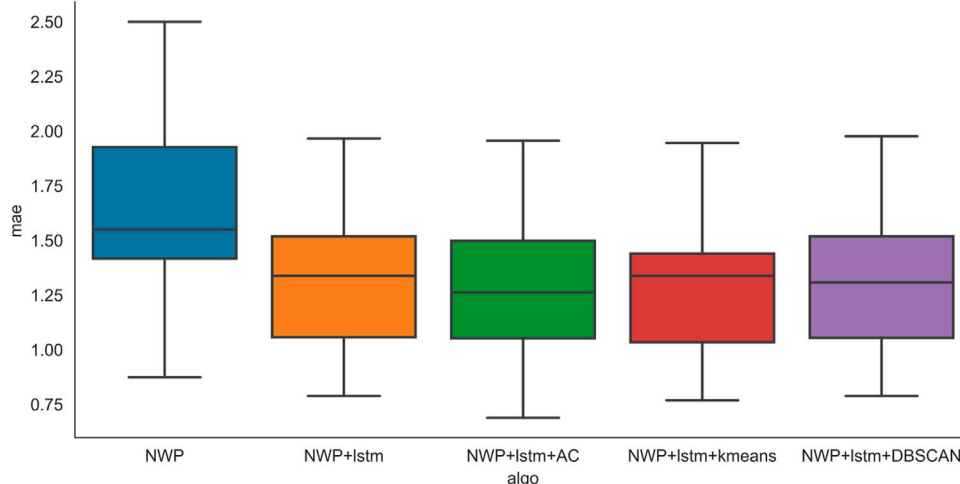


FIGURE 13
Overall mae results for different clustering methods based on the location.

methods, agglomerative clustering has the best performance on reducing the rmse, while k means showed a better effect than others in terms of the mae.

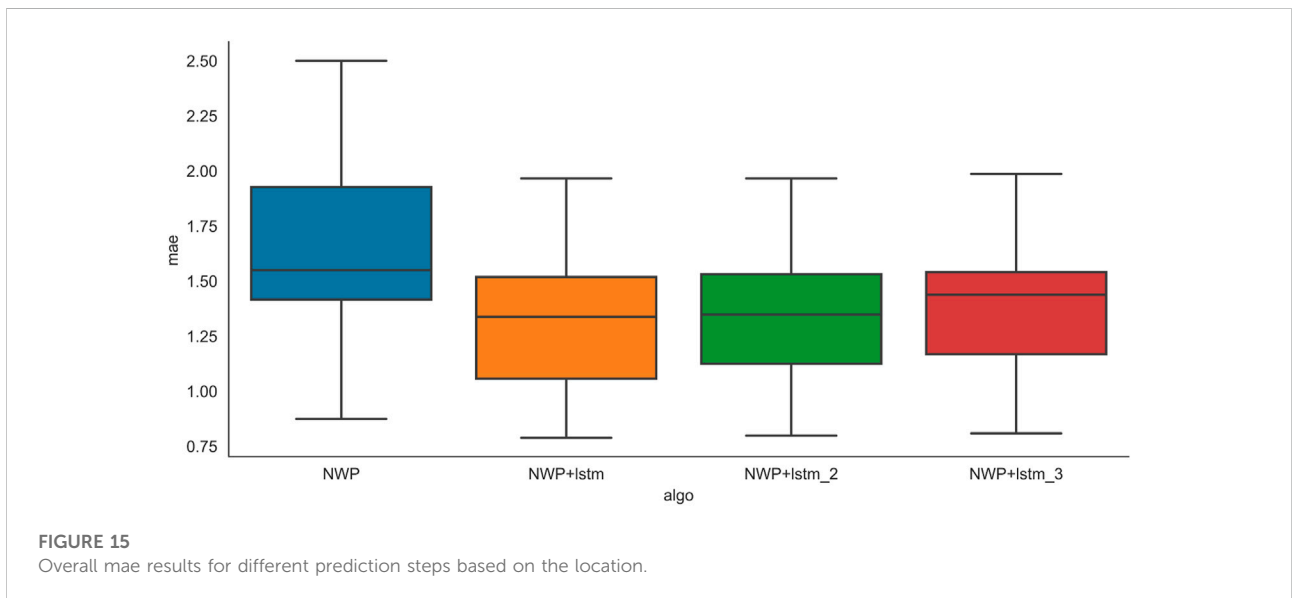
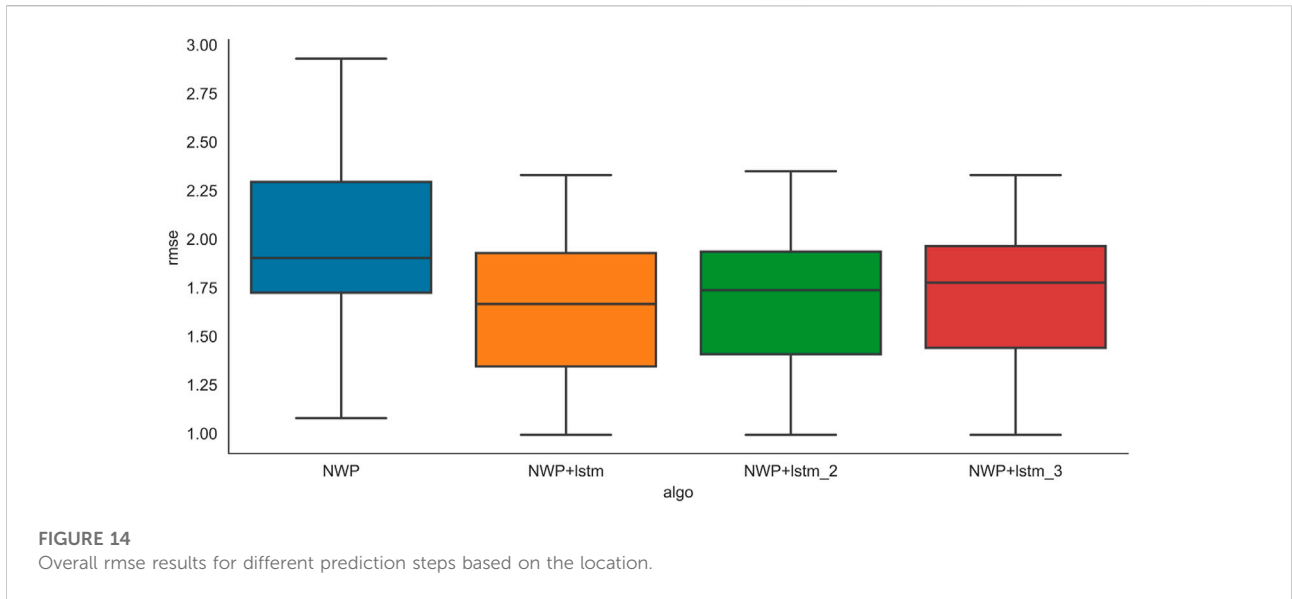
4.1.4 Multi-step prediction evaluation

Previously, all results are one-step predictions, where historical data are used to predict the next time slot. In this subsection, multi-step prediction performance is learned. Figure 14 and Figure 15 show the rmse and mae results of the different step prediction performances, respectively. From the

results, the predicting performance drops slightly as the prediction step increases.

5 Discussion

With the rapidly increasing demand for wind energy, the fluctuation and intermittence pose challenges to power dispatch. Thus, it is desired to have an accurate prediction of the wind speed. From the experimental results presented in Section 4, the NWP



model shows considerable prediction errors, and this is also reported by Lima et al. (2020). Therefore, forecasting correction is necessary. In industry applications, how to minimize prediction error is still a major challenge. This study presents the application of deep learning algorithms on the forecasting correction for the NWP prediction results. Several conventional methodologies including rolling mean, ETS, and ARIMA are compared with deep learning methodologies such as LSTM and CNN. Both methodologies show superiority in terms of prediction accuracy enhancement. Based on the analysis demonstrated in this article, the accuracy of the wind speed prediction can be enhanced from the following perspectives.

5.1 Improved NWP model

Wind speed is an important output of the NWP model, which is utilized to describe meteorological evolution. Its accuracy can significantly increase prediction accuracy. The modeling of the local information is comprehensive progress. Generally, the accuracy of the model is impacted by multiple factors, such as the time step. However, with higher resolution, the computational load increases dramatically. Thus, the NWP model should consider the tradeoff between the computational load and accuracy.

5.2 Application of the deep learning-based error correction algorithm

From the analysis of this paper, both TSP-based and deep-learning-based error correction algorithms can effectively reduce prediction error. The experimental study shows that both methodologies can realize the same effect in terms of prediction error minimization. TSP algorithms are generally easier to be implemented when the computational load is lower. However, repeated modeling is needed if the location information changes. Also, the selection of the TSP algorithm can have a great impact on the prediction. Hence, the TSP algorithm should be estimated prior to using it.

The deep learning algorithm is data-driven, and it just needs the local weather information to train the algorithm. It can save time in mathematical modeling. Therefore, the penetration of deep learning-based methods is increasing in the industry. The experimental study is conducted to compare the accuracy of the proposed method with ARIMA, ETS, and LSTM. LSTM shows the best overall performance among the listed methods. It should be noted that clustering does not show critical improvement to prediction accuracy. However, it can increase the computational speed, which makes it still necessary.

Data availability statement

The data analyzed in this study are subject to the following licenses/restrictions: confidential meteorological data which are not published. Requests to access these datasets should be directed to sunqilong@cgjt.ac.cn.

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Author contributions

XZ proposed the idea and finished this article. QS provided the original data for the experimental study and wrote the code of the algorithms. WT, SY, and BW assisted in deep learning algorithm training and running the algorithm.

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Conflict of interest

Authors WT, SY, and BW are employed by China Merchants Fintech Company Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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