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Short-term wind power combination forecasting method based on wind speed correction of numerical weather prediction

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The temporal variation of wind power is primarily influenced by wind speed, exhibiting high levels of randomness and fluctuation. The accuracy of short-term wind power forecasts is greatly affected by the quality of Numerical Weather Prediction (NWP) data. However, the prediction error of NWP is common, and posing challenges to the precision of wind power prediction. To address this issue, the paper proposes a NWP wind speed error correction model based on Residual Network-Gated Recurrent Unit (ResNet-GRU). The model corrects the forecasted wind speeds at different heights to provide reliable data foundation for subsequent predictions. Furthermore, in order to overcome the difficulty of selecting network parameters for the combined prediction model, we integrate the Kepler Optimization Algorithm (KOA) intelligent algorithm to achieve optimal parameter selection for the model. We propose a Convolutional Neural Network-Long and Short-Term Memory Network (CNN-LSTM) based on Attention Mechanism for short-term wind power prediction. Finally, the proposed methods are validated using data from a wind farm in northwest China, demonstrating their effectiveness in improving prediction accuracy and their practical value in engineering applications.

KEYWORDS

short-term wind power prediction, ResNet-GRU, wind speed correction, CNN-LSTM-attention, kepler optimization algorithm(KOA)

1 Introduction

In the context of "dual carbon" goals, accelerating the transformation of the energy structure towards a low-carbon, clean, and renewable energy system, with a focus on new energy sources, is an important initiative to achieve the dual carbon targets (REN et al., 2022). Currently, China's wind power industry is experiencing rapid development, with a continuously thriving market and increasing wind power grid integration (Hui et al., 2021). However, the current power system scheduling and operation mechanisms in China are not sound, and there is insufficient peak-shifting capacity to meet the requirements of large-scale wind power grid integration, leading to significant curtailment of wind power in some regions. To effectively address wind curtailment and improve the scheduling and operation capabilities of the power system, precise wind power output forecasting is essential. The accuracy of wind power forecasting directly affects the scheduling optimization of the power grid (Yusheng et al., 2015; Weisheng et al., 2021).

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Currently, wind power forecasting techniques can be broadly classified into two categories based on modeling mechanisms: physical methods and statistical learning methods (Ahmed and Khalid, 2019; Wang et al., 2021). Physical methods utilize fluid dynamics and thermodynamics models to solve for wind speed, wind direction, and other information based on the topography and terrain of the wind farm. The wind power output is then calculated using the wind power curve. Due to limitations in spatiotemporal resolution, physical methods are generally more suitable for medium to long-term forecasting. On the other hand, statistical learning methods analyze historical data from wind farms to establish nonlinear mappings between wind power characteristics and forecast results. With the rapid development of artificial intelligence in recent years, many researchers have introduced deep learning algorithms to address the aforementioned issues (Anbo et al., 2022). Deep learning methods, such as LSTM (Zhu et al., 2017), backpropagation (Liu et al., 2020), Dropout (Niu et al., 2018), Attention Mechanism (AM) (Zhou et al., 2021), and others, have been widely applied in forecasting tasks, benefiting from the increased availability and complexity of collected data.

In short-term wind power forecasting, utilizing NWP for wind power prediction is more realistic and practical (DU, 2019). However, the quality of NWP data significantly impacts the accuracy of the forecasts, and it has been observed that there are inherent errors between NWP data and actual measurements. To mitigate these inherent errors, numerous researchers have focused on correcting NWP wind speed. In reference (Ding et al., 2019), a variational mode decomposition technique was used to decompose NWP wind speed, followed by correction using the GRU. Reference (Hu et al., 2021) considered the spatial correlation of wind speed and employed Gaussian Process Regression (GPR) to improve the correlation between forecasted and actual wind speeds. Reference (Song et al., 2018) analyzed NWP data from multiple locations and established a wind speed correction model using temporal convolutional neural networks, which enhanced the accuracy of wind speed correction. However, most of the mentioned correction methods rely on a single neural network, and the exploration of the relationship between NWP data and actual measurements is not fully comprehensive. Additionally, these models are prone to issues such as gradient explosion during the training process.

Due to the limited predictive capability of a single model, it often results in low robustness and weak applicability. Therefore, the combination prediction model has gradually demonstrated its advantages. However, although the combination model integrates the advantages of individual models, it can also increase the complexity of the model. The complex network structure of the combination model leads to increased uncertainty and difficulty in selecting prediction model parameters. Hence, many scholars have made improvements by combining a series of optimization algorithms. In reference (Li et al., 2022), the Isolation Forest Algorithm (IAO) was used to detect abnormal data, and the improved Eagle Optimization Algorithm (EOA) was employed to optimize the parameters of the LSTM model, thereby establishing the IAO-LSTM model for wind power prediction. In reference (Guangzheng et al., 2022a), the Improved Grey Wolf Optimization (IGWO) algorithm was utilized to determine the number of hidden layer nodes and the learning rate of the model's weight, proposing a LightGBM-GRU point prediction model that achieved better predictive performance compared to other algorithms. However, the aforementioned optimization algorithms have complex structures, slow convergence speeds, and are prone to getting trapped in local optimal solutions. Therefore, it is necessary to select more suitable intelligent algorithms, especially for cases with multiple hyperparameters to be optimized.

To address the aforementioned limitations, this paper proposes a NWP wind speed error correction model based on a combination of ResNet and GRU models. It corrects the multi-height forecasted wind speeds of NWP prediction points to accurately reflect the wind speed at hub height, which characterizes the wind farm power output more precisely. Finally, by combining the corrected NWP wind speeds with real-time wind farm power output data, a KOA-CNN-LSTM-Attention combination prediction model is constructed, which incorporates the KOA intelligent optimization algorithm. Experimental results demonstrate that the proposed method significantly improves the prediction accuracy compared to existing methods, providing new insights for enhancing the accuracy of short-term wind power prediction.

2 NWP wind speed correction method

2.1 Wind speed error analysis

NWP is a method of predicting future weather conditions by solving fluid mechanics and thermodynamics equations that describe the process of weather evolution based on certain boundary and initial conditions (Guangzheng et al., 2024). However, the spatial and temporal resolution of NWP data, geographic location, terrain, and other factors may result in deviations between NWP data and the measured data at wind farm sites. Short-term wind power prediction models are established based on NWP data and measured operational data at wind farms, but errors in NWP wind speed can greatly affect the accuracy of short-term wind power predictions (Miao et al., 2022).

The distribution and error curves of NWP wind speed and measured wind speed are compared in Figure 1, which shows that both NWP wind speed and actual wind speed follow a two-parameter Weibull distribution mainly in the wind speed range of 3–15 m/s. However, compared with measured wind speed, NWP wind speed has fewer subdivisions in the main wind speed range, indicating that measured wind speed fluctuates more frequently in this wind speed range, while the overall fluctuation of predicted wind speed is lower. The error between NWP wind speed and measured wind speed can be divided into longitudinal error and lateral error. The longitudinal error mainly manifests as amplitude differences between NWP wind speed and measured wind speed, as shown in Figure 1C. The lateral error mainly manifests as phase delay between NWP wind speed and measured wind speed, as shown in Figure 1D. Moreover, the error between NWP forecasted wind speed and measured wind speed at wind farms varies dynamically in different seasons, including different directions and step sizes of delays, differences in amplitude, and varying degrees of missed and false forecasting information for wind energy fluctuations.

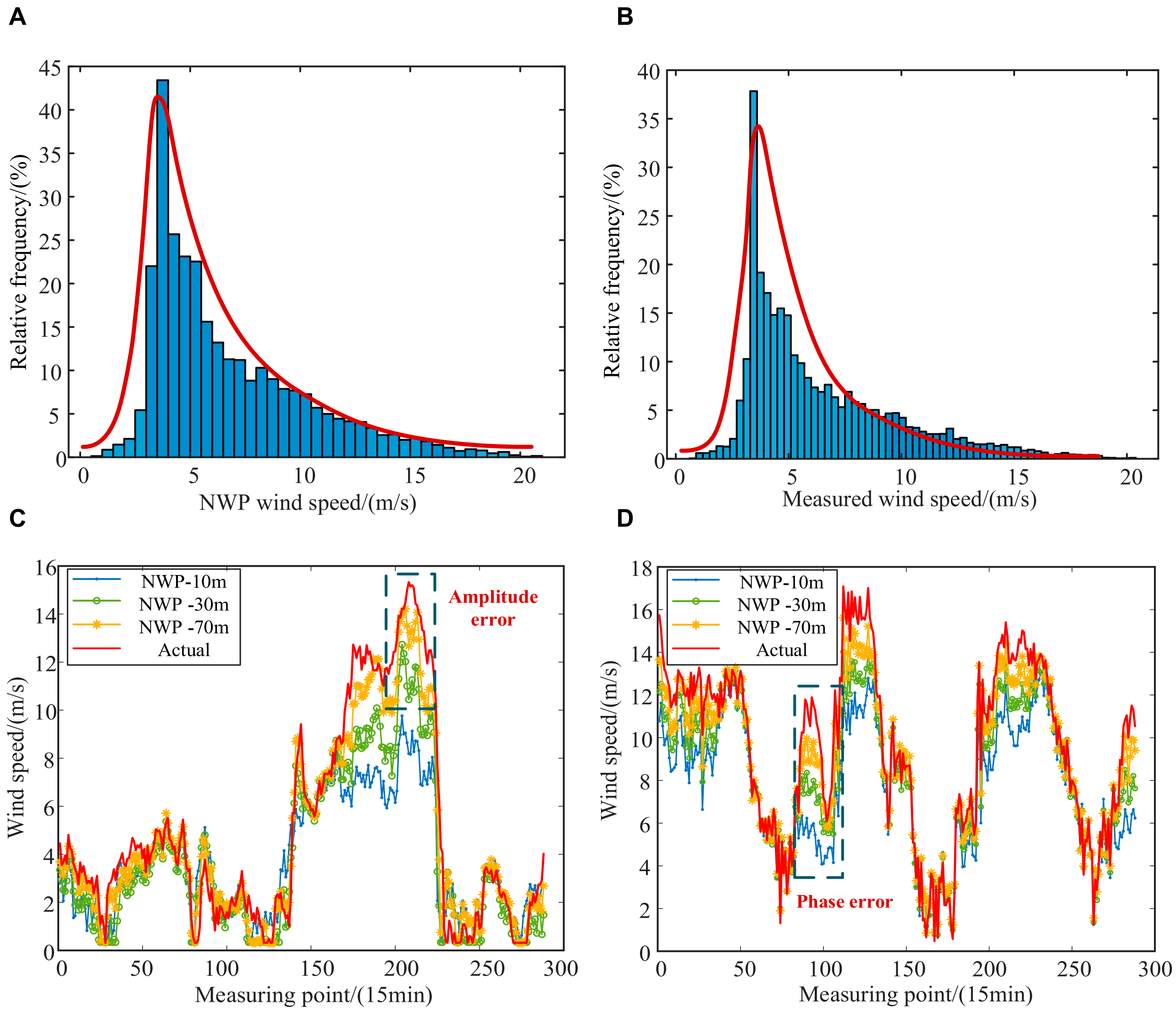

FIGURE 1
Error analysis of wind speed. **(A,B)** are the wind speed distribution map. **(A)**: NWP wind speed distribution, **(B)**: Measured wind velocity distribution. **(C,D)** are the analysis of wind speed error. **(C)**: Error analysis of NWP Wind Speed and Measured Wind Speed (winter), **(D)**: Error analysis of NWP Wind Speed and Measured Wind Speed (summer).

2.2 Wind speed correction model of ResNet-GRU

Due to the significant fluctuations in measured wind speeds, this study aims to leverage the ResNet module's powerful feature extraction capabilities to uncover the periodicity and temporal relationships within the historical wind speed sequences. The ResNet module, known for its deep residual structure, effectively addresses the issues of gradient vanishing and explosion in deep neural networks, thereby enhancing feature extraction capabilities (Yldz et al., 2021). Moreover, the ResNet module mitigates information loss and facilitates smooth information flow through the use of shortcut connections. To capture the volatility of wind speed, the GRU model is employed as the learning model. The GRU model, equipped with gate mechanisms, effectively addresses the long-term dependency problem while avoiding the issues of gradient vanishing and explosion present in traditional Recurrent Neural Network (RNN) models (Yu et al., 2023). Consequently, the GRU model demonstrates excellent performance in time-series data modeling tasks. Therefore, this study proposes the ResNet-GRU wind speed correction model, which not only effectively learns and utilizes the relationship between NWP model and measured data but also predicts more accurate wind speeds. Additionally, both the ResNet module and GRU model have been optimized classic models, requiring fewer computational resources and less time compared to other complex models during training and prediction, thus demonstrating characteristics of computational efficiency. The schematic diagram of the proposed model is presented in Figure 2.

In this study, the fully connected layer following the time-series modeling layer is utilized for wind speed correction. The

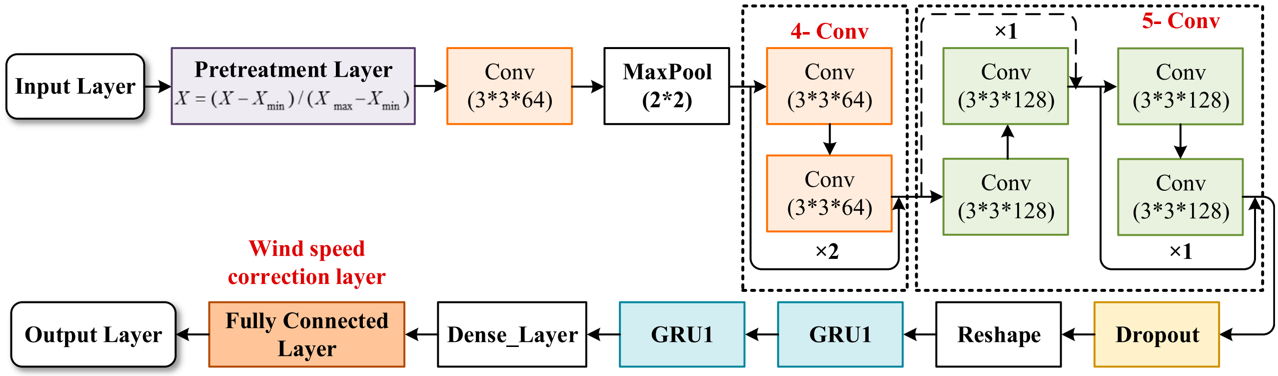

FIGURE 2
Wind speed correction schematic diagram based on ResNet-GRU model.

known actual wind speed data and the output of the numerical model are employed as supervisory signals to optimize the model parameters by minimizing the error between the predicted and actual values. The Mean Squared Error (MSE) is adopted as the loss function for this purpose. The formula for MSE is as follows:

$$J(\theta) = \frac{1}{2m}\sum\nolimits_{i=1}^{m} \left(h_\theta(x^i) - y^i\right)^2 \tag{1}$$

where, $h_\theta(x^i)$ represents the model for the i th input sample x^i, y^i represents the corresponding real output value, θ represents the parameters to be learned in the model,m is ample size。

3 KOA-CNN-LSTM-attention combined prediction model

3.1 CNN-LSTM-attention prediction model

The CNN-LSTM hybrid model is designed to handle time-series matrices composed of relatively independent feature sequences. It effectively utilizes CNN to extract spatially local correlated features from the data, while LSTM compensates for CNN's limitation in capturing long-term dependencies within sequential data (Guangzheng et al., 2021). Since the features used for wind power prediction (such as wind speed, wind direction, temperature, precipitation, and air pressure) are relatively independent time-series features, it becomes challenging to describe the inherent relationships between these features over time. Using either CNN or LSTM alone fails to simultaneously extract the inter-sequence correlations and long-term patterns in feature time-series. Traditional CNN-LSTM networks simply concatenate the CNN and LSTM components, which may disrupt the temporal correlations between sequences. Therefore, improvements upon the traditional CNN-LSTM model are necessary to overcome these drawbacks. This paper proposes an enhanced neural network algorithm that combines the Attention mechanism with CNN-LSTM. The key advantage of this algorithm lies in the inclusion of an Attention layer between the CNN network and LSTM layer. By computing the relevance scores between the input sequence's hidden layer vectors and the output, different attention weights are assigned to meteorological factors, highlighting the critical influencing features. Consequently, this approach addresses the challenge of preserving crucial information when dealing with long input sequences.

CNN input is wind power historical power data and multi-impact characteristic data. The data is divided into d days, n data per day, and m meteorological factors per data, to form an $n{\times}m{\times}d$ matrix as the input structure of CNN model. The output expression of CNN convolution layer is shown in Eq. 2:

$$\bar{X}_{i,j} = f_{\text{cov}}\left(\sum_{n=0}^{k}\sum_{m=0}^{k} w_{n,m}X_{i+n,j+m} + b_{n,m}\right) \tag{2}$$

where: $f_{\text{cov}}(\cdot)$ is the activation function, k is the sliding window size, $w_{n,m}$ is the weight of n rows and m columns of the convolution kernel, $X_{i+n,j+m}$ are the value of row n and column m of the feature matrix of the input data, $b_{n,m}$ is the convolution kernel deviation.

The CNN pooling layer uses 2×2 filters and a sliding window of step 1 to sample, reduce the data feature size, reduce network parameters, and then input the data to the LSTM layer via the fully connected layer. First, the input vector calculates the intermediate state of meteorological data through the hidden layer of LSTM, and the attention mechanism uses the function $score([\boldsymbol{h}_{t,i}, \boldsymbol{h}_t])$ to calculate the similarity between the feature vector of the intermediate state $\boldsymbol{h}_{t,i}$ and the hidden state $\boldsymbol{h}_t$. The expression is shown in Eq. 3:

$$score([\boldsymbol{h}_{t,i}, \boldsymbol{h}_t]) = \boldsymbol{W}_s \boldsymbol{h}_t^{\mathrm{T}} + \boldsymbol{b}_s \tag{3}$$

where: $\boldsymbol{W}_s$ and $\boldsymbol{b}_s$ are the weight matrix and bias vector of the fully connected layer respectively.

Secondly, the attention weight α_i of the hidden layer vector of meteorological data is obtained by the softmax function, and the weighted sum with $\boldsymbol{h}_{t,i}$ is obtained to obtain the output $\boldsymbol{h}_t^*$ of the attention layer., and the expression of α_i, $\boldsymbol{h}_t^*$ are as follows:

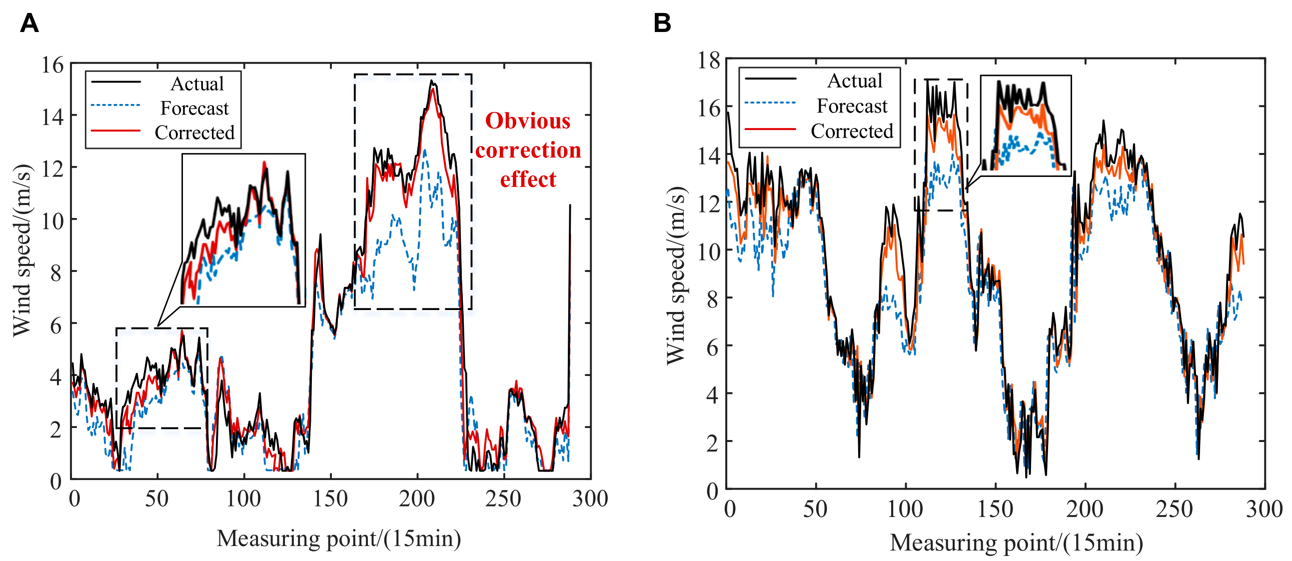

FIGURE 3
Comparison of NWP wind speed correction results in different seasons. **(A)**: Comparison of NWP wind speed correction results (winter), **(B)**: Comparison of NWP wind speed correction results (summer).

TABLE 1 Comparison of prediction results of different algorithms.

Model	MAE/%	RMSE/%	MAPE/%
LSTM	24.650	25.185	17.496
CNN-LSTM	10.834	11.538	14.903
CNN-LSTM-Attention	11.528	10.406	11.340
KOA-CNN-LSTM-Attention	5.293	4.125	3.720

$$\alpha_i = \frac{\exp\left[score\left(\boldsymbol{h}_{t,i}, \boldsymbol{h}_t\right)\right]}{\sum_{j=1}^{\tau}\exp\left[score\left(\boldsymbol{h}_{t,i}, \boldsymbol{h}_t\right)\right]} \tag{4}$$

$$\boldsymbol{h}_t^{*} = \sum_{i=1}^{\tau}\alpha_i \boldsymbol{h}_{t,i} \tag{5}$$

where: τ is the fully connected output node. Finally, $\boldsymbol{h}_t^{*}$ is input to the fully connected layer to obtain the predicted value of wind power $y_t{}'$.

3.2 Kepler optimization algorithm (KOA)

Due to the numerous hyperparameters involved in the training process of the CNN-LSTM-Attention hybrid model, such as learning rate, kernel size, and number of LSTM units, it is a challenging task to select and adjust these hyperparameters appropriately. The selection of these parameters directly impacts the quality of the prediction results in practical applications, thus necessitating the integration of optimization algorithms for parameter selection. The Kepler optimization algorithm (KOA) is a heuristic optimization algorithm based on Kepler's law in the natural world. This algorithm simulates the motion of planets in the Solar System and utilizes iterative search to find the optimal solution (Abdel-Basset et al., 2023) In KOA, each planet and its position represent a candidate solution, and the optimization process is achieved by randomly updating based on the best solution found so far (the Sun), enabling more efficient exploration and utilization of the search space. Its advantages lie in its fast convergence speed, high search accuracy, and strong interpretability. The mathematical expression of this algorithm is as follows:

$$\vec{X}_i(t+1) = \vec{X}_i(t)\times\vec{U}_1 + \left(1-\vec{U}_1\right)\times\left(\frac{\vec{X}_i(t)+\vec{X}_S+\vec{X}_a(t)}{3.0} + h\times\left(\frac{\vec{X}_i(t)+\vec{X}_S+\vec{X}_a(t)}{3.0} - \vec{X}_b(t)\right)\right) \tag{6}$$

where: $\vec{X}_i(t+1)$ is the new position of object i at time $t+1$, $\vec{X}_i(t)$ represent object i at time t, $\vec{U}_1$ represents the universal gravitational constant, $\vec{X}_S$ is the best position of the Sun found thus far, $\vec{X}_a(t)$ represents solutions that are selected at random from the population at time t, h is an adaptive factor for controlling the distance between the Sun and the current planet at time t, as defined below:

$$h = \frac{1}{e^{\eta r}} \tag{7}$$

where r is a number that is generated randomly on the basis of the normal distribution, while η is a linearly decreasing factor from one to −2, as defined below:

$$\eta = (a_2 - 1)\times r_4 + 1 \tag{8}$$

Where: r_4 is randomly generated numerical values at interval [0, 1], a_2 is a cyclic controlling parameter that is decreasing gradually from −1 to −2 for $\bar{T}$ cycles within the whole optimization process as defined below:

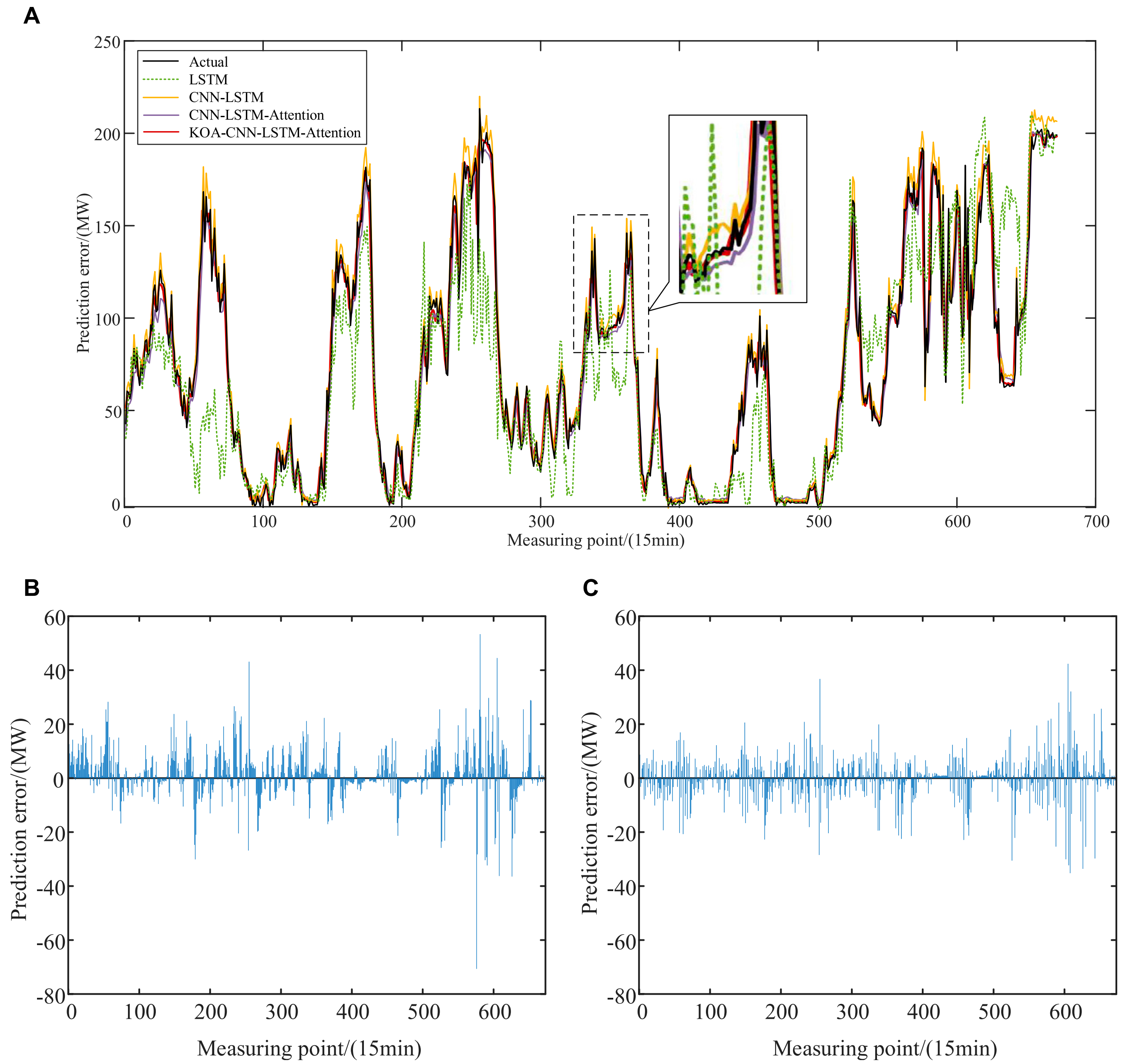

FIGURE 4
Comparison of prediction results of different algorithms. **(A)**: Comparison of prediction curves of different algorithms; **(B, C)** is the comparison of results with or without KOA optimization algorithm error, **(B)**: the prediction error when the model does not use KOA optimization algorithm, **(C)**: the prediction error after the model uses KOA optimization algorithm.

$$a_2 = -1 - 1 \times \left(\frac{t\% \frac{T_{\max}}{T}}{\frac{T_{\max}}{T}} \right) \tag{9}$$

In this paper, KOA algorithm is used to optimize the learning rate, convolution kernel size, number of neurons and other parameters in the CNN-LSTM-Attention model, taking the minimum Mean Absolute Percentage Error (MAPE) as the objective function. The formula is as follows:

$$MAPE = \frac{1}{n} \sum_{n}^{1} \frac{|y_i - \tilde{y}_i|}{y_i} \tag{10}$$

where: y_i is the true value, $\tilde{y}_i$ is the predicted value of the algorithm, n is the number of samples.

4 Example verification

4.1 Description of experimental data

This paper conducts a case study using data from a wind farm in northwest China. The installed capacity of the wind farm is 200 MW, and the experimental data and information includes the output power of the wind farm and various meteorological factors throughout 2018–2019. Specifically, data from January 25th to 31st, 2019 was selected for validating the prediction results. The data is divided into observed data and NWP data, both with a resolution of 15 min. The observed data contains measured values of wind turbine active power and hub-height wind speed, while the NWP data contains wind speed forecast values at four heights: 10 m, 30 m, 50 m, and 70 m. The NWP data is updated once a day at 00:00, so the wind power day-ahead forecast results are also updated on a rolling basis at 00:00 each day.

4.2 Verification of wind speed correction results

In this section, the proposed ResNet-GRU network is employed to correct the NWP wind speed data of the wind farm. To validate the applicability of the proposed correction model, meteorological and wind power data from the winter and summer seasons of 2019 are selected for wind speed correction result verification. During each correction, 80% of the data from the preceding time period is used to train the correction model, while the remaining 20% is used to validate the effectiveness of the wind speed correction. The comparison graph of forecasted wind speed before and after correction against the measured wind speed is shown in Figure 3.

From the curve fitting results shown in the above figure, the following observations can be made:

1) The NWP wind speed forecasts for this wind farm exhibit relatively small errors during the summer season, while the forecast errors are relatively larger during the winter season.
2) The NWP wind speed curve appears relatively smooth, whereas the measured wind speed curve exhibits more pronounced fluctuations and may experience sudden changes. These changes manifest as local peaks or valleys, which are of short duration and difficult for NWP to accurately predict, resulting in missed forecasts. This is evident in the highlighted section of the graph.
3) During periods of significant wind speed fluctuations, the NWP wind speed forecasts for this wind farm tend to underestimate the measured wind speed to a considerable extent. To address this issue, the error correction model developed in this study learns from the differences between NWP and measured wind speeds in historical samples and effectively corrects the errors between NWP and measured wind speeds during the application phase.

4.3 Prediction result verification

This study employs the Keras framework in Python to construct a short-term wind power prediction model based on the CNN-LSTM architecture. The model's initialization parameters, including the learning rate of the model's network weights, the size of the convolution kernel, and the number of neurons, are determined by the KOA algorithm, while the sigmoid function is selected as the model's activation function. The original training data range for the model comprises winter season data from 2018–2019, with a test set consisting of 7 days after the cutoff range of this training set. To validate the predictive performance of the proposed algorithm, the LSTM(Guangzheng et al., 2022b), CNN-LSTM (ZHAO et al., 2019), CNN-LSTM-Attention (Guangzheng et al., 2021), and KOA-CNN-LSTM-Attention methods are applied to predict the wind power output of the wind farm, with corresponding results presented in Table 1. Deterministic prediction error can be manifested as horizontal and vertical errors. In this paper, we selected vertical error evaluation indicators including Mean Absolute Error (MAE), MAPE, Root Mean Square Error (RMSE), and horizontal error evaluation indicators such as correlation coefficient as the performance evaluation indicators for prediction. A comparison of the forecast curves and error metrics across different methods is shown in Figure 4.

The KOA-CNN-LSTM-Attention algorithm proposed in this paper has the best overall prediction performance. Compared with the sub-optimal CNN-LSTM-Attention algorithm, the error indicators MAE, RMSE and MAPE are reduced by 6.235%, 6.281% and 7.620%, respectively. It shows the superiority of KOA algorithm. Combined with KOA algorithm, the parameters of the model are better selected on the basis of single CNN-LSTM algorithm, so the prediction accuracy is further improved.

5 Conclusion and prospect

Improving the accuracy of NWP is crucial for enhancing the precision of short-term wind power forecasting. However, current NWP forecast data exhibits significant discrepancies compared to the measured wind speeds, thereby limiting the accuracy of short-term wind power prediction. In light of this issue, this study proposes the following approaches:

1) An error correction model based on ResNet-GRU is established to effectively rectify the discrepancies between NWP and measured wind speeds during the application stage. By learning from historical samples, this model captures the differences between NWP and actual measurements.
2) A short-term wind power prediction model based on KOA-CNN-LSTM-Attention is developed to optimize key parameters such as learning rate, convolution kernel size, and number of neurons in complex models. This optimization significantly enhances the predictive performance of the model.

Furthermore, the measured wind power and wind speed data exhibit greater randomness and volatility compared to NWP forecast data. This indicates that smooth NWP data faces challenges in accurately tracking and predicting wind energy fluctuations at high spatiotemporal resolutions, leading to increases in both missed detection rates and false alarm rates. Therefore, our future research will focus on exploring how to utilize real-time wind farm and anemometer data with higher update frequencies to perform rolling corrections on NWP data, thereby achieving more accurate wind power forecasts.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

SW: Writing–original draft. HL: Writing–review and editing. GY: Writing–review and editing.

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Conflict of interest

Author SW was employed by Power Dispatching Control Center of State Grid Shaanxi Electric Power Co., Ltd. Author HL was employed by Electric Power Research Institute of State Grid Hubei Electric Power Co., Ltd.

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

Publisher's note

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