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Multiplex parallel GAT-ALSTM: A novel spatial-temporal learning model for multi-sites wind power collaborative forecasting

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In order to improve the accuracy of wind power output forecasting and ensure reliability of the power grid, multiplex parallel GAT-ALSTM, a spatial-temporal learning model for multi-sites wind power collaborative forecasting is proposed in this study. Topography was generated by using geographic information (longitude and latitude) obtained from the wind power generation sites. The GAT layer was used to capture the spatial correlation characteristics of multi-sites wind power. Feature dimension enhancement of each wind power generation site was achieved by aggregating the information from the adjacent sites. The ALSTM layer was used to capture the temporal correlation of each power output time series. The multiplex parallel structure of the model is designed to provide fast prediction of large-scale distributed wind power generation. The validity of the proposed multiplex parallel GAT-ALSTM was confirmed by comparison with the forecast results obtained by RNN, LSTM, ALSTM, and GNN-ALSTM. The testing results showed that, compared to RNN, LSTM, ALSTM, and GNN-ALSTM, the forecast results of the multiplex parallel GAT-ALSTM had the lowest mean absolute value error and the highest accuracy.

KEYWORDS

wind power forecast, multi-sites, multiplex parallel, graph attention network, attention-based LSTM

1 Introduction

With the sharp increase in wind farms and installed capacity, the proportion of wind power in the total power grid capacity is also increasing. However, due to the intermittence and volatility of wind power, it will bring challenges to the safety and stable operation of the power grid (Yan et al., 2018; Li, 2022). Accurate forecasting of wind power can relieve the pressure of peak shaving and frequency modulation and effectively improve wind power accommodation capability on the power grid (Li et al., 2022; Liu et al., 2022).

Wind power prediction has been widely used and extensively researched recently. Wind power prediction algorithms are mainly divided into two categories: one based on a statistical model and the other on a deep learning algorithm. Tan et al. (2021) proposed a method to use an improved LSTM network with a new gating mechanism to build a prediction model for ultra-short-term wind power. González-Sopeña et al. (2020) introduced a multi-step wind power prediction model using variational mode decomposition and an extreme learning machine. Verma et al. (2018) proposed a short-term wind power model enhanced by support vector machines. Cao and Gui (2018) combined an LSTM algorithm based on deep learning with a LightGBM algorithm based on a statistical model for wind power prediction. Yatiyana et al. (2017) established wind power generation prediction technology based on an ARIMA statistical model. Peng et al. (2016) proposed a new ultra-short-term wind power prediction method based on numerical weather forecasting and an error correction method. These methods have advantages and applicability in different wind power forecasting situations; however, most of them only focus on the data of a single site, and ignore the correlation of data between adjacent sites. At the same time, if it is necessary to predict the wind power of a large-scale station, model training should be carried out separately, which is inefficient.

A graph neural network is a deep learning algorithm based on the topological relationships of nodes to extract their spatial correlation. In the field of traffic, Tang et al. (2020) proposed the use of a GAGCN network to predict traffic flow speed. In the field of communication, He and Zhao (2020) proposed a fault diagnosis scheme for a telecommunication network based on a graph neural network. At present, the most widely used and effective graph neural network is the graph attention network (GAT) (Hu et al., 2021; Tian et al., 2022). The GAT introduces an attention mechanism in the process of the graph neural network, which makes the net pay more attention to neighboring nodes with large correlations and can achieve better results (Dong et al., 2022; Xu et al., 2022).

In this study, we propose a collaborative forecasting model for multi-sites wind power forecasting with strong generalization ability and greater accuracy. The proposed model was termed the multiplex parallel GAT-ALSTM, which aimed to simultaneously capture the spatial-temporal correlations in multi-sites wind power systems and achieve multi-sites wind power multiplex parallel forecasts. In this model, the spatial correlation feature of wind power was extracted by a multi-channel parallel graph attention network. After that, the temporal features of multi-sites wind power were extracted by a multi-channel parallel ALSTM network. The efficiency and accuracy of the forecast were improved by the aforementioned method. The rest of this article is organized as follows: Section 2 describes the prerequisite knowledge for the graph attention network and attention-based short- and long-term networks; Section 3 introduces the concrete realization scheme of multiplex parallel GAT-ALSTM; Section 4 provides experimental simulation and results analysis; and, Section 5 discusses the experimental conclusions.

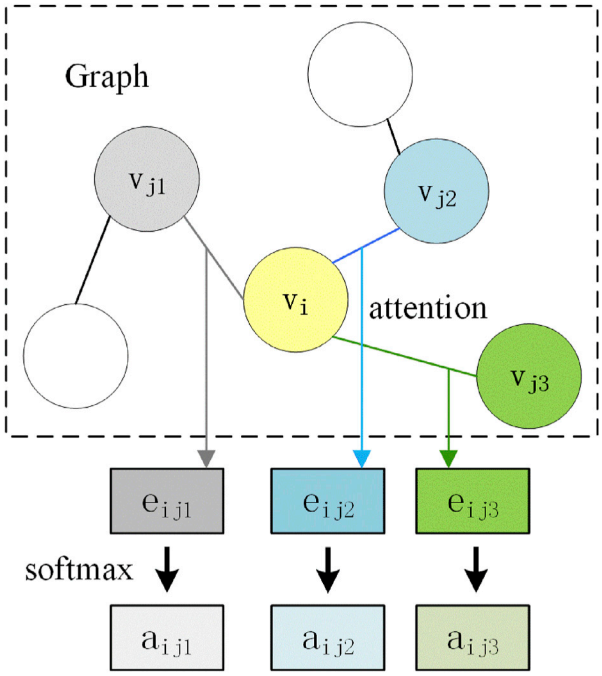

FIGURE 1
GAT network attention coefficient calculation diagram.

2 Preliminaries

To interpret the multiplex parallel GAT-ALSTM model, some basic knowledge of GAT and ALSTM is essential.

2.1 Graph attention network

The graph attention network is a variant and improvement of the traditional graph neural network, which considers the topological relationship between the target node and the neighbor node from spatial dimension, and can adaptively assign different weight coefficients to the surrounding nodes in the aggregation process, which improves the learning and expression ability of the graph neural network for non-Euclidean data.

The key of GAT lies in the attention mechanism, and the attention mechanism is defined as follows:

$$e_{ij} = attention\left(h_i, h_j\right) \tag{1}$$

$$attention = \begin{cases} < h_i, h_j > \\ OR \quad LeakyReLU\left(a^T\left[Wh_i, Wh_j\right]\right) \end{cases} \tag{2}$$

where h_i represents the feature vector of node v_i, h_j represents the feature vector of node v_j, and e_{ij} represents attention coefficients that indicate the importance of node j's features to node i. Attention refers to the attention mechanism layer, which can be in a form without

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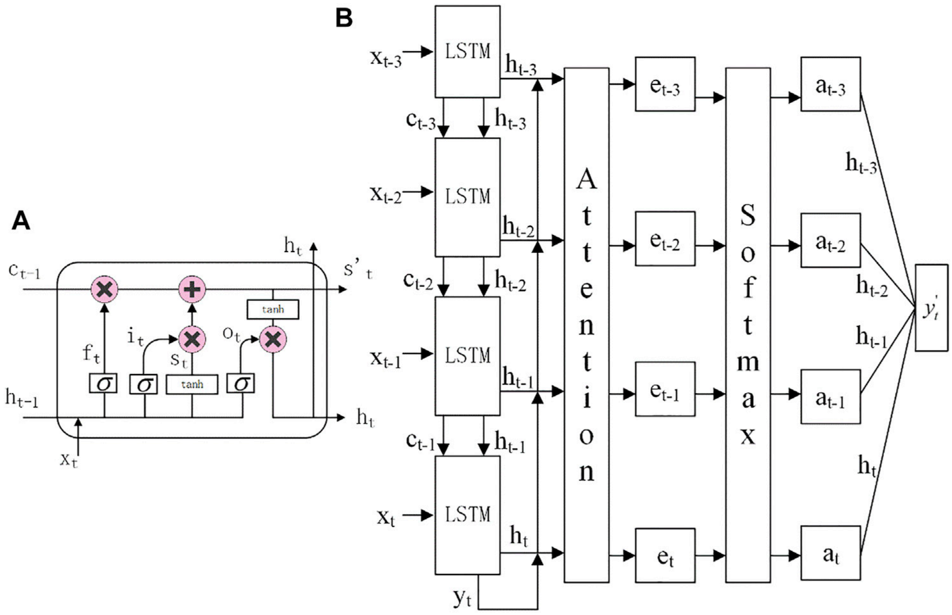

FIGURE 2
Single LSTM model diagram and ALSTM model diagram. **(A)** Single LSTM model. **(B)** ALSTM model.

parameters, such as the inner product of two vectors, or in a form with parameters, such as a single-layer linear fully connected layer.

To make attention coefficients easily comparable among different nodes, we normalized them with the softmax function, and obtained the normalized attention coefficient a_{ij}:

$$a_{ij} = soft\max\left(e_{ij}\right) = \frac{\exp\left(e_{ij}\right)}{\sum \exp\left(e_{ik}\right)} \tag{3}$$

Figure 1 shows the process of computing the attention coefficients of the nodes in a graph attention network. In order to simplify the calculation, we only compute e_{ij} for nodes $j \in N_i$, where N_i is some neighborhood of node i in the graph. In all our experiments, they are exactly the first-order neighbors of i. The attention coefficients of n-order neighbor nodes also can be obtained by overlaying and n-layer attention mechanism.

After the attention coefficients have been calculated, the features of all neighboring nodes are weighted and summed up to obtain the new feature vector of node v_i, Where h_i' represents the new feature vector of node v_i , W represents the linear transformation weight matrix, and σ represents the activation function:

$$h_i' = \sigma\left(\sum a_{ij} W h_j\right) \tag{4}$$

The features of first-order neighbor nodes can be extracted by a single layer network, while the features of second-order or multi-order neighbor nodes can be extracted by stacking multiple GATs. The attention mechanism is introduced in the graph attention network when updating the node information, which makes the graph neural network focus more on the useful feature information of the neighbor node to easily capture the spatial correlations of the neighboring node according to the topology structure, which largely improves the generalization and learning ability of the network.

2.2 Attention-based long short-term memory network

A long short-term memory network (LSTM) is a popular and effective deep learning model for processing time series data. The gating mechanism introduced in LSTM solves the problem of gradient disappearance in the training process of a recurrent neural network. The LSTM model is shown in Figure 2A, and the transfer function of each unit is given by:

$$\begin{bmatrix} S_t \\ O_t \\ i_t \\ f_t \end{bmatrix} = \begin{bmatrix} \tanh \\ \sigma \\ \sigma \\ \sigma \end{bmatrix} \left(W \begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix} + b \right) \tag{5}$$

$$S_t' = f_t \cdot S_{t-1}' + i_t \cdot S_t \tag{6}$$

$$h_t = O_t \cdot \tanh\left(S_t'\right) \tag{7}$$

where, O_t, i_t and f_t represent the output information of the three gating mechanisms, S_t' represents the new LSTM unit status information at time t, and h_t represents the output of the LSTM unit at time t.

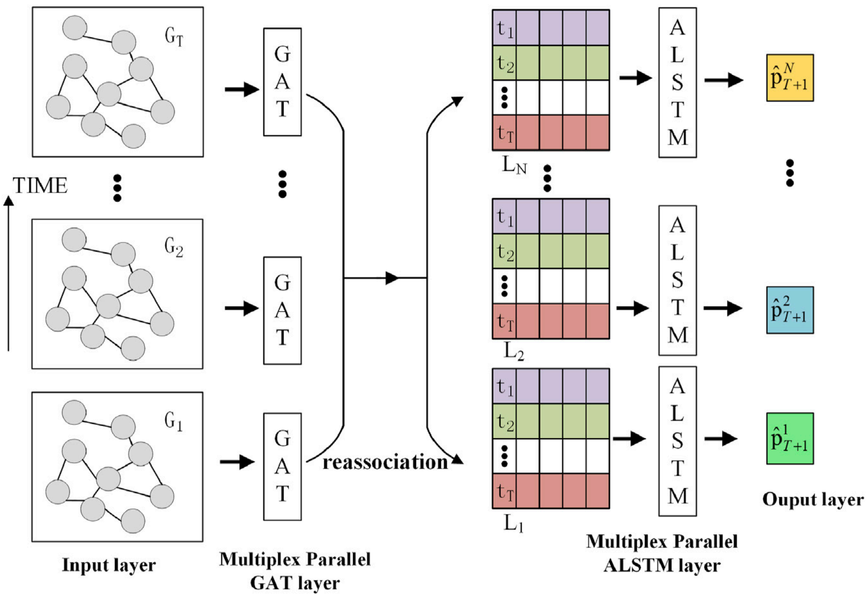

FIGURE 3
GAT—ALSTM model diagram.

When LSTM processes a time series, there is a problem that the input information in front of the time series will be diluted by the later input information. The longer the input time series is, the more obvious this phenomenon becomes. Therefore, in order to solve this problem, an attention mechanism is added to the LSTM model. The attention mechanism makes the LSTM network focus on the more important part of the time series, so as to improve the accuracy and efficiency of the network. The attention mechanism is given by:

$$e_i = at\left(h_i, y_t\right) = \tanh\left(h_i^T W_i y_t\right) \tag{8}$$

$$a_i = soft\max\left(e_i\right) \tag{9}$$

$$y_t^{'} = \sum a_i h_i \tag{10}$$

where, h_i represents the output of the ith LSTM unit, y_t represents the initial output of LSTM, and $y_t^{'}$ is the final output of the LSTM with attention mechanism. Figure 2B shows the schematic diagram of the ALSTM model.

3 Implementation of multi-sites wind power collaborative forecasting based on a multiplex parallel GAT-ALSTM model

3.1 Model design

Figure 3 shows the structure of the multiplex parallel GAT-ALSTM model. It consists of an input layer, a multiplex parallel GAT layer, a multiplex parallel ALSTM layer, and an output layer.

(1) Input layer: Using the geographic information (longitude and latitude) of the wind sites, a topology graph G with N nodes is generated. Each node corresponds to a wind site. The input of the GAT-ALSTM model is the wind power generation of N sites at T slots before the prediction time, $T + 1$. The wind power generation is embedded into the topology graph G as node features.
(2) Multiplex parallel GAT layer: T parallel GAT networks are used to simultaneously learn the correlation of wind power between different sites at T slots from the spatial dimension. GAT uses different weights to aggregate the information of neighbor nodes according to the learned correlation among sites. The features of each site are dynamically updated.
(3) Multiplex parallel ALSTM layer: A multiplex parallel ALSTM layer is used to capture the temporal correlation of time series.
(4) Output layer: uses a linear transform layer to predict wind power at all sites at time, $T + 1$.

3.2 Prediction based on a multi-channel parallel GAT-ALSTM model

A set of wind power data of model input is denoted as:

$$\{p_t^n | n = 1, 2, \cdots, N; t = 1, 2, \cdots, T\} \tag{11}$$

where, $p_t^n \in R$ means the nth wind power of N wind sites at time t, N represents the number of wind sites, and T is the input time window of the model. The input sequences of the nth wind site are written as:

$$P^n = (p_1^n, p_2^n, \ldots, p_T^n) \in \mathbf{R}^T \tag{12}$$

The model input matrix is denoted as:

$$P = (P^1, P^2, \ldots, P^N)^T \in \mathbf{R}^{N\times T} \tag{13}$$

A one-step ahead forecast is applied in the model, which inputs the content sequences of N wind sites from time 1 to time T, and outputs the predicted wind power of N wind sites at time $(T + 1)$, which is denoted as:

$$\hat{P} = \left(\hat{p}_{T+1}^1, \hat{p}_{T+1}^2, \cdots, \hat{p}_{T+1}^N\right)^T \in \mathbf{R}^{N\times 1} \tag{14}$$

The prediction model can be described as follows:

$$\hat{P} = F(P, \boldsymbol{\theta}), \tag{15}$$

where, θ is the parameter set and F is the multiplex parallel GAT-ALSTM model.

In order to achieve wind power prediction at multiple sites based on the multiplex parallel GAT-ALSTM model, the specific steps are as follows:

Step 1: Data preprocessing, such as data cleaning and normalization, is performed first, then the history power data of the selected N wind turbines are divided into training sets and test sets for model training and testing.

Step 2: Generate topography by using the geographic information (longitude and dimension) of the sites. The history power data of the selected N wind turbines and the wind power of N stations at the same time are used as features of nodes in each topological structure graph. T GAT networks are used for parallel computation. Finally, the characteristic matrix of n sites of T moments that aggregate the information of neighbor node is output by the GAT.

Step 3: Use the output of the GAT network as the input to the ALSTM. After processing by the GAT network, the initial features of the n sites at each time are increased from one dimension to high dimensions. Finally, the ALSTM uses enhanced feature data to output the wind power at N sites.

Step 4: Train the neural network.

Step 5: Use the model obtained by the aforementioned steps to make predictions on the test set sample and analyze the results.

4 Application and results

The wind power of seven adjacent sites from January to March 2013 was collected from NREL West. The training data set was from January 1 to March 20. The test data set was from March 21 to March 31. The data is in the form of csv files containing power values at 10-min resolution for seven wind sites.

4.1 Data preprocessing

Due to measurement errors or data storage errors in the data sampling equipment, there may be random errors in the original sampling data. These erroneous values will interfere with the efficacy of the model in wind power forecasting. In order to improve the speed of the machine learning model gradient descent to find the optimal solution, it is also necessary to preprocess the original data. The formula is as follows, where x_t represents the wind power at a certain moment, and X represents the wind power sequence:

$$x_t = \frac{x_t - \min(X)}{\max(X) - \min(X)}$$

For wind power generators with a capacity of 1.5 MW, the reasonable range of power outputs is 0–1.5 MW. Data beyond this range are regarded as abnormal and are eliminated and replaced with interpolated data. Lastly, all data are normalized.

4.2 Evaluation methods

To evaluate the accuracy of the prediction results, the mean absolute error (MAE) is used to evaluate the forecast results accuracy and the correlation coefficient (CC) is used to evaluate the time lag. The formula is as follows:

$$\mathrm{MAE}\left(P^n, \hat{P}^n\right) = \frac{1}{T}\sum_{t=t_1}^{t_1+T}\left|p_t^n - \hat{p}_t^n\right| \tag{16}$$

$$CC = \frac{\mathrm{cov}\left(P^n, \hat{P}^n\right)}{\sqrt{\sigma_{P^n}}\cdot\sqrt{\sigma_{\hat{P}^n}}} \tag{17}$$

where T represents the number of consecutive one-step-ahead forecasts from time $\mathbf{t}_1$, $\mathrm{cov}(P^n, \hat{P}^n)$represents the covariance, and σ_{P^n} $\sigma_{\hat{P}^n}$ represent standard deviation.

4.3 Experimental results

To verify the validity of the proposed model in an actual wind power forecasting task, the multiplex parallel GAT-ALSTM

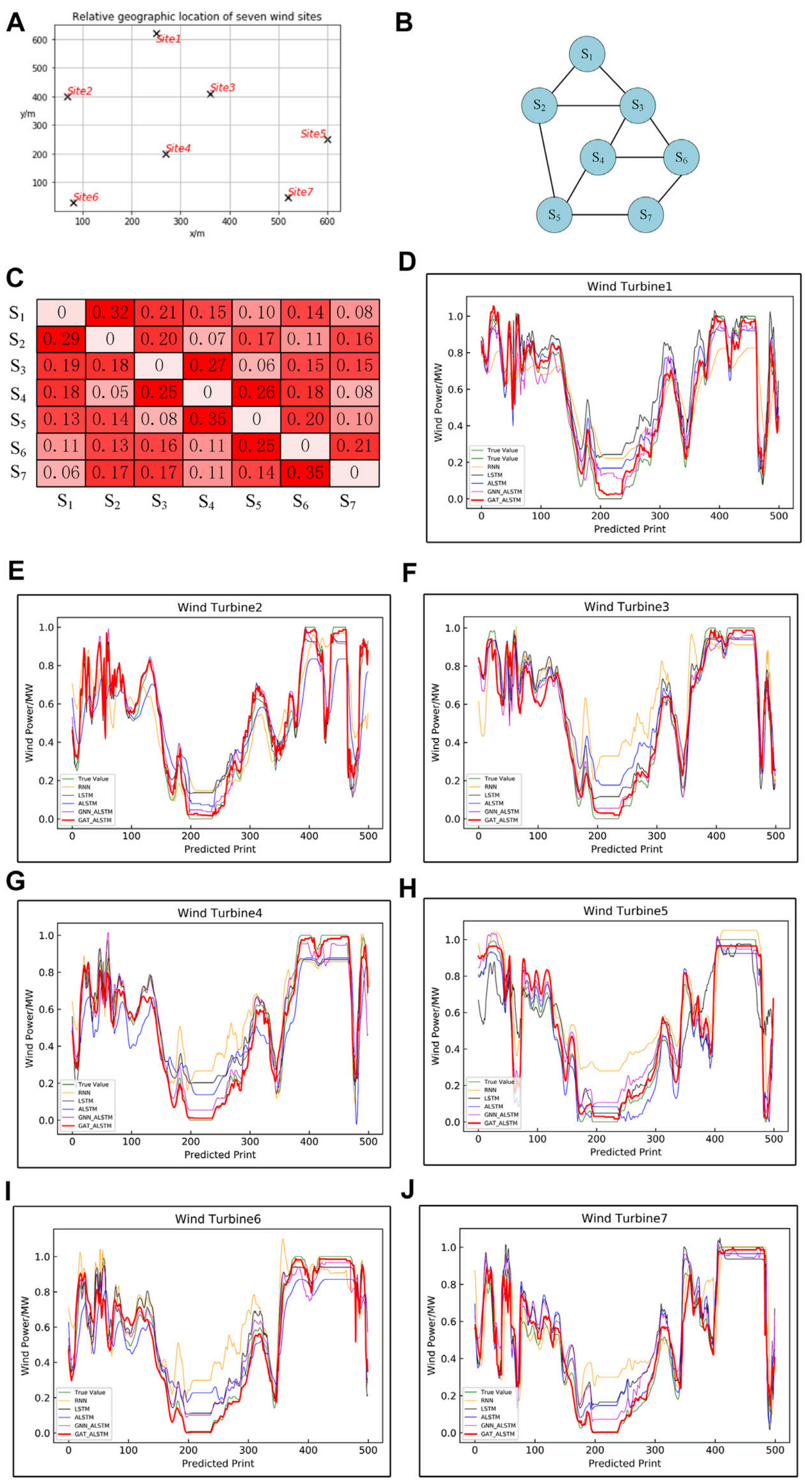

FIGURE 4
Experimental result diagram. **(A)** Relative geographical locations of seven wind sites. **(B)** Topology graph of seven wind sites. **(C)** Site weight coefficient diagram learned by the GAT layer. **(D)** Wind power forecast chart of Site 1. **(E)** Wind power forecast chart of Site 2. **(F)** Wind power forecast chart of Site 3. **(G)** Wind power forecast chart of Site 4. **(H)** Wind power forecast chart of Site 5. **(I)** Wind power forecast chart of Site 6. **(J)** Wind power forecast chart of Site 7.

TABLE 1 Performance comparisons of five models for predicting wind power generation at sites 1 and 5.

Model / Indicators	RNN (%)	LSTM (%)	ALSTM (%)	GNN-ALSTM	Multiplex parallel GAT-ALSTM (%)
MAE of site 1	9.21	8.77	8.47	8.02%	7.41
CC of site 1	94.32	94.58	95.38	96.97%	98.56
MAE of site 2	9.32	9.02	8.76	8.32%	7.67
CC of site 2	94.12	94.65	95.33	95.98%	97.24
MAE of site 3	9.06	8.85	8.31	7.98%	7.32
CC of site 3	94.43	94.87	95.43	96.11%	98.04
MAE of site 4	9.51	8.54	8.29	8.01%	7.58
CC of site 4	94.69	95.01	96.59	97.55%	98.43
MAE of site 5	9.10	8.64	8.32	8.11%	7.52
CC of site 5	94.07	94.87	95.33	96.86%	98.06
MAE of site 6	9.10	8.21	8.07	7.89%	7.44
CC of site 6	94.76	95.01	95.78	97.32%	98.10
MAE of site 7	9.11	8.91	8.41	7.99%	7.36
CC of site 7	94.76	95.11	96.78	97.33%	98.21

model and other associated models were used for wind power forecast experiments. The RNN and LSTM networks are common time series prediction models, and the ALSTM and GNN-ALSTM networks are used to verify the effectiveness of the attention mechanism. The experiment consists of one-step ahead forecasting of wind power. Figure 4A shows the location of each site. Figure 4B shows the topology graph of the seven wind sites. Figure 4C shows the attention weight coefficient between the wind sites learned by the GAT layer. It can be seen that the attention coefficient basically conforms to the rule of "near large and far small" in the spatial dimension. Figure 4D–J shows a comparison diagram of wind power forecasts at wind sites 1 to site 7 using five network models. Table 1 shows the evaluation index values of five network models for wind power forecast at sites 1 to 5.

It can be seen from the experimental results that, compared to the RNN network, theMAEof LSTM was reduced due to the introduction of the gating mechanism. ALSTM introduced a time attention mechanism into LSTM, and the CC of site one was increased by 0.8%, which indicates that a temporal attention mechanism can improve the time lag in time series prediction to a certain extent. Compared with ALSTM and GNN-ALSTM, the multiplex parallel GAT-ALSTM can fully utilize the information of adjacent sites, and theMAEof site 1 and site 5 decreased by 0.45% and 0.84%, respectively. Lastly, by comparing the forecast results of GNN-ALSTM with those from multiplex parallel GAT-ALSTM, the MAEof multiplex parallel GAT-ALSTM for site 1 was 0.39% lower than that of GNN-ALSTM, and the *CC* of multiplex parallel GAT-ALSTM for site 1 was 0.26% higher than that of GNN-ALSTM. It can be concluded from Table 1 that multiplex parallel GAT-ALSTM had the best prediction results among the five models because it introduced the attention mechanism for both temporal and spatial dimensions.

5 Conclusion

This study has proposed multiplex parallel GAT-ALSTM, a spatial-temporal learning model for multi-sites wind power collaborative forecasting. Leveraging the geographical information and historical power output data of adjacent wind sites, the model simultaneously captured the spatial-temporal correlation in multi-sites wind power by two attention mechanisms. Based on the learned spatial-temporal correlation, it improved the accuracy of the forecast. The multiplex parallel structure of the model is suitable for fast prediction of large-scale distributed wind power generation. The validity of the proposed multiplex parallel GAT-ALSTM is confirmed by comparing its forecast results with those obtained from RNN, LSTM, ALSTM, and GNN-ALSTM. It was found that forecast errors were minimized by the proposed model; hence, the proposed model shows good performance in forecasting wind power.

In potential future work, we plan to incorporate atmospheric factors such as wind speed and temperature as exogenous variables in the learning process to further enhance the forecasting ability.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding authors.

Author contributions

HH: conceptualization, methodology, validation, and writing—review. FF: software, visualization, and writing—original draft. DL: methodology and experimental verification.

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Conflict of interest

The 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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