

Combined Wind Speed Prediction Model based on GAT-LSTM

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Abstract

Wind speed has strong volatility, intermittency, and high variability. To predict wind speed, a comprehensive analysis should be conducted based on its temporal and spatial characteristics. This article proposes a combined wind speed prediction model based on graph attention network and long short term memory network (GAT-LSTM), which uses graph structure to describe the spatial correlation of time-series data and establishes a GAT wind field spatial feature model, Introducing attention mechanism to calculate the correlation between nodes in the neighborhood and selectively aggregate weather features of surrounding areas, Input the time series information extracted by GAT network at different time points into LSTM network for wind speed prediction. Based on the wind speed dataset of meteorological observation stations in Denmark and a city in the Netherlands, a comparative analysis was conducted with LSTM model, Multidimensional model, and GCN model. The experimental results showed that the combined wind speed prediction model based on GAT-LSTM had higher prediction accuracy.

Keywords

Wind Speed Prediction; Graph Attention Neural Network; Long Short-Term Memory Network; Combination Model.

1. Introduction

Wind speed, as one of the most fundamental meteorological elements in routine meteorological observations, has always been a key focus of meteorological forecasting, climate change research, meteorological service guarantee, and wind turbine operation and maintenance monitoring^[1]. To predict wind speed, it is usually necessary to combine its spatiotemporal characteristics and construct a physical model or neural network model for comprehensive analysis^[2].

This article proposes a combined wind speed prediction model based on graph attention network and long short term memory network (GAT-LSTM). Meteorological observation station data from a city in Denmark and the Netherlands are selected to construct a graph attention spatial feature extraction model. Based on historical data from the stations, a wind speed time series model is established to achieve combined wind speed prediction.

2. Wind Speed Prediction Model based on GAT-LSTM

2.1 Graph Modeling

A graph is usually represented by $G=(V, E)$, where G represents the graph, V is the set of vertices in the graph, E is the set of edges, and the direction of edges depends on whether there is a directional dependency between vertices ^[3]. This article simulates the spatial correlation of wind speed data sequences between multiple meteorological observation stations using a graph structure. Assuming node n is the set of various meteorological observation stations, edge E is the spatial relationship

between multiple meteorological observation stations, and adjacency matrix A is the information of neighboring nodes in the spatially convolved aggregated graph. In a single time step, treat meteorological observation stations as a graph, where each meteorological observation station is a node in the graph, and the node attributes are weather variables such as wind speed, wind speed, temperature, and pressure.

2.2 Spatial Feature Modeling of Meteorological Observation Stations based on GAT

The schematic diagram of spatial modeling of meteorological observation stations based on GAT is shown in Figure 1. The topology structure of meteorological observation stations corresponds to the input graph adjacency matrix. A single meteorological observation station is abstracted as a single node, and the distance between stations is abstracted as edges. Meteorological elements such as wind direction, wind speed, temperature, and pressure are the feature vectors of nodes. Establish a GAT model, assuming that node 4 in Figure 1 is the target meteorological observation station node. To predict the wind speed value of this node, the influence of the node itself and its adjacent nodes needs to be considered. The nodes in the circle in the figure are directly connected to node 4. The meteorological features of node 4 and its connected nodes are extracted through the graph attention network model, and the number of attention heads is set to 2 to further improve the fitting ability of the model.

Introducing attention mechanisms between nodes, adaptively adjusting attention coefficients, using a single-layer graph attention layer to aggregate node features of first-order neighbors, and constructing multiple graph attention layers to model complex graph structures, obtaining high-order neighbor node features and improving the representation ability of the model ^[4]. Node features are iteratively updated through aggregation between nodes, and when the topological structure of the graph changes, the adjacency matrix and node features also change accordingly ^[5]. The hyperparameter values of the model in the graph attention layer depend on the number of multi head attention ^[6]. In this paper, parameter tuning is performed using trial and error method, with values of [1, 2, 4, 8]. Based on the performance of the model under different head numbers, the most suitable number of attention heads is adaptively matched ^[7].

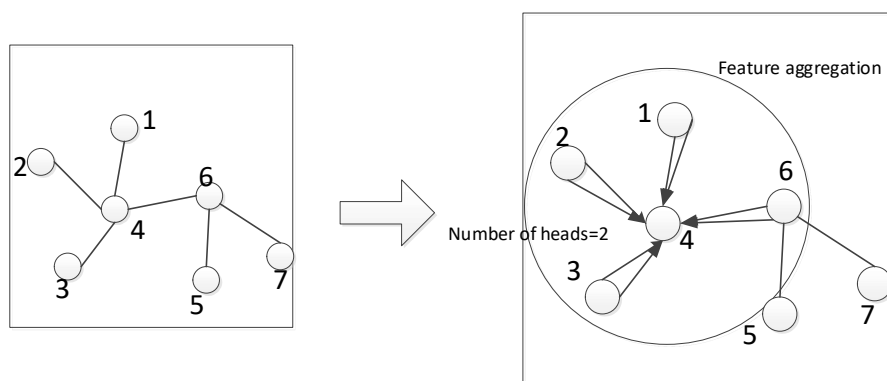


Figure 1. Spatial feature modeling based on GAT

2.3 Time Series Feature Modeling based on LSTM

The time series feature modeling based on LSTM is shown in Figure 2, where cells represent neurons ^[8]. This article establishes a two-layer LSTM network to extract time series features of observed data, with each layer consisting of multiple LSTM units. The complexity of the model increases with the number of layers. The preprocessed and normalized data is input into the GAT model in time series, and the powerful spatial feature extraction ability of graph attention networks is utilized to obtain the spatial feature information implied in the original observation data. The LSTM layer is then input to extract the temporal features of the time-series data through long short-term memory networks.

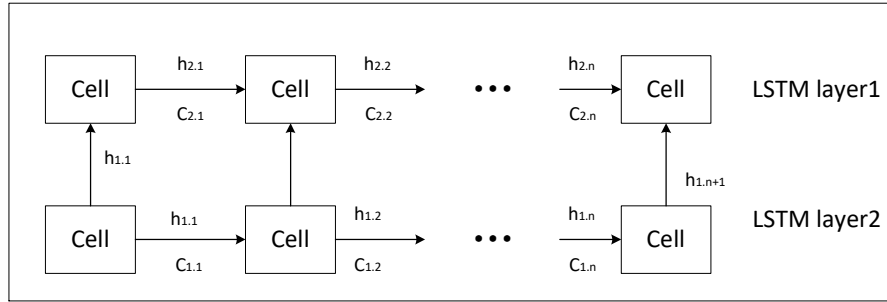


Figure 2. Time series feature modeling based on LSTM

2.4 GAT-LSTM Wind Speed Prediction Model

The structure of the GAT-LSTM wind speed prediction model is shown in Figure 3, which consists of an input layer, graph attention module, RNN module, and output layer. The GAT module consists of a dual layer graph attention layer to achieve spatial feature extraction^[9], The RNN module consists of two layers of LSTM, with the first layer used for temporal feature learning and the second layer used for temporal information prediction, The output layer is a fully connected layer that outputs a sequence.

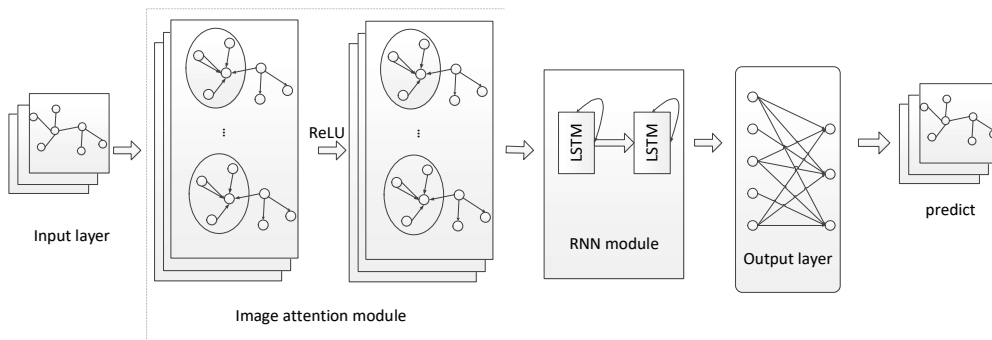


Figure 3. GAT-LSTM Wind Speed Prediction Model

The connection between the attention layer and the LSTM layer is shown in Figure 4, where is the input time series representing the updated features after the GAT layer.

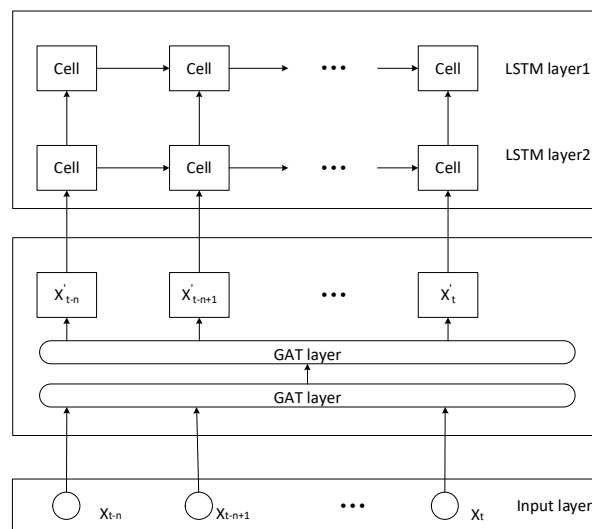


Figure 4. GAT-LSTM model network structure

This article extracts the spatial relationships between meteorological observation stations mapped to the graph through the GAT module. Based on the GAT network, the features of each node's neighboring nodes are extracted and the node status is updated. The second layer GAT network iteratively extracts features on the basis of the first layer GAT network, and expands the receptive field of a single node to extract surrounding information through multiple layers of GAT network. Adopting a multi head attention mechanism between two graph attention layers further enhances the learning ability and stability of the model. The feature information extracted by the GAT module is input into the time series and RNN modules, and a multi-layer LSTM network is used for temporal feature extraction to capture temporal dependencies. The fully connected layer of the output layer maps the extracted feature information to all nodes in the graph through full connections, and the node values are the predicted results.

3. Experimental Analysis

3.1 Data Preprocessing

This article uses hourly meteorological observation data from multiple city meteorological observation stations in the Netherlands from 2011 to 2019, including meteorological elements such as wind speed, wind direction, temperature, dew point temperature, air pressure, and rainfall. The data from 2011 to 2018 is used as the training set, and the data from 2019 is used as the test set.

Select hourly meteorological observation data from multiple Danish city meteorological observation stations from 2000 to 2010, including meteorological elements such as temperature, pressure, wind direction, and wind speed. Divide the dataset into three parts: training set, validation set, and testing set, with data from 2000 to 2009 as the training set and validation set, and data from 2010 as the testing set.

To ensure the temporal integrity and continuity of the input data for the model and improve the quality of meteorological observation data, linear interpolation is used to interpolate missing data segments and outlier data. The interpolation calculation formula is shown in (1):

$$x_k = x_w + \frac{(x_r - x_w)(k - w)}{r - w} \quad (1)$$

Among them, x_k is the value to be filled in, x_w is the most recent known data before x_k , x_r is the most recent known data after x_k .

Use the MinMaxScaler() function to normalize the training set, limiting the input features to [0,1].

$$f(x_i) = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (2)$$

Among them, $f(x_i)$ is the normalized value, $\max(x)$ and $\min(x)$ are the maximum and minimum values of the input parameters, respectively.

3.2 Evaluating Indicator

Mean Absolute Error (MAE) and Mean Square Error (MSE) are used as evaluation metrics^[10]. The calculation announcement is as follows:

$$MAE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n} \quad (3)$$

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n} \quad (4)$$

Among them, y_i refers to the true value, $\hat{y}_i$ refers to the predicted value.

3.3 Result

3.3.1 Comparison of Wind Speed Prediction Models based on Danish Urban Dataset

To further validate the accuracy of the model, a two-dimensional convolutional neural network, multi-dimensional, graph convolutional neural network model, and GAT+LSTM model were constructed based on the Danish urban dataset for comparative verification. Mean absolute error (MAE) and mean square error (MSE) were used as evaluation indicators.

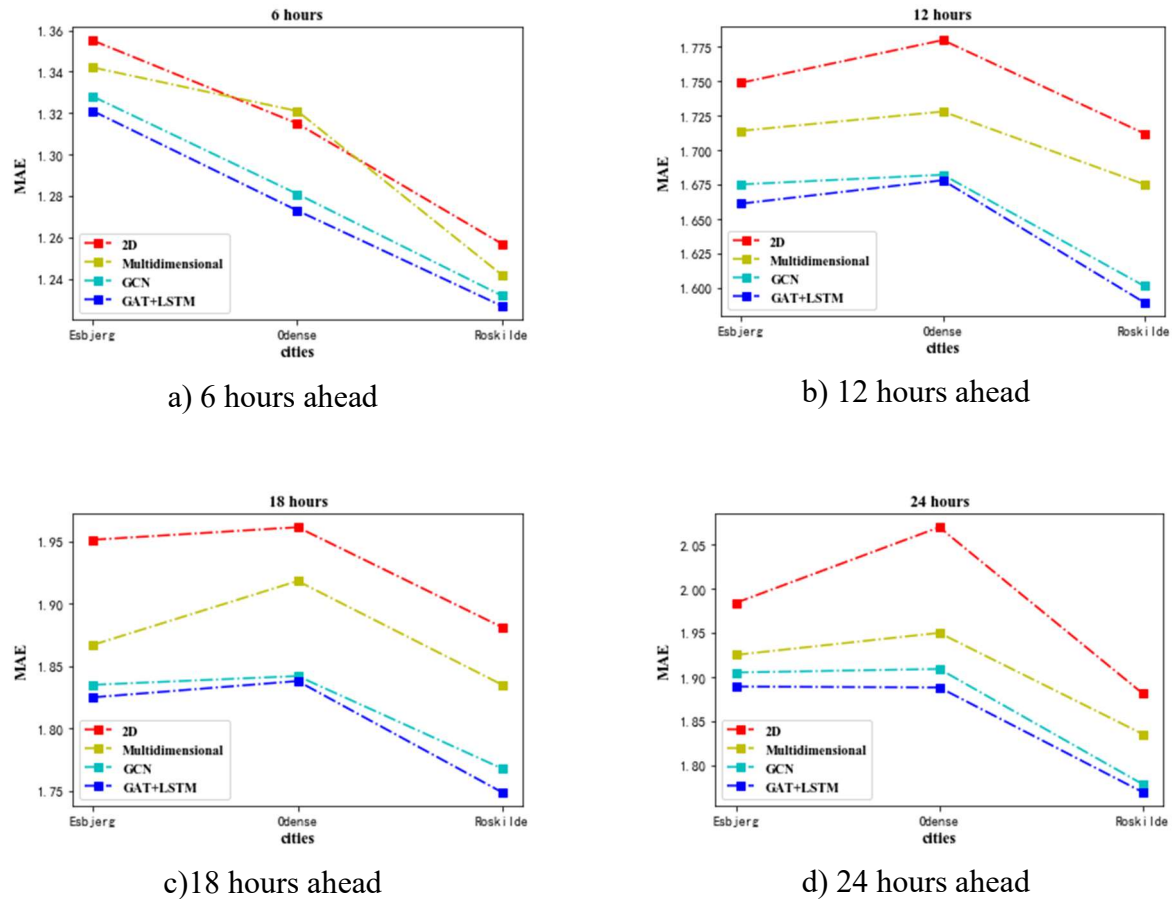


Figure 5. MAE evaluation indicators for four models with different prediction times in the Danish urban dataset

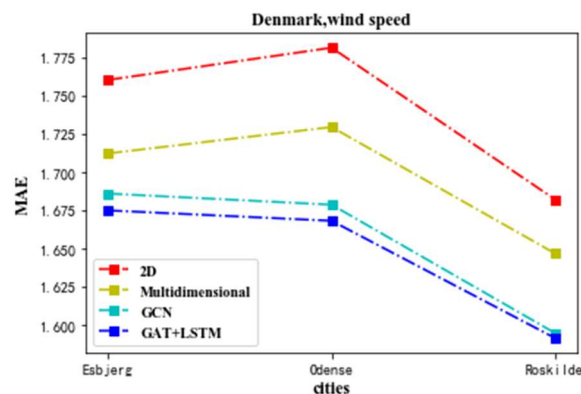


Figure 6. The average MAE evaluation index of four models under the Danish urban dataset

The MAE evaluation indicators for different prediction times of the four models are shown in Figure 5, and the average MAE evaluation indicators for each prediction time of the four models are shown in Figure 6. The experimental comparison results show that the combined wind speed prediction model based on GAT-LSTM has the best model performance and the lowest prediction error at different prediction times.

3.3.2 Comparison of Wind Speed Prediction Models based on Dutch Urban Dataset

Based on the Dutch urban dataset, four comparative models were trained to predict wind speeds for 2 hours, 6 hours, and 10 hours. The average MAE evaluation index of the four models was calculated, as shown in Figure 7.

The experimental results show that under the Dutch urban dataset, the combined wind speed prediction model based on GAT-LSTM has the best model performance and the lowest prediction error at different prediction times.

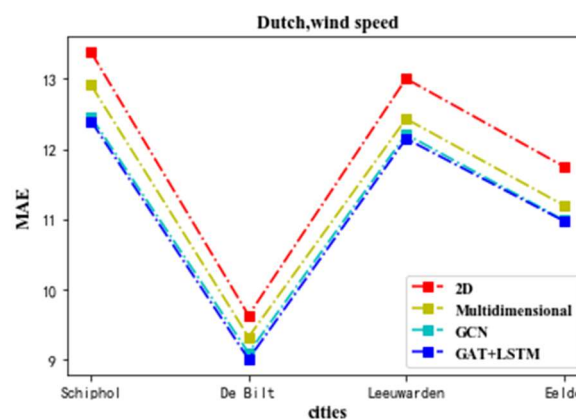


Figure 7. The average MAE evaluation index of four models under the Dutch urban dataset

4. Conclusion

This paper proposes a combined wind speed prediction model based on graph attention network and long short-term memory network. The GAT network is used to extract spatial features of the wind field, and the LSTM network is used to extract temporal features of wind speed. The performance of the model on two test datasets is verified through experiments, and compared with Multidimensional model, LSTM model, and GCN model. The experimental results show that the combined wind speed prediction model based on GAT-LSTM has the smallest MAE and MSE, and the model has high prediction accuracy.

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