Research on Predicting Wind Turbine Power Generation based on Hybrid LSTM-GNN Model

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Abstract

Wind power, as a significant clean energy source, faces challenges related to intermittency and uncertainty in its forecasting. This paper presents a hybrid LSTM-GNN wind power forecasting method based on spatiotemporal data. The proposed method first utilizes LSTM to process time series data and extract temporal features. It then employs GNN to handle the graph-structured data of wind farms to extract spatial features. Finally, these two types of features are combined for wind power prediction. By integrating both temporal and spatial information, this approach offers more accurate wind power forecasts, which contributes to grid stability and energy management. Experimental results demonstrate that the LSTM-GNN hybrid model performs exceptionally well in wind turbine forecasting, with RMSE and MAE values aligning with expectations, indicating that the combined model effectively enhances prediction accuracy and learning efficiency.

Keywords

Wind Power; LSTM; GNN; Spatiotemporal Data; Forecasting Model.

1. Introduction

In the context of energy transition and renewable energy utilization, wind power stands out as a crucial clean energy source, and accurate prediction of its output is vital for grid stability and effective energy management. However, the intermittent and uncertain nature of wind power poses significant challenges for forecasting. Recent advancements in deep learning technologies offer new approaches and solutions to this problem.

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network that effectively addresses long-term dependencies in time series data [1]. By incorporating gating mechanisms, LSTM networks control the flow of information, allowing the model to retain information over extended periods and better capture dynamic changes in time series data [2, 3].

Graph Neural Networks (GNNs) are designed to handle graph-structured data, efficiently capturing spatial relationships and interactions between nodes [4]. In wind power forecasting, wind farms can be represented as graphs with multiple wind turbines as nodes. GNNs can effectively extract spatial features and spatiotemporal coupling relationships within the wind farm [5].

Leveraging the strengths of both LSTM and GNN, this paper proposes a hybrid LSTM-GNN wind power forecasting method based on spatiotemporal data. The method first employs LSTM to process time series data and extract temporal features, then uses GNN to process the graph-structured data of the wind farm to extract spatial features. Finally, the integration of these two feature types is used for wind power prediction. By combining temporal and spatial information, this hybrid LSTM-GNN forecasting approach provides more accurate wind power predictions, offering robust support for grid stability and effective energy management.

2. Related Work

In the study of wind turbine efficiency prediction, researchers have employed various methods and techniques to enhance forecasting accuracy. For instance, studies have explored probabilistic wind power forecasting [6], the performance evaluation of standardized short-term wind power prediction models [7], and the calculation of annual energy output for wind turbines [8]. Additionally, advanced computational methods and data processing techniques, such as Computational Fluid Dynamics (CFD) methods [9] and numerical optimization techniques [10, 11], have been introduced to improve prediction precision and efficiency. Despite these significant achievements in turbine efficiency forecasting, a key limitation persists: most research primarily focuses on temporal data, such as wind speed, pitch angle, and environmental temperature, with less attention given to spatial data, such as the relative positions of turbines.

In 2022, the Baidu KDD Cup introduced wind power forecasting that integrates spatiotemporal information. Building on this, we propose a lightweight hybrid LSTM-GNN wind power forecasting method, aiming to address the shortcomings of existing research more effectively by leveraging spatiotemporal data.

3. Methods

LSTM (Long Short-Term Memory) networks are highly suited for handling time series data due to their ability to maintain long-term dependencies. The model consists of multiple layers of LSTM networks along with a fully connected layer to process sequential data. In the context of wind turbine data, where time series features such as wind speed, wind direction, and temperature vary over time, LSTM networks can learn the long-term dependencies of these features, thereby automatically identifying patterns and trends in the time series data. For wind turbine data, factors such as seasonality and diurnal cycles may influence power output, and LSTM can effectively capture these patterns in the time series data.

Graph Neural Networks (GNNs) are typically employed to handle data with a graph structure. We have found that wind turbine data can be considered as having an implicit graph structure [12]. The specific reasons are as follows:

(1) Implicit Graph Characteristics: In a wind farm, each wind turbine can be viewed as a node in a graph. Although these turbines are physically distributed in space, they have potential relationships with each other. For instance, adjacent turbines may be influenced by similar meteorological conditions or have connections related to energy transmission and maintenance. These implicit relationships can be represented as edges in a graph.

(2) Edge Construction Basis: In the implementation, edges are constructed by traversing all possible turbine pairs. An edge is established between turbines i and j if they are different ($i \neq j$). While this edge construction method is relatively simple and direct, it still reflects the potential connections between turbines to some extent.

LSTM is primarily used for handling time series data, extracting features from the temporal dimension, while GNN models the spatial relationships within the wind turbine network. By combining these two approaches in a Combined Model, the output of LSTM serves as the input to the GNN, allowing for simultaneous use of temporal and spatial information for predictions. The input to the Combined Model includes LSTM input data, graph edge indices, and node features. Specifically, the output of the LSTM is repeated and extended to serve as input for the GNN, enabling the GNN to further integrate temporal features and spatial relationships, thus enhancing prediction accuracy.

Although the data itself does not have a traditional graph structure and is more related to time series forecasting, constructing a graph structure and leveraging the characteristics of GNNs can provide an effective modeling approach for predicting wind turbine data.

In summary, this study employs a Combined Model of LSTM and GNN, utilizing sequential data (processed by LSTM) and graph-structured data (processed by GNN). In the Combined Model, LSTM handles temporal or sequential input features and generates outputs, while GNN processes node information based on graph structure and uses LSTM outputs as node features. This architecture is particularly suited for applications requiring analysis of both time-based and relational data. The structure of the experimental model is illustrated in Figure 1.

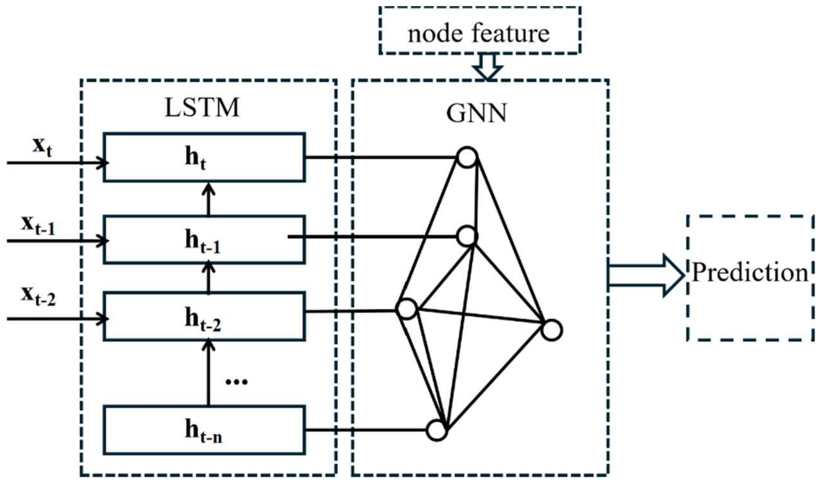

Figure 1. Model Architecture Diagram

4. Experiment

4.1 Dataset

Most datasets for wind turbine efficiency prediction primarily focus on temporal distribution. This experiment utilizes a specialized wind power prediction dataset: SDWPF, provided by Baidu for the 2022 KDD Cup. It contains fine-grained temporal scale location data of wind turbines. This combined time and spatial distribution prediction method overcomes the limitations of traditional turbine prediction [13].

SDWPF offers information in two dimensions:

(1) Spatial Distribution: Provides the relative positions of wind turbines within the power generation field. Each turbine generates wind power independently, and the total output power of the wind farm is the sum of all turbine outputs. This information aids in modeling spatial correlations.

(2) Dynamic Environment: Includes various signals such as weather conditions and internal states of the turbines, facilitating the design of multi-source input models to enhance prediction performance.

To prevent overfitting, L2 regularization was applied during training. For data anomalies, nan values were filled with 0, and the data was normalized to reduce the impact of outliers on the model. The normalization stage used a min-max scaler, which helps concentrate the data distribution and further mitigate the effects of outliers.

4.2 Experimental Conditions

The experiment was conducted on a cloud server with the following environment configuration: Ubuntu 22.04-cuda 12.10-py 3.10-to-rch 2.3.0-1.17.1, featuring an 8-core processor, 32GB of memory, and 24GB of GPU memory.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202412_10(12).0008

4.3 Evaluation Metrics

To comprehensively evaluate the performance of the hybrid LSTM-GNN wind power prediction method, the following metrics were used:

Root Mean Square Error (RMSE): Measures the difference between predicted and actual values. RMSE is the square root of the prediction error squared, reflecting the overall error level of the predictions. The calculation formula is given in (1).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of samples.

Mean Absolute Error (MAE): Assesses the absolute error between predicted and actual values. MAE is the average of the absolute prediction errors, with the calculation formula provided in (2).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

These two metrics provide a comprehensive assessment of model prediction accuracy, with RMSE being more sensitive to larger errors and MAE offering a direct average of the errors. The average values are computed based on errors from multiple test sets or time periods to ensure the stability and reliability of the evaluation.

4.4 Experimental Results and Analysis

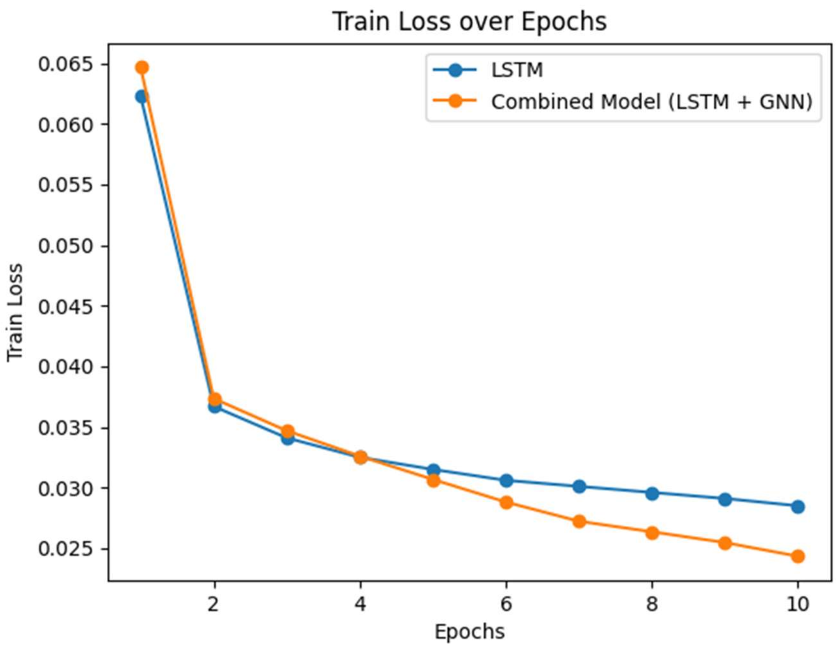

Figure 2. Training loss across different epochs

ISSN: 2414-1895 DOI: 10.6919/ICJE.202412_10(12).0008

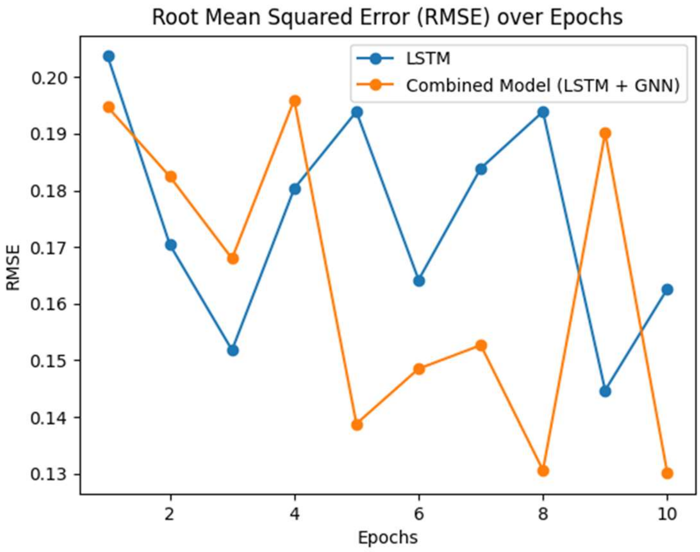

Figure 3. Root Mean Square Error (RMSE) across different epochs

During the limited number of training epochs, the LSTM model exhibited a favorable convergence trend in training loss. Figure 2 illustrates the training loss across different epochs. It is evident from the figure that the training loss decreased, indicating an improvement in model performance. Both RMSE and MAE showed a stable decreasing trend throughout each training epoch, as depicted in Figure 3 and Figure 4. Despite some fluctuations in training and validation loss in later epochs, the overall trend remained positive.

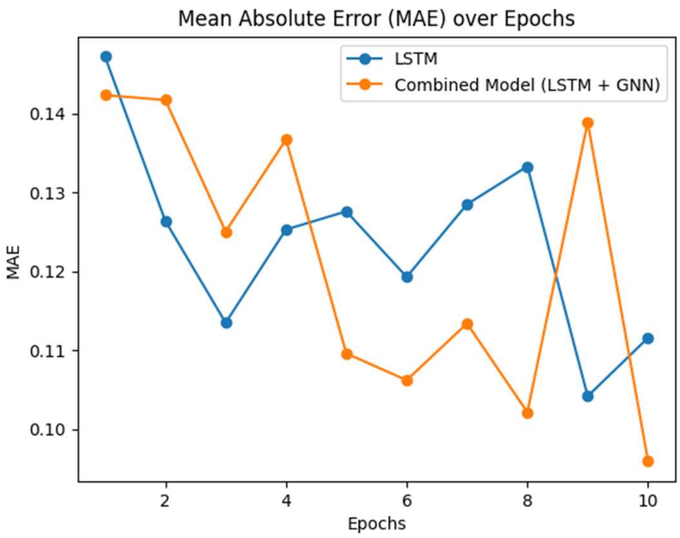

Figure 4. Mean Absolute Error (MAE) across different epochs

In the hybrid LSTM and GNN model, the LSTM + GNN combination also demonstrated good convergence after initialization. The reduction in training loss was more substantial, reflecting a better fitting performance and effective learning capability. The RMSE and MAE analysis of the combined model shows significant improvements in performance during the later stages of training. Compared to the standalone LSTM model, the combined model's loss decreased more rapidly, indicating that the inclusion of GNN significantly enhanced the model’s learning ability, likely by better capturing the structure or interrelationships within the data.

5. Conclusion

The LSTM + GNN combined model demonstrates exceptional performance in wind turbine prediction, outperforming the standalone LSTM model. This indicates that incorporating Graph Neural Networks (GNNs) can significantly enhance the learning efficiency and predictive accuracy of complex tasks. However, there remains room for further improvement in the model. Enhancements could include increasing the number of training epochs, adjusting the learning rate, strengthening regularization, or applying early stopping to prevent overfitting. Additionally, employing cross-validation techniques could further validate the model's robustness. Exploring different GNN architectures or integrating other types of networks might also lead to more substantial performance gains.

Experimental results reveal that this hybrid model exhibits superior predictive performance on several real-world wind farm datasets compared to single models, primarily due to LSTM's effective capture of long-term dependencies in time series data and GNN's deep understanding of spatial relationships within the wind farms. Future improvements could involve hyperparameter optimization methods such as grid search or random search to fine-tune model parameters, including the hidden layer sizes and number of layers in LSTM, as well as the hidden layer dimensions and learning rate in GNN. Additionally, employing data augmentation techniques, such as adding noise and random cropping, could increase data diversity and further enhance the model's generalization capabilities.

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