

BiLSTM-Based Bidirectional Time Feature Learning for Wind Power Interval Forecasting

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Abstract

Wind power features strong randomness and fluctuation, which greatly hinders stable and safe grid system operation. Interval prediction can effectively characterize the variation bounds of wind power generation, thus serving a critical function in the grid-integrated scheduling of wind farms. However, existing methods often struggle to balance interval coverage and interval width, and the bidirectional temporal dependencies in wind power series are not fully exploited. To solve these problems, this research constructs a wind power interval prediction model based on bidirectional long short-term memory (BiLSTM). Using actual operational data from a North China wind farm, the Pearson correlation coefficient is employed to select input features, while Min-Max normalization is utilized to remove dimensional differences among various data types. The model extracts bidirectional temporal features by integrating forward and backward sequence information, and constructs prediction intervals by combining point forecasts with an error superposition method. At a 90% confidence level, performance comparisons are performed between our model and typical recurrent networks including RNN, GRU, LSTM and BiGRU. The findings demonstrate that the BiLSTM model obtains an MAE of 2.091, a PICP of 91.89% and a PINAW of 0.135, which realizes an excellent trade-off between interval coverage and compactness. The proposed method is able to effectively balance point forecasting accuracy and interval prediction quality, and can provide useful support for wind power dispatch and operation.

Keywords

Wind Power, Interval Prediction, Bidirectional Long Short-Term Memory, Feature Selection

1. Introduction

Driven by the goals of carbon peaking and carbon neutrality, the large-scale application of renewable energy has become a core trend in global energy transformation. Owing to its cleanliness, resource abundance, and high development potential, wind energy has become one of the most rapidly developing renewable energy forms [1] [2]. However, wind energy is inherently random, intermittent, and volatile. Large fluctuations in wind power output may cause grid frequency deviations and voltage fluctuations, thereby affecting the secure and stable operation and economic dispatch of power systems [3]. Therefore, accurate wind power forecasting is of great significance for reducing the uncertainty associated with grid integration and improving dispatching performance [4]. Compared with conventional point forecasting, interval forecasting not only provides predicted values but also describes the possible fluctuation range of power output, making it more suitable for practical engineering applications [5].

Different from traditional point prediction, interval prediction can not only output the predicted value of wind power, but also describe the possible fluctuation interval of power output, which is more in line with the actual engineering demands of wind farm scheduling. Existing wind power forecasting methods can generally be divided into physics-driven models [6], statistical models [7], and deep learning models [8]. Physics-driven models are usually built on numerical weather prediction and wind turbine aerodynamic mechanisms, and are suitable for medium- and long-term forecasting. However, they are highly dependent on the quality of meteorological data and modeling conditions. Traditional statistical models, such as support vector machines and time-series analysis methods, can exploit historical data for forecasting, but they are limited in representing complex nonlinear relationships. In recent years, deep learning has emerged as a dominant research direction in wind power forecasting, owing to its powerful capacity in capturing nonlinear relationships and mining time-series dependent features. Among them, RNN [8], GRU [9], and LSTM [10] have been widely used. For example, Zhao *et al.* [11] adopted the BiLSTM network to develop an ultra-short-term forecasting model for offshore wind power, which significantly enhanced the prediction precision. Sun *et al.* [12] proposed a CEEMDAN-GWO-BiLSTM model and also achieved favorable forecasting performance. Nevertheless, several issues remain. Some studies focus mainly on point forecasting accuracy while paying insufficient attention to the trade-off between interval coverage and interval width. Unidirectional recurrent neural networks cannot fully exploit bidirectional dependency information in time series. In addition, input feature selection is sometimes too coarse, and the effects of feature correlation and multicollinearity on prediction performance are not adequately considered. Therefore, there is still room for further improvement in the overall balance among different evaluation metrics in existing interval prediction models.

To overcome the above limitations, this research presents a BiLSTM-based wind power interval prediction framework. The model integrates forward and

backward time information to enhance the mining of dynamic characteristics of wind power sequences, uses error superposition method to construct prediction intervals based on point prediction results, and selects features through Pearson correlation coefficient and standardizes data by Min-Max method. The main novelties of the present research can be concluded below:

- 1) A BiLSTM-based wind power interval prediction model is built, which fuses forward and backward time information to better characterize the dynamic change law of wind power sequences.
- 2) Prediction intervals are constructed on the basis of point forecasting results through an error superposition method, and model performance is comprehensively evaluated using RMSE, MAE, PICP, and PINAW.
- 3) Pearson correlation coefficients are used to select input features, and Min-Max normalization is implemented for data preprocessing, thereby reducing the influence of scale differences and redundant features on prediction performance.

2. Methodology

2.1. Bidirectional Long Short-Term Memory Network

BiLSTM is an improved structure of LSTM network. Traditional RNN is prone to gradient vanishing during training and therefore has difficulty learning long-term dependencies. As shown in **Figure 1**, although LSTM alleviates this problem by introducing memory unit and gating mechanism, it only processes sequence information in the forward direction, which limits the utilization of backward context information. BiLSTM is composed of forward and reverse LSTM structures, which can process time series in two opposite directions at the same time, so as to obtain the past and future context information of the current moment. This structure makes BiLSTM have stronger sequence feature extraction ability and is more suitable for wind power time series prediction tasks.

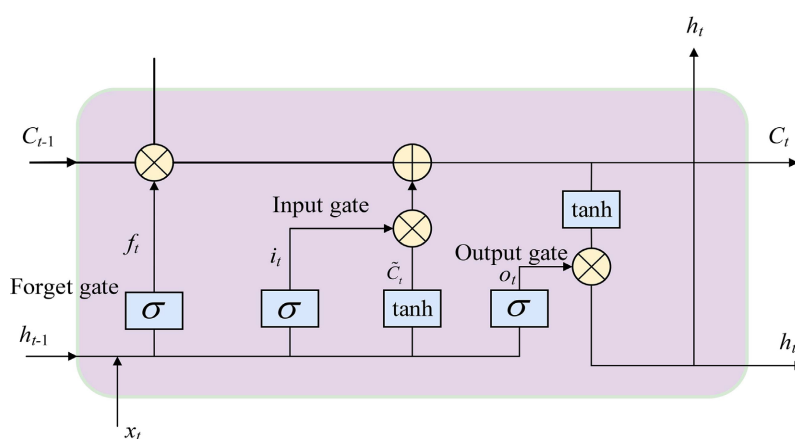


Figure 1. Structural sketch of LSTM network.

The basic cell of BiLSTM inherits the core unit architecture of LSTM, which is made up of forget gate, input gate and output gate. In both the forward and back-

ward LSTM, Sigmoid and hyperbolic tangent (tanh) functions are used to control the forgetting, updating, and output of information. By traversing the sequence in two directions and fusing the hidden states of the same time step, BiLSTM realizes the bidirectional modeling of time information. The structure of BiLSTM is shown in **Figure 2**.

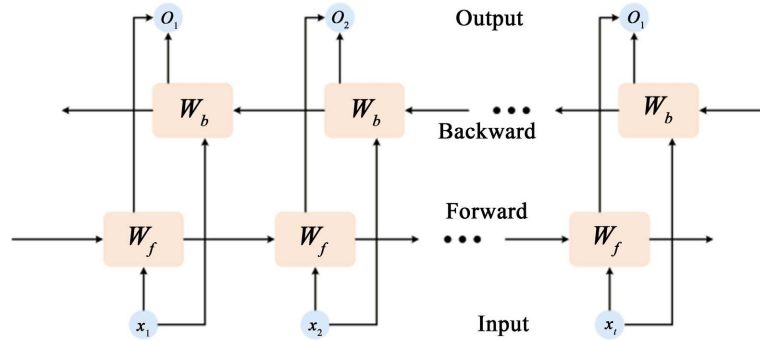


Figure 2. Structural sketch of BiLSTM network.

Suppose x_t represents the input information at time t , while h_{t-1} and c_{t-1} refer to the hidden and cell states of the prior moment. The calculation formulas for gating units within BiLSTM are given below:

$$g_t^{(f)} = \sigma \left(W_f \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_f \right) \quad (1)$$

$$g_t^{(i)} = \sigma \left(W_i \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_i \right) \quad (2)$$

$$\tilde{c}_t = \tanh \left(W_c \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_c \right) \quad (3)$$

$$c_t = g_t^{(f)} \odot c_{t-1} + g_t^{(i)} \odot \tilde{c}_t \quad (4)$$

$$g_t^{(o)} = \sigma \left(W_o \cdot \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b_o \right) \quad (5)$$

$$h_t = g_t^{(o)} \odot \tanh(c_t) \quad (6)$$

where W and b stand for weight matrices as well as bias vector of the corresponding gating units in the forward and backward LSTM, respectively; $g_t^{(f)}$, $g_t^{(i)}$, and $g_t^{(o)}$ are the forget gate, input gate, and output gate; σ denotes the Sigmoid function, and $\tanh$ denotes the hyperbolic tangent function.

2.2. Kernel Density Estimation

Kernel density estimation (KDE) is a nonparametric probability density estimation method, which does not need to assume the prior distribution of data. It can adaptively fit the probability density function through observation samples, and is especially suitable for modeling the complex distribution of wind power prediction errors. By adaptively fitting the probability density function (PDF) from ob-

served samples, KDE is particularly suitable for modeling complex distributions such as wind power forecasting errors. The KDE can be expressed as follows:

$$Z(x) = \frac{1}{nv} \sum_{i=1}^n P\left(\frac{x - X_i}{v}\right) \quad (7)$$

where $Z(x)$ is the PDF of the forecasting error, n is the number of samples, v represents the bandwidth, and $P(\cdot)$ represents the kernel function.

The kernel function is a crucial component of KDE, as it determines how each data point contributes to the overall density estimation. The Gaussian kernel and Epanechnikov kernel are two frequently adopted kernel functions. The selection of the kernel function is able to affect the fitting performance of the estimated probability density. Considering the continuity and nonparametric characteristics of wind power forecasting errors, together with the smoothness and differentiability of the Gaussian kernel, it is adopted in this study. Its expression is given by:

$$P(u) = \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{u^2}{2}\right)} \quad (8)$$

where u is the variable of the Gaussian kernel function.

2.3. Wind Power Interval Prediction

The wind power interval prediction method is developed on the basis of the point forecasting results obtained from the BiLSTM model. KDE is utilized to fit historical prediction error distributions, so as to establish interval boundary values. The core concept is to capture the underlying distribution of prediction errors via nonparametric density estimation after acquiring point forecasts. This design effectively integrates the temporal feature learning capability of BiLSTM with the inherent flexibility of KDE in handling nonlinear and non-Gaussian error distributions. This hybrid framework improves both the reliability and sharpness of interval forecasting. **Figure 3** depicts the detailed implementation steps of the method:

1) The BiLSTM model is trained using the training dataset after feature selection and standardization. Through the backpropagation algorithm, the model parameters, including the weight matrices and bias vectors, are iteratively optimized so that the model is able to adequately learn the forward and backward temporal dependencies embedded in wind power measurement sequences. After convergence, the preprocessed test dataset is fed into the trained model to generate point forecasts at each time step, which are then assembled into the point forecasting sequence x_i .

2) The actual wind power values and the corresponding point forecasting results over the entire training period are extracted, and the historical forecasting error sequence is obtained by calculating their differences. KDE is then applied to this global error sequence to estimate its probability density without imposing any prior distributional assumptions, such as normality. In this way, the actual distributional characteristics of the forecasting errors can be captured more accurately.

Under a 90% confidence level, the lower and upper quantiles of the global forecasting error are derived from the cumulative distribution function estimated by KDE, thereby quantifying the uncertainty range of the forecasting errors.

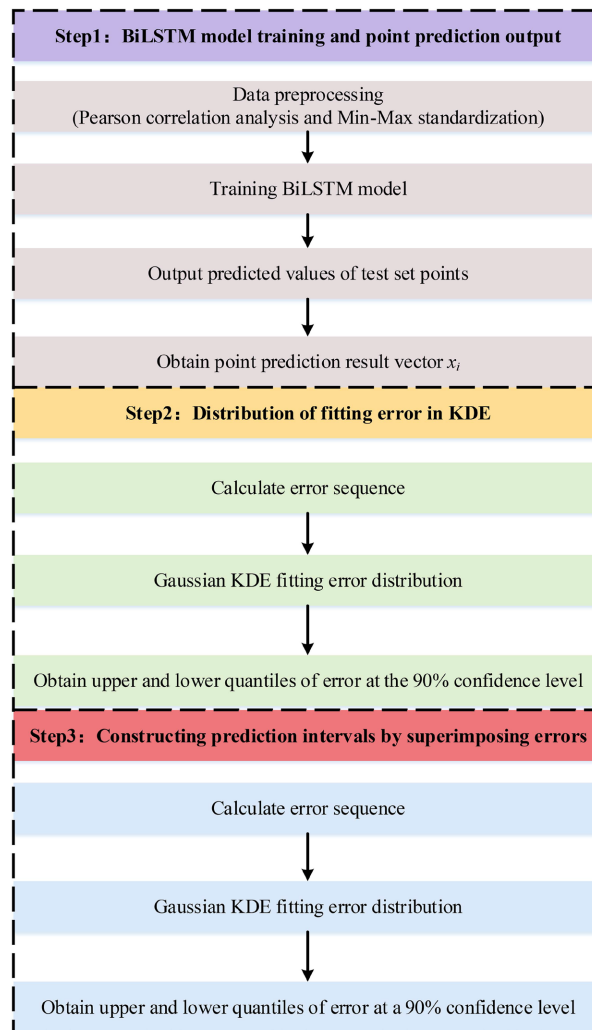


Figure 3. BiLSTM-driven architecture for wind power interval prediction.

3) The lower and upper error quantiles obtained from KDE are then superimposed onto the point forecasting result at each time step in the test set to determine the upper and lower edges of the prediction interval, respectively, under the 90% confidence level. By repeating this process for the entire test sequence, the final interval forecasting results of wind power are obtained.

2.4. Performance Evaluation Indicators

To further examine the comprehensive performance of this method, four metrics are utilized, including RMSE, MAE, PICP, and PINAW. Specifically, RMSE and MAE are adopted to quantify the errors between point predictions and real measurements, while PICP and PINAW are applied to evaluate the reliability and com-

pactness of the generated prediction intervals. The computational equations of RMSE and MAE are presented below:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_{\text{real},i} - y_{\text{pred},i})^2} \quad (9)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_{\text{real},i} - y_{\text{pred},i}| \quad (10)$$

where n is the quantity of test set, $y_{\text{real},i}$ is the actual value of the i -th, and $y_{\text{pred},i}$ is the predicted value of the i -th. A smaller RMSE indicates higher point prediction accuracy. MAE represents the average absolute forecasting error and has the same unit as the original data, making it more intuitive and relatively less sensitive to a small number of outliers.

PICP serves as an indicator for evaluating the dependability of interval forecasts, representing the ratio of actual power values lying inside the estimated range under a specified confidence level. The closer the PICP is to the preset confidence level, the more reliable the interval forecasting result is. PINAW reflects the average width of the prediction interval, and standardization is applied to eliminate the influence of dimensional differences. A smaller PINAW indicates a narrower interval and, under the premise of satisfying the coverage requirement, a more practically useful interval forecasting result. The formulas are given as follows:

$$\text{PICP} = \frac{1}{n} \sum_{i=1}^n I(y_i \in [L_i^\tau, U_i^\tau]) \quad (11)$$

$$\text{PINAW} = \frac{1}{nC} \sum_{i=1}^n (U_i^\tau - L_i^\tau) \quad (12)$$

where I represents a binary indicator that outputs 1 if the observed value lies inside the forecast interval and 0 otherwise; y_i stands for the real power output of the i -th sample; U_i and L_i represent the upper and lower thresholds for the forecast interval under the $1 - \tau$ confidence level, respectively; C refers to the span from the minimum to the maximum of the observed power data. In this work, the 90% confidence level is employed as the standard for evaluating and comparing the interval prediction performance of various models.

3. Results and Discussion

3.1. Dataset Analysis and Preparation

The experimental dataset is sourced from the real operational records of a North China wind farm, covering the period from January 1 to May 31, 2019, and the data are sampled at 15-minute intervals. The collected data involves wind generation data alongside climatic parameters including wind velocity, wind direction, pressure, temperature and relative humidity. Because the Pearson correlation coefficient is computationally efficient and suitable for linear correlation analysis, it is used here to assess the linear relationship between each input variable and wind power generation. The comparative outcomes are shown in **Figure 4**. The dataset contains 14,496 observations. The last 2900 observations were used for testing,

while the remaining data were divided into training and validation sets. After constructing four-step input sequences, the training, validation, and test sets contained 9273, 2319, and 2896 samples, respectively.

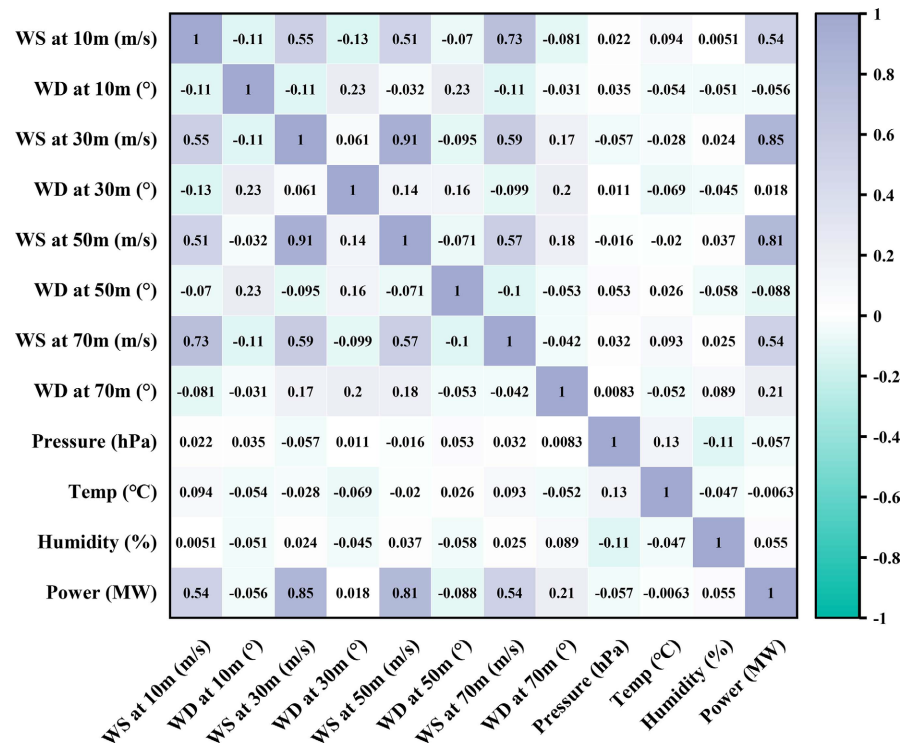


Figure 4. Analysis on the association between wind power output and diverse influencing factors.

Based on the results illustrated in **Figure 4**, the wind speeds at 30 m and 70 m are strongly correlated with wind power. To weaken the adverse effects of feature multicollinearity on forecasting accuracy, this study takes wind speed data at 30 m and 70 m as core input variables, and keeps the 70 m wind direction data for auxiliary analysis. Because the selected features have different units and scales, Min-Max normalization is applied to map them into the interval [0, 1] as follows:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (13)$$

where x_{norm} refers to the standardized data, x denotes the raw sample data, and $x_{\min}$ and $x_{\max}$ stand for the extremum values of all sample points.

Since the original data are sampled at 15-min intervals, the prediction horizon is one time step, corresponding to a 15-min-ahead wind power forecast. The input sequence length is set to four time steps, representing the meteorological observations over the previous 1 h. Specifically, wind speed at 30 m, wind speed at 70 m, and wind direction at 70 m from time $t-3$ to time t are used to predict the wind power at time $t + 1$. The samples are generated chronologically using a sliding window with a step size of one. It should be emphasized that the backward branch

of the BiLSTM only processes the same four available historical observations in reverse order and does not access any observations after the forecasting origin. Therefore, no future-information leakage occurs during model training or inference.

3.2. Point Forecasting Result

All models were trained using the Adam optimizer with a learning rate of 0.001 and the mean squared error loss. The batch size and maximum number of epochs were set to 32 and 200, respectively. A dropout rate of 0.3 and early stopping with a patience of 30 epochs were adopted.

Figure 5 presents wind power single-point forecasting outputs achieved via the BiLSTM model. The abscissa stands for time series data sampled every 15 minutes, while the vertical axis denotes the measured wind power and the corresponding values predicted by the BiLSTM model. The point forecasting performance of the model can therefore be intuitively evaluated by comparing the fitting trends of the two curves.

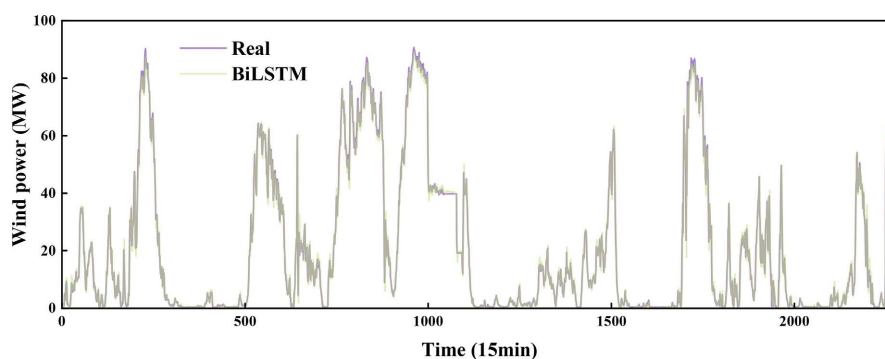


Figure 5. Point forecasting results using the BiLSTM model.

As illustrated in **Figure 5**, the predicted power curve generated by the BiLSTM model agrees closely with the actual power curve, which proves this method can precisely grasp time-varying fluctuation rules of wind generation data. The model responds effectively not only during relatively stable periods but also during sudden rises and drops in power output, with no evident lagging behavior. In peak power intervals, predicted data stays close to real measured values with minor errors, proving the proposed method is able to greatly ease the over-prediction and under-prediction defects of traditional time series methods in extreme value prediction. When wind power operates at low and stable output levels, the predicted values only exhibit minor fluctuations around the real measurements, which further verifies that the model can effectively capture the inherent changing rules of wind power. These findings demonstrate that the BiLSTM model, by combining forward and backward temporal information, is capable of fully utilizing the bidirectional correlations contained in wind power time series.

Moreover, no systematic bias is observed over the entire time series, and the

forecasting errors appear to be randomly distributed without any obvious trend deviation. This indicates that the selected input features, namely wind speed at 30 m and 70 m and wind direction at 70 m obtained through Pearson correlation analysis, can effectively characterize the variation patterns of wind power. In addition, the Min-Max normalization method helps reduce the influence of scale differences and feature redundancy, thereby providing a solid data foundation for efficient BiLSTM training and offering reliable support for the subsequent construction of high-accuracy prediction intervals based on point forecasting results.

3.3. Wind Power Interval Prediction Result

For confirming the feasibility and performance of the BiLSTM model for wind power interval prediction, this work carries out a comparative analysis with RNN, GRU, LSTM and BiGRU under the 90% confidence level, and assesses all models from two key aspects: point prediction precision and interval prediction quality. Relevant findings are summarized in **Table 1**. Overall, the PICP values of all models are close to the preset confidence level of 90%, and the PINAW values range from 0.134 to 0.139, indicating that all models can provide reasonably effective interval forecasts. Among them, the BiLSTM model exhibits a better balance across the evaluation metrics.

Table 1. Performance comparison of various models for interval prediction.

Model	RMSE	MAE	PICP	PINAW
RNN	3.816	2.256	92.11%	0.139
GRU	3.754	2.195	92.11%	0.134
LSTM	3.702	2.121	92.06%	0.135
BiGRU	3.738	2.127	91.45%	0.136
BiLSTM	3.735	2.091	91.89%	0.135

According to the statistical results in **Table 1**, BiLSTM yields the least MAE at 2.091 compared with other counterparts, which is 7.31% and 4.74% superior to the RNN and GRU models, respectively, demonstrating a stronger ability to fit variations in wind power. Although LSTM achieves a slightly lower RMSE, BiLSTM obtains the lowest MAE, and its PICP is closer to the nominal confidence level of 90% while maintaining the same PINAW as LSTM, indicating competitive and balanced overall performance.

The coverage probability matches the set confidence standard, meanwhile keeping narrow interval width, the BiLSTM model also achieves the best MAE, indicating that it effectively balances point forecasting accuracy, interval coverage, and interval width. As shown in **Figure 6**, most real wind power values fall within the predicted interval, and the estimated range perfectly matches wind power changing trends with reasonable width, fully verifying the reliability of this designed interval forecasting framework.

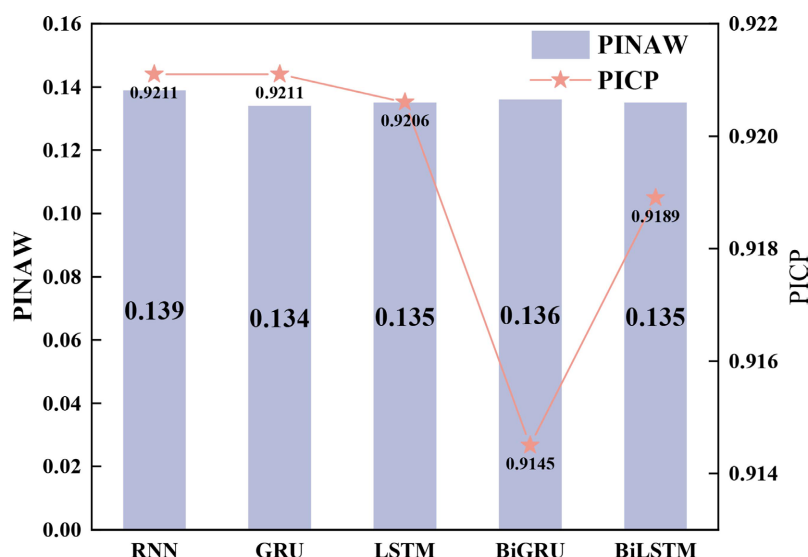


Figure 6. Prediction results of wind power intervals using different models.

4. Conclusions

Utilizing on-site operating records of local wind power farms in North China, a BiLSTM wind power range prediction approach is established with layered wind characteristic parameters selected as inputs. Min-Max normalization is adopted to preprocess input variables. Under 90% confidence degree, this constructed model is contrasted against RNN, GRU, LSTM and BiGRU. Experimental outcomes demonstrate that BiLSTM excels at extracting bidirectional time-dependent correlations within wind power sequences. For point forecasting, it achieved the lowest MAE of 2.091. For interval forecasting, the PICP reached 91.89% and the PINAW was 0.135, indicating that the proposed model maintained good interval sharpness while ensuring satisfactory coverage.

Wind power interval prediction exerts a critical supporting role in the dispatch of wind farms and the stable operation of electrical grids. The BiLSTM model presented in this work demonstrates competitive overall performance compared with the baseline models, which reveals its promising prospect in wind power time-series prediction. However, this study considered only limited input features and data from a single wind farm. Subsequent research will introduce additional meteorological factors and verify the model with more extensive datasets.

Author Contributions

Conceptualization, Shuwen Xue; methodology, Shuwen Xue; software, Runyu Gui; validation, Bohua Zha, and Runyu Gui; formal analysis, Shuwen Xue; investigation, Runyu Gui; resources, Lexuan Ye; data curation, Lexuan Ye; writing-original draft preparation, Shuwen Xue; writing-review and editing, Shuwen Xue, Lexuan Ye and Runyu Gui; visualization, Lexuan Ye; supervision, Bohua Zha; project administration, Bohua Zha. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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