Proceedings of the 4th International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/48/20241676

A combined approach for wind power generation prediction based on CNN and double BiLSTM neural network

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Abstract. With the demand for electricity is increasing in the world. The power supply share of renewable energy generation is currently increasing and will require a large amount of power supply. However, renewable energy generation will cause large power fluctuations, which will affect the charging efficiency and security of the power system. Improving the prediction accuracy of renewable energy generation can effectively control and reduce power fluctuations in power supply. In this paper, the method based on convolutional neural network (CNN) and bi-directional long-term and short-term memory (BiLSTM) is applied to wind power generation prediction using the past time-series data sets. Experimental results on 12 different really world datasets show that the proposed model can reduce the prediction error by up to 77.8% compared with CNN-LSTM.

Keywords: Renewable energy, wind power forecasting, deep learning

1. Introduction

Nowadays, renewable energy's share of global electricity generation is continuing to grow, which plays a key role in decreasing carbon emissions. wind power currently accounts for the majority of renewable energy generation. In 2019, the wind energy generation of the whole world has exceeded 600GW, 96% of which is onshore wind energy [1]. Therefore, the problems of short-term forecasting of renewable energy generation are crucial for electric management.

In the past, model-based optimization theory has been widely used in scientific research [2, 3]. However, traditional machine learning methods are unable to determine the complex linear relationships between the renewable energy generation data, such as support vector regression (SVR) [4]. Therefore, methods based on deep learning were proposed by scholars for renewable energy generation in the past few years. However, the above-mentioned methods also cannot provide the prediction accuracy that can meet the current needs.

In this paper, a novel CNN-BiLSTM based data-fully-driven short-term wind power prediction model is proposed. the Bayesian optimizer algorithm is used to tune the hyperparameters of the model. To fully demonstrate the prediction performance of the proposed models in this paper, CNN-LSTM, BiLSTM, LSTM and GRU models are used for comparison. Comparison with other deep learning models on twelve recent real-world data sets. The main contributions of this paper are the following:

(1) A novel data-fully-driven short-term wind power prediction model based on CNN and double BiLSTM layers is proposed for wind power generation.

(2) A total of twelve data sets from three regions and four seasons over the past year in the United States are used to validate the predictive performance of the model. The experimental results demonstrate the good prediction efficiency of the model proposed in this paper.

2. Materials and methods

2.1. Bidirectional LSTM network

The BiLSTM model has two hidden layers with two opposite directions, the forward layer and the backward layer. With using the LSTM model twice, the prediction accuracy of the model will be improved because the long-term learning effect is improved. LF_n and LB_n denote the outputs of the forward and backward hidden layers, respectively.

$$y_i = \sigma\big(LF_i(x_i), LB_i(x_i)\big) \qquad \forall i \in [0,1,2,\dots,n] \tag{1}$$

where y_i and x_i denotes the output and input of the BiLSTM model, respectively.

2.2. CNN-Double BiLSTM based wind power generation prediction approach

In this section, a novel wind energy generation forecasting method that is based on deep convolutional neural network and double layers Bidirectional LSTM network with Bayesian operation is proposed by us. The hybrid method is based data-fully-driven, which is proposed for the next three days power generation by using the history wind power generation data set. In **Figure 1**, we can clearly see the flowchart of the proposed method. The main steps are shown as following:

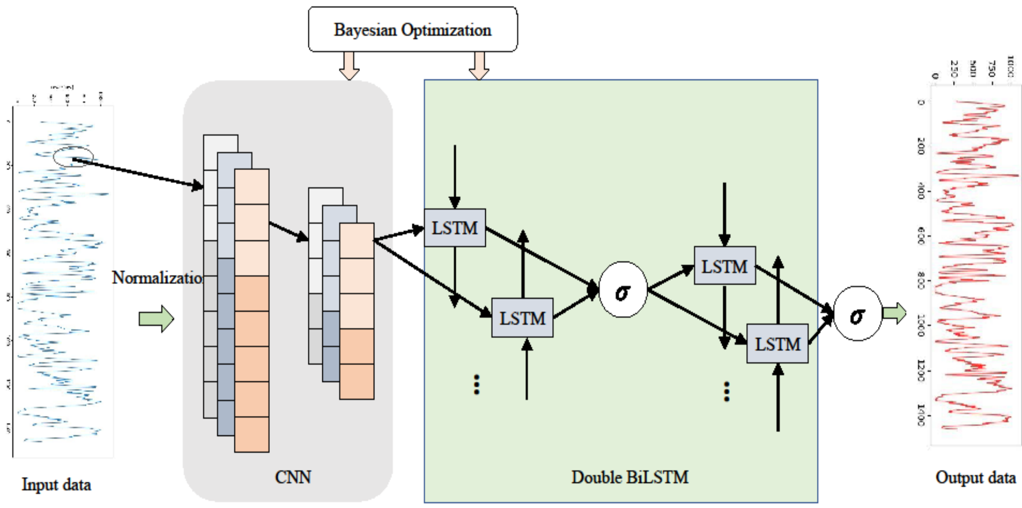


Figure 1. The whole framework of the proposed method.

(1) Normalization: Use pandas to read a cvs file downloaded from a publicly available dataset to obtain a historical time series dataset of wind power generation (marked as $r_t = (r_1, r_2, \cdots, r_n)$). The range of values of the acquired raw data (r_t) is so large that it is used as input to the deep learning model which can greatly increase the training time of the model. The maximum and minimum values of the r_t are used to normalize the r_t to a range from 0 to 1, as shown below:

$$d_t = \frac{r_t - r_{min}}{r_{max} - r_{min}} * 0.9999 \qquad \forall t \in [0,1,2,\dots,n] \tag{2}$$

where d_t means the normalized data, r_{max} and r_{min} mean the maximum and minimum of the original data set r_t, respectively. Then, the input (s_i) data and target data (l_i) are determined according to the time step (marked as p)), as follows:

$$s_i = [d_i, d_{i+1}, \dots, d_{i+p}] \qquad \forall i \in [0,1,2,\dots,n-p] \tag{3}$$

$$l_i = d_{i+1+p} \qquad \forall i \in [0,1,2,\dots,n-p] \tag{4}$$

Finally, s_i and l_i are divided into training set and test set in the ratio of 7:3.

(2)1-D CNN: The wind energy generation data used in this paper is one-dimensional vector, so one-dimensional convolutional neural network (1-D CNN) is used to extract features from the data. A classic 1-D CNN consists of input layer, convolutional layer, maxpooling layer and output layer. The convolution kernels and feature map in the convolution layer are the keys to implement the feature extraction function of 1-D CNN for the input data. The specific calculation procedure for the input data s_i in the training set at 1-D CNN is shown below:

$$q_j^{k+1} = \sigma\left(b_j^k + \sum_{i=1}^{k} Conv1D\left(\omega_{ij}^k, q_j^k\right)\right) \tag{5}$$

where q_j^k denotes the jth input of s_i at the kth layer, b_j^k denotes the bias, ω_{ij}^k denotes the weight matrix, $Conv1D(\cdot)$ denotes one-dimensional convolution function and $\sigma(\cdot)$ denotes the ReLU activation function.

(3) Double BiLSTM: The output data of 1-DNN q_j is used as the input data of the Double BiLSTM, and the prediction process of the Double BiLSTM is as follows:

$$y_j^1 = \sigma\left(LF_j^1(q_j), LB_j^1(q_j)\right) \tag{6}$$

$$y_j^2 = \sigma\left(LF_j^2(y_j^1), LB_j^2(y_j^1)\right) \tag{7}$$

where LF_j^1 and LB_j^1 denote the outputs of the forward and backward hidden layer in the first BiLSTM layer, and LF_j^2 and LB_j^2 denote the outputs of the forward and backward hidden layer in the second BiLSTM layer. After the first BiLSTM layer we added the dropout layer, which randomly silences some data to improve the generalization ability of the model. The Bayesian optimization is used to optimizing the deep learning hybrid model. Using the training set to find the best hyperparameters of the proposed model, such as timesteps, learning rate, batch size, kernel units, filters and dropout and so on.

(4) Denormalization: The test set data is fed into the model that has been trained with hyperparameters by the training set, and desnormalizing the output of the model. Evaluate the prediction results of the proposed model and the prediction results of other models as well as the real data.

3. Performance Indicators

The error of renewable energy generation forecasting should be decreased and fully evaluate the effectiveness of the prediction model [5]. In this paper, the mean absolute error (MAE), root mean square error ($RMSE$) and mean absolute percentage error ($MAPE$) are selected to evaluate the prediction results of the model. To better reflect the predictive performance between the proposed model and the comparison model, P_{MAE}, P_{RMSE} and P_{MAPE} are introduced. The evaluation metrics introduced are used to evaluate the predictive performance of the model proposed in this paper against the compared model, with greater (less) than 0 indicating that its predictive performance is better (worse) than that of the compared model. These metrics are defined as follows:

$$MAE = \frac{1}{N}\sum_{i=0}^{N} |y_i - \hat{y}_i| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=0}^{N} |y_i - \hat{y}_i|^2} \tag{9}$$

$$MAPE = \frac{1}{N}\sum_{i=0}^{N} \left|\frac{y_i - \hat{y}_i}{\hat{y}_i}\right| \times 100\% \tag{10}$$

$$P_{MAE} = \frac{MAE_i - MAE_p}{MAE_i} \times 100\% \qquad \forall i \in [0,1,2,\dots,n] \tag{11}$$

$$P_{RMSE} = \frac{RMSE_i - RMSE_p}{RMSE_i} \times 100\% \qquad \forall i \in [0,1,2,\dots,n] \tag{12}$$

$$P_{MAPE} = \frac{MAPE_i - MAPE_p}{MAPE_i} \times 100\% \qquad \forall i \in [0,1,2,\dots,n] \tag{13}$$

where N represents the number of data seris, y_i and $\hat{y}_i$ denote the prediction and real values, $\overline{y_i}$ is the mean of y_i, MAE_p, $RMSE_p$ and $MAPE_p$ denote the vlaues of the proposed method, MAE_p, $RMSE_p$ and $MAPE_p$ denote the values of the compared methods.

4. Experiment and analysis

4.1. Data description

In order to fully test the performance of the model proposed in this paper, data sets are set from the past few months, where the spring data set is from March 1 to April 30, 2021, the summer data set is from June 1 to July 30, 2021, the autumn data set is from October 1 to November 30, 2020, and the winter data set is from December 1, 2020 to January 30, 2021. These data sets are sampled every one hour for a total of 24 samples per day. Therefore, each of these twelve datasets contains 61 days of data for a total of 1464 points. A total of 72 points from the last 3 days of the data set were used as the test set in order to fully train the hyperparameters of the model.

Figure 2, **Figure 3** and **Figure 4** mean the boxplot of the three different regions of the United States. we can find that the wind power generation is significantly less in summer than other seasons, and the data variability characteristics of the three regions are quite different, which creates a huge challenge for short-term wind power forecasting methods.

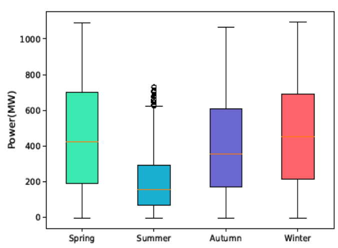


Figure 2. The boxplot of the four seasons of the Midatl datasets.

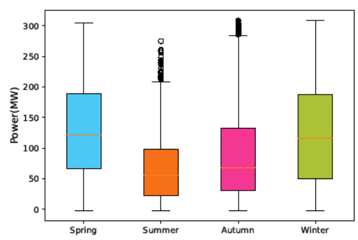


Figure 3. The boxplot of the four seasons of the South datasets

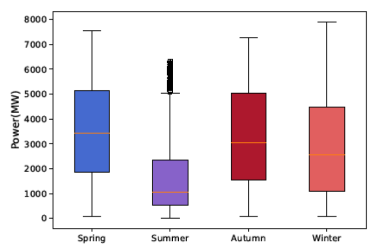
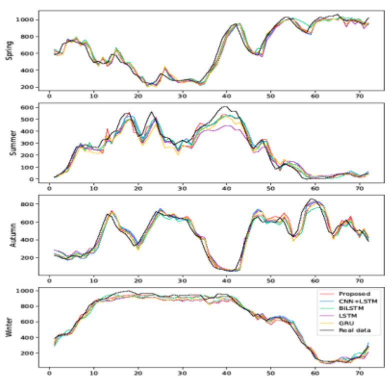


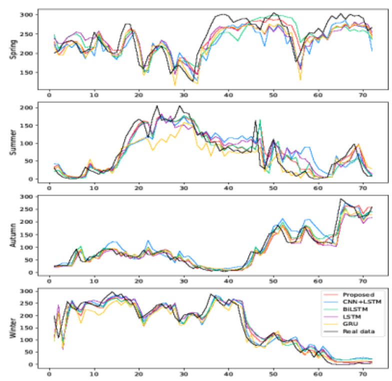
Figure 4. The boxplot of the four seasons of the West datasets.

DOI: 10.54254/2755-2721/48/20241676

4.2. Experimental Results Analysis

Figure 5 shows the prediction results of the proposed model and compared models for the testing set in Midatl. In order to show the predictive effect of the model more clearly, MAE, $RMSE$, $MAPE$, P_{MAE}, P_{RMSE} and P_{MAPE} evaluation metrics are listed in **Table 1**. The proposed model improves MAE, $RMSE$ and $MAPE$ by 30.2%, 25.3% and 31.3%, respectively, compared with CNN+LSTM model in winter dataset. The proposed model improves MAE, $RMSE$ and P_{MAPE} by 15.6%, 13.9% and 25.8%, respectively, compared with BiLSTM model in winter dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 34.1%, 30.8% and 77.8%, respectively, compared with LSTM model in summer dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 29.2%, 24.6% and 82.6%, respectively, compared with GRU model in summer dataset. **Figure 6** shows the prediction results of the proposed model and compared models for the testing set in South. In **Table 2,** we find that the proposed model improves MAE, $RMSE$ and $MAPE$ by 27.7%, 26% and 43.7%, respectively, compared with CNN+LSTM model in autumn dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 31.6%, 34.3% and 13%, respectively, compared with BiLSTM model in autumn dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 14.5%, 12.6% and 13.2%, respectively, compared with LSTM model in spring dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 10.1%, 7.2% and 55.7%, respectively, compared with GRU model in winter dataset. **Figure 7** shows the prediction results of the proposed model and compared models for the testing set in West. In **Table 3** , we find that the proposed model improves MAE, $RMSE$ and $MAPE$ by 28.3%, 20.4% and 28%, respectively, compared with CNN+LSTM model in winter dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 15.8%, 14.1% and 34.4%, respectively, compared with BiLSTM model in summer dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 40%, 33% and 32.2%, respectively, compared with LSTM model in winter dataset. The proposed model improves MAE, $RMSE$ and $MAPE$ by 13.1%, 8.2% and 50.6%, respectively, compared with GRU model in winter dataset.





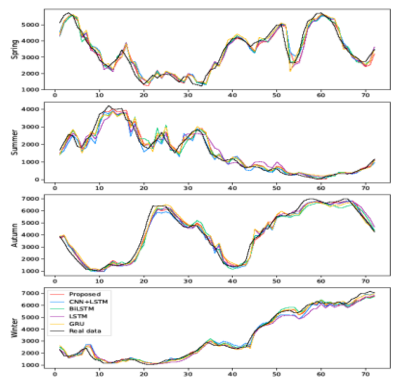


Figure 5. The boxplot of Midatl **Figure 6.** The boxplot of South **Figure 7.** The boxplot of West

5. Conclusion

In this article, a novel data-fully-driven deep learning hybrid method based on CNN and double BiLSTM layers was presented for electric management strategy of grid. The model proposed in this paper accurately predicts the short-term wind power generation from historical generation data from publicly available datasets. CNN was used to extract features from the data, and BiLSTM with bi-directional hidden layers was used to predict future power generation. To ensure that the model gets the best prediction results, the Bayesian optimizer algorithm is used to tune the hyperparameters of the CNN and BiLSTM. To fully validate the effectiveness of the model proposed in this paper, CNN+LSTM, BiLSTM, LSTM and GRU models are used for comparison on twelve different real-world datasets. Moreover, MAE, $RMSE$, $MAPE$, P_{MAE}, P_{RMSE} and P_{MAPE} evaluation metrics were chosen to test the predictive performance of these models. The final experimental results demonstrate

DOI: 10.54254/2755-2721/48/20241676

that the models proposed in this paper have somewhat better performance in most examples. In future work, real-time rate adjustments for power management optimization can be studied on this basis.

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Acknowledgments

This work was supported in part by the National Key Research and Development Program of China (Nos. 2019YFE0104800, 2019YFE0126600).

Appendix

Table 1. performance evaluations for the testing set in Midatl

Dataset	Metrics	Proposed	CNNLSTM	BiLSTM	LSTM	GRU
Spring	MAE	39.13	41.36	42.81	46.99	45.76
	$RMSE$	51.88	53.48	52.23	58.20	56.27
	$MAPE$	0.071	0.078	0.074	0.082	0.081
	P_{MAE}	-	0.054	0.086	0.167	0.145
	P_{RMSE}	-	0.03	0.007	0.109	0.078
	P_{MAPE}	-	0.089	0.041	0.155	0.128
Summer	MAE	31.51	34.27	34.4	47.79	44.51
	$RMSE$	43.38	44.26	43.81	63.6	57.5
	$MAPE$	0.032	0.053	0.054	0.144	0.184
	P_{MAE}	-	0.081	0.084	0.341	0.292
	P_{RMSE}	-	0.015	0.001	0.308	0.246
	P_{MAPE}	-	0.396	0.407	0.778	0.826
Autumn	MAE	46.102	48.445	47.89	48.72	48.91
	$RMSE$	59.748	61.734	61.459	59.9	59.82
	$MAPE$	0.116	0.126	0.122	0.139	0.127
	P_{MAE}	-	0.048	0.037	0.054	0.057
	P_{RMSE}	-	0.032	0.028	0.003	0.001
	P_{MAPE}	-	0.079	0.049	0.165	0.087
Winter	MAE	28.146	40.338	33.368	44.06	39.01
	$RMSE$	34.991	46.818	40.636	51.729	46.26
	$MAPE$	0.066	0.096	0.089	0.105	0.081
	P_{MAE}	-	0.302	0.156	0.361	0.279
	P_{RMSE}	-	0.253	0.139	0.292	0.251
	P_{MAPE}	-	0.313	0.258	0.382	0.185

Table 2. performance evaluations for the testing set in South

Dataset	Metrics	Proposed	CNNLSTM	BiLSTM	LSTM	GRU
Spring	MAE	20.808	26.097	26.18	24.337	22.791
	$RMSE$	25.384	32.684	32.389	29.029	27.856
	$MAPE$	0.092	0.11	0.114	0.106	0.096
	P_{MAE}	-	0.203	0.205	0.145	0.083
	P_{RMSE}	-	0.315	0.216	0.126	0.089
	P_{MAPE}	-	0.163	0.193	0.132	0.042
Summer	MAE	19.544	28.769	20.625	23.04	24.67
	$RMSE$	27.887	36.817	30.059	29.34	33.89
	$MAPE$	-	-	-	-	-
	P_{MAE}	-	0.32	0.05	0.152	0.208
	P_{RMSE}	-	0.24	0.07	0.05	0.177
	P_{MAPE}	-	-	-	-	-
Autumn	MAE	15.283	21.131	22.339	17.794	16.43
	$RMSE$	21.03	28.263	32.01	25.919	23.75
	$MAPE$	0.241	0.428	0.277	0.337	0.339
	P_{MAE}	-	0.277	0.316	0.141	0.07
	P_{RMSE}	-	0.26	0.343	0.189	0.115
	P_{MAPE}	-	0.437	0.13	0.285	0.289
Winter	MAE	22.624	24.677	24.83	23.259	25.168
	$RMSE$	32.478	32.906	33.842	35.122	34.984
	$MAPE$	0.145	0.153	0.158	0.284	0.328
	P_{MAE}	-	0.083	0.089	0.027	0.101
	P_{RMSE}	-	0.013	0.04	0.075	0.072
	P_{MAPE}	-	0.052	0.082	0.489	0.557

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Table 3. performance evaluations for the testing set in West

Dataset	Metrics	Proposed	CNNLSTM	BiLSTM	LSTM	GRU
Spring	MAE	262.5	281.09	267.8	284.3	271.1
	$RMSE$	356	366.8	358.6	372.8	357.2
	$MAPE$	0.091	0.102	0.094	0.099	0.097
	P_{MAE}	-	0.066	0.02	0.077	0.003
	P_{RMSE}	-	0.029	0.007	0.045	0.003
	P_{MAPE}	-	0.108	0.032	0.081	0.06
Summer	MAE	178.2	207.5	211.7	231.5	205.1
	$RMSE$	246.7	295.3	287.3	307.2	268.8
	$MAPE$	0.154	0.205	0.235	0.297	0.312
	P_{MAE}	-	0.141	0.158	0.23	0.131
	P_{RMSE}	-	0.164	0.141	0.197	0.082
	P_{MAPE}	-	0.249	0.344	0.481	0.506
Autumn	MAE	261.2	277.4	315.1	298.3	317.8
	$RMSE$	328.8	369	396.5	377.4	402.1
	$MAPE$	0.08	0.087	0.089	0.088	0.102
	P_{MAE}	-	0.058	0.171	0.124	0.178
	P_{RMSE}	-	0.109	0.171	0.129	0.182
	P_{MAPE}	-	0.0875	0.1125	0.100	0.215
Winter	MAE	149.1	208.3	173.5	251	161.6
	$RMSE$	210.7	264.4	226.4	315.7	218.5
	$MAPE$	0.059	0.082	0.066	0.087	0.066
	P_{MAE}	-	0.283	0.141	0.4	0.077
	P_{RMSE}	-	0.204	0.069	0.33	0.036
	P_{MAPE}	-	0.28	0.106	0.322	0.106