Short-term Wind Power Prediction based on Combined LSTM

Yuyang Zhao[1,2], Lincong Li[1] Yingjun Guo[1,2] Boming Shi[1], Hexu Sun [1,2]

1. School of Electrical Engineering, Hebei University of Science and Technology, Shijiazhuang, Hebei 050018, China
E-mail: zhaoyuyang@hebust.edu.cn
2. Hebei Engineering Laboratory of Wind Power and Photovoltaic Coupling Hydrogen Production and Comprehensive Utilization, Shijiazhuang, Hebei 050018, China
E-mail: shx_prof@163.com

Abstract: Wind power is an exceptionally clean source of energy, its rational utilization can fundamentally alleviate the energy, environment, and development problems, especially under the goals of "carbon peak" and "carbon neutrality". A combined short-term wind power prediction based on LSTM artificial neural network has been studied aiming at the nonlinearity and volatility of wind energy. Due to the large amount of historical data required to predict the wind power precisely, the ambient temperature and wind speed, direction, and power are selected as model input. The CEEMDAN has been introduced as data preprocessing to decomposes wind power data and reduce the noise. And the PSO is conducted to optimize the LSTM network parameters. The combined prediction model with high accuracy for different sampling intervals has been verified by the wind farm data of Chongli Demonstration Project in Hebei Province. The results illustrate that the algorithm can effectively overcome the abnormal data influence and wind power volatility, thereby provide a theoretical reference for precise short-term wind power prediction.

Key Words: wind power prediction, complete empirical mode decomposition of adaptive noise, particle swarm algorithm, long and short-term memory network, the combined model

1 Introduction

As the foundation of social economic development and people's production and life, energy promotes the development and progress of society. From climate governance to energy structure transformation, achieving the goals of "carbon peaking" and "carbon neutrality" is an inevitable choice for China in terms of ecological civilization, and it has practical significance for promoting efficient energy allocation and utilization[1]. Among the large amount of new energy, wind energy is widely distributed with huge reserves and pollution-free. Its rational use can fundamentally solve the energy shortage and environmental problems. The gradual maturity of wind power technology and the optimization and upgrade of wind power equipment has promoted the continuous development of the global wind power industry, giving the energy system a strategic opportunity for deep decarbonization [2].

To improve the reliability of the power supply and ensure the stable operation of the power system, wind power prediction is the key to solving the problem of large-scale wind power grid connection. Accurate wind power prediction can provide a reference for the future wind power transmission from the wind power system to the high-voltage transmission grids, help the power system deployment department to modify the deployment plan in a timely and effective manner, solve the problem of ambiguity in wind power deployment to varying degrees, guarantee the supply and demand balance of the power system, and improve the safety and stability of the high-voltage transmission grid operation [3-4]. Wind power forecasting technology can be divided into ultra-short-term, short-term and medium and long-term forecasting according to the forecasting time [5]. The time scale of short-term prediction is 0~72h. Short-term wind power forecasting provides conditions for future wind power bidding and online access, and provides a reference for the organization of wind farms to arrange maintenance and maintenance time, effectively reducing the number of wind farms to be shut down for maintenance, increasing the effective capacity of wind farms, and providing guarantees for the safe and stable operation of wind farms [6-7].

With the development of wind power forecasting technology, the application of a single model does not show good performance in prediction. A hybrid approach combining several single algorithms can overcome the drawbacks of single algorithm based models and improve the accuracy of wind power prediction [8]. most forecasting models follow the steps of "data preprocessing- forecasting model construction- forecasting model optimization", using neural networks, support vector machines and deep learning networks, etc. as forecasting models, using particle swarm algorithms, Bee colony algorithm, genetic algorithm, etc. to optimize the parameters of the prediction model to improve the prediction accuracy of the prediction model [9-11]. Among the above methods, the Ensemble Empirical Mode Decomposition(EEMD) has the characteristics of intuitiven ess and strong adaptability, and can effectively process nonlinear and non- stationary data signals; As a typical repr esentative of a deep learning network, Long Short Term Me mory (LSTM) network has the characteristics of wide app lication range and strong adaptability in time series; Particle Swarm Optimization (PSO) algorithm has fast convergence speed and can effectively alleviate local optim ization problems [12-13].

In view of the characteristics of wind power data volatility, this paper uses the EEMD-improved Complete EEMD with Adaptive Noise (CEEMDAN) to reduce the noise of the original wind power data components during data preprocessing, to eliminate abnormal data and improve the applicability of the data. When optimizing the prediction model, the parameters of the LSTM model are optimized by PSO to improve the prediction accuracy of the LSTM model. Finally, a CEEMDAN-PSO-LSTM combined prediction model is constructed, which is verified by wind field data to effectively improve the prediction accuracy of the model.

2 Algorithm principle

In this paper, CEEMDAN is selected to preprocess the historical data collected by wind farms to solve the modal aliasing phenomenon of traditional EEMD; LSTM network is chosen as the core prediction model to solve the long-term dependence of traditional neural networks; the LSTM network model parameters are optimized by PSO algorithm to further improve the prediction accuracy of the model [14-16].

2.1 Complete Ensemble Empirical Mode Decompositi on Adaptive Noise (CEEMDAN)

The Complete Ensemble Empirical Mode Decomposit ion Adaptive Noise (CEEMDAN) is a variation of the EEMD algorithm [17-18] that provides an exact reconstruction of the original signal and a better spectral separation of the Intrinsic Mode Functions (IMFs), which is calculated according to the average value of the results. the process is as follows:

1) Add the signal item $x(t)$ to be decomposed to the white noise signal $n_0(t)$ of equal length multiple times to obtain the noise signal $x_n(t)$, the expression is as follows:

$$x_n(t) = x(t) + k \times n_0(t) \tag{1}$$

Where k is the oscillation amplitude parameter. Decompose the expanded data $x_n(t)$ for n times to obtain the IMF data component $c_{n,i}(t)(i=1,2,...,n)$, which is the i^{th} IMF data component obtained by data decomposition after adding white noise for the n^{th} time.

2) Expand the overall average of $c_{n,i}(t)$ to eliminate the influence of the white noise data signal and the IMF added multiple times, and the finally obtained i^{th} IMF component is obtained, the expressed is as follows:

$$c_i(t) = \frac{1}{N}\sum_{n=1}^{N} c_{n,i}(t) \tag{2}$$

3) Calculate the effective error between the initial data signal and the processed data signal, the expression is as follows:

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{n}} \tag{3}$$

Where ε is the magnitude of white noise; n is the overall average number.

4) Calculate the residual term of the n^{th} order until it is no longer allowed to decompose, the expression is as follows:

$$R_n(t) = x(t) - \sum_{i=1}^{n} x_i(t) + \varepsilon_i \omega_i(t) \tag{4}$$

2.2 Particle Swarm Optimization（PSO）

Particle Swarm Optimization (PSO) distributes individ ual information to the whole so that the whole can make the best judgment while obtaining the information [19]. Assuming that there are M particles in an N-dimensional target search space, the i^{th} particle represents an N-dimensional distribution vector, and Pi represents the specific position of the i^{th} particle, the expression is as follows:

$$P_i = (P_{i1}, P_{i2}, ..., P_{iN}), i = 1,2,...,M \tag{5}$$

The expression for the moving speed of the i^{th} particle is as follows:

$$V_i = (V_{i1}, V_{i2}, ..., V_{iN}), i = 1,2,...,M \tag{6}$$

The optimal position currently searched by the i^{th} particle, the expression is as follows:

$$E_{best} = (P_{i1}, P_{i2}, ..., P_{iN}), i = 1,2,...,M \tag{7}$$

The global optimal position searched by the particle swarm, the expression is as follows:

$$G_{best} = (P_{g1}, P_{g2}, ..., P_{gN}) \tag{8}$$

The individual extreme value and the global optimal value are combined to update the velocity and position of the particle, the expression is as follows:

$$V_i = W \times V_i + C_1 \times R_1(E_{best} - P_i) + C_2 \times R_2(G_{best} - P_i) \tag{9}$$

$$X_i = x_0 + v_i(k+1) \tag{10}$$

In the formula, C_1 and C_2 are the learning ratios; W is the inertia constant; R_1 and R_2 are the random probability numbers in the control range [0,1].

2.3 Long Short-Term Memory (LSTM)

As an improved model of recurrent neural network, long short-term memory (LSTM) network replaces ordinary neuron modules with special memory neurons to enhance the ability to remember the long-term training state and effectively solve the problem of gradient disappearance and explosion in recurrent neural networks to alleviate the problem of falling into the local optimum caused by over-fitting [20-23]. Its network selectively exchanges information through the structure of information and control gates. The network structure is shown in Figure 1.

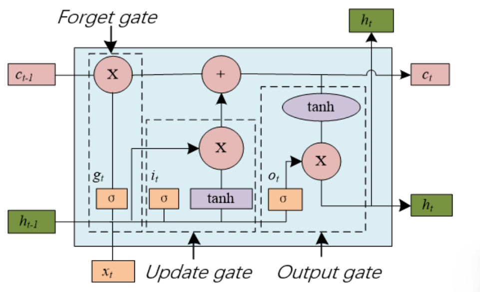


FIGURE 1 LSTM Network Structure

The forget gate transmits the information of the previous hidden state and the current input information to the sigmoid function at the same time, and the output value is between 0 and 1, and whether to leave the information according to the ratio. The closer to 0, the more information should be discarded; the closer to 1, the more information should be retained.

$$g_t = \sigma\left(w_{xg} x_t + w_{hg} h_{t-1} + w_{cg} c_{t-1} + b_g\right) \tag{11}$$

The update gate adds the input characteristics at the current moment to the shared information, which is used to update the cell state. Adjust the sigmoid function value between 0-1. Closing to 0 means that the information is not updated, closing to 1 means that the information is updated.

$$i_t = \sigma\left(w_{xi} x_t + w_{hi} h_{t-1} + w_{ci} c_{t-1} + b_i\right) \tag{12}$$

The output gate is used to determine the output value at the next moment. Pass the updated state to the tanh function, and finally multiply the output of tanh with the output of sigmoid to determine the information that the hidden state should carry, and use this hidden state as the current output and pass it to the next time step.

$$c_t = g_t c_{t-1} + i_t \tanh\left(w_{xc} x_t + w_{hc} h_{t-1} + b_c\right) \tag{13}$$

$$o_t = \sigma\left(w_{xo} x_t + w_{ho} h_{t-1} + w_{co} c_t + b_o\right) \tag{14}$$

$$h_t = o_t \tanh\left(c_t\right) \tag{15}$$

Where $\sigma(\cdot) = \dfrac{1}{1+e^{-x}}$, $\tanh = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$. where w_{xg} , w_{xi} , w_{xc} , w_{xo} represents the weight matrix connecting the input information x_t ; w_{hg} , w_{hi} , w_{hc} , w_{ho} represents the weight matrix connected to the output information h_{t-1} at the previous moment; w_{cg} , w_{ci} , w_{co} represents the weight matrix of the connected memory unit information c_{t-1} ; b_g , b_i , b_c , b_o represents the bias vector.

3 CEEMDAN-PSO-LSTM combined prediction model

In the wind power prediction model, the data collected from wind farms are usually used as the input of the prediction model for short-term wind power prediction. When selecting data, most prediction models only consider the influence of wind speed on the output power of wind farms [24]. Considering the comprehensiveness of the influencing factors, this research selects wind power, wind speed, wind direction, and ambient temperature as the input of the prediction model. In order to effectively improve the prediction accuracy, preprocess the historical data collected by wind farms, and a reliable sample data set is established through data decomposition and screening, which is divided into training set, verification set, and test set to obtain the wind power prediction results. The schematic diagram of the prediction process is shown in Figure 2.

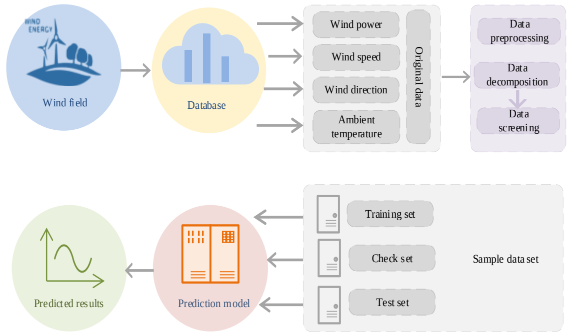


FIGURE 2 Schematic diagram of forecast process

The proposed research is based on the historical data of Chongli Large-scale Wind-solar Complementary Coupled Hydrogen Production System Application Demonstration Project in Zhangjiakou city, Hebei Province. First, sampling the output power of a single fan in the wind farm, and conduct sampling every 10 min. In the sample data set after processing, 2000 data points are obtained, and 50% of the sample data are selected to train and optimize the model, so that the model parameters are optimized. The optimized model parameters are verified with 25% sample data to verify the feasibility of the prediction model. The remaining 25% of the sample data are used as test sets for short-term wind power prediction. This paper is based on the output data of wind farms for 13 consecutive days, the short-term wind power output in the next 3 days is predicted.

The CEEMDAN-PSO-LSTM combined model is pre-processed by the CEEMDANE algorithm, and the PSO algorithm optimizes the LSTM network model. Model parameters are optimized as particles, and PSO algorithm is used to update the learning factor to reduce the learning rate, and the speed and position of particles are constantly updated. By evaluating the fitness value of the objective function, the optimal model parameters can be obtained when the global optimum is achieved. The prediction flow chart of CEEMDAN-PSO-LSTM network combination prediction model is shown in Figure 3, and the specific prediction steps are:

Step1. The original data of the wind farm are preprocessed by CEEMDAN, and the preprocessed sample data are divided into training set, verification set, and test set.

Step2. Initialize the PSO parameters, including the number of iterations of the population, the learning factor, and the bound interval of the particle position and velocity.

Step3. Build the LSTM prediction model and determine the parameter optimization range.

Step4. The fitness value of PSO was calculated, and the relative error between the real value and the predicted value of the training sample was taken as fitness function.

Step5. Update the speed and position of particles, evaluate the fitness value of particles, and update the individual optimal position and global optimal position of particles.

Step6. Determine whether the end condition is met. When the maximum number of iterations is reached, the optimal parameters are assigned to the LSTM model, and the test set is used for prediction, and the prediction results are obtained. Otherwise, continue training the LSTM model until the end condition is satisfied.

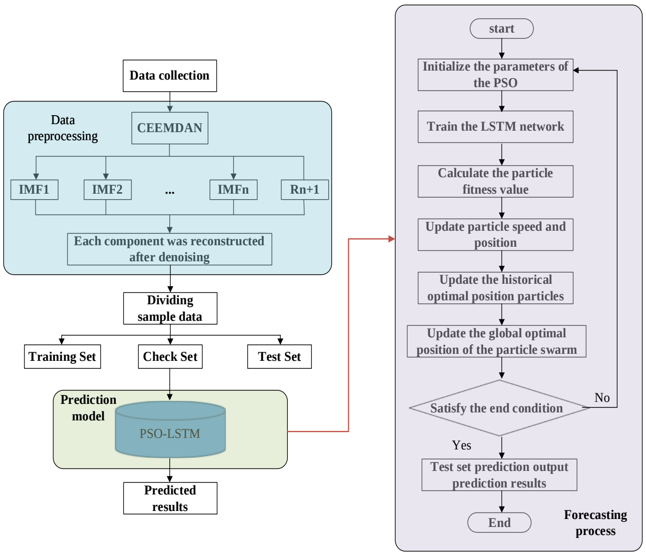
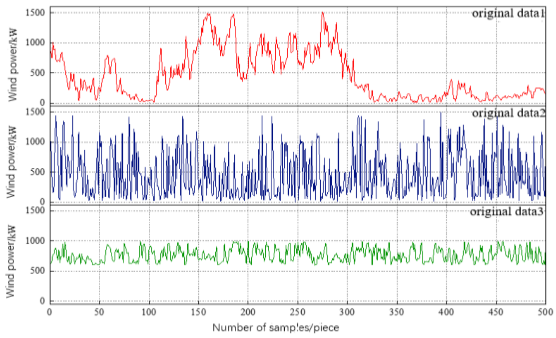


FIGURE 3 CEEMDAN-PSO-LSTM forecast process



FFIGURE 4 Sample data partition

Aiming at the problem of wind farm data fluctuation caused by the instability of wind energy, in order to better test the prediction effect of the prediction model, the accuracy of the prediction model is verified, and the original data is divided according to the degree of data fluctuation. Wind speed is the main factor affecting wind power. When wind speed changes, wind power fluctuations are different. When the wind speed changes dramatically, the output wind power fluctuates greatly. When the wind speed changes gently, the fluctuation of the wind power output from the wind farm is small. Therefore, when the wind speed changes normally within [2m/s, 12m/s], the data output from the wind farm is defined as the original data 1; When the wind speed changes drastically within the interval of [2m/s, 12m/s], the data output from the wind farm is defined as the original data 2; When the wind speed changes gently within the range of [7m/s, 10m/s], the output data of the wind farm is defined as the original data 3, and the specific partition results are shown in Figure 4.

4 Experiment and analysis

The measured wind power of a wind farm in Zhangjiakou city, Hebei Province for 20 consecutive days in August 2019 is selected as the original data for the experiment. The rated capacity of the unit is 1.5 MW, and conduct sampling every 10 min. Data are preprocessed by CEEMDAN, and the decomposition results are shown in Figure 5.

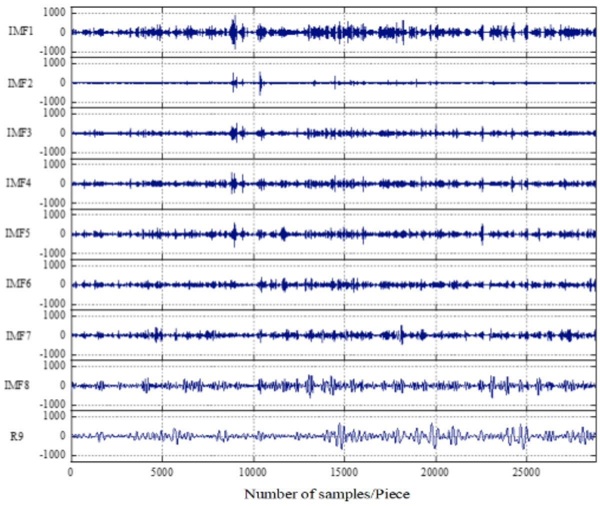


FIGURE 5 CEEMDAN Decomposition component

As can be seen from Figure 5, CEEMDAN decomposes the data into IMF1-IMF8 and a residual component R9. The variation trend of each component is different, and there are obvious extreme values in each component. The more the number of extreme points, the faster the component fluctuation speed, and the higher the frequency, so the number of extreme points reflects the frequency of the component. In order to better divide the components decomposed by CEEMDAN, the number of extreme values in each component and the correlation coefficients between the components and the original data is calculated respectively. The results are shown in Table.1.

TABLE 1 The number of extreme values of different components and the coefficient with the original data signal

components	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	R9
The number of extreme points	9715	7191	6878	3983	2257	1291	613	293	146
the correlation coefficients	0.1952	0.1435	0.1972	0.2313	0.2578	0.2935	—	—	—

As can be seen from Table 1, the number of extreme values in IMF1-IMF6 component is greater than 1000, so IMF1-IMF6 is regarded as high frequency component, and the rest as low frequency component. In the high-frequency component, the correlation coefficient between IMF1-IMF4 and the original wind power signal is less than 0.25, indicating that the correlation between IMF1-IMF4 and the original wind power signal is small, which affects the prediction accuracy, and it is removed as noise. Finally, the IMF5-IMF8 and R9 components are reconstructed, and the comparison with the original wind power is shown in Figure 6.

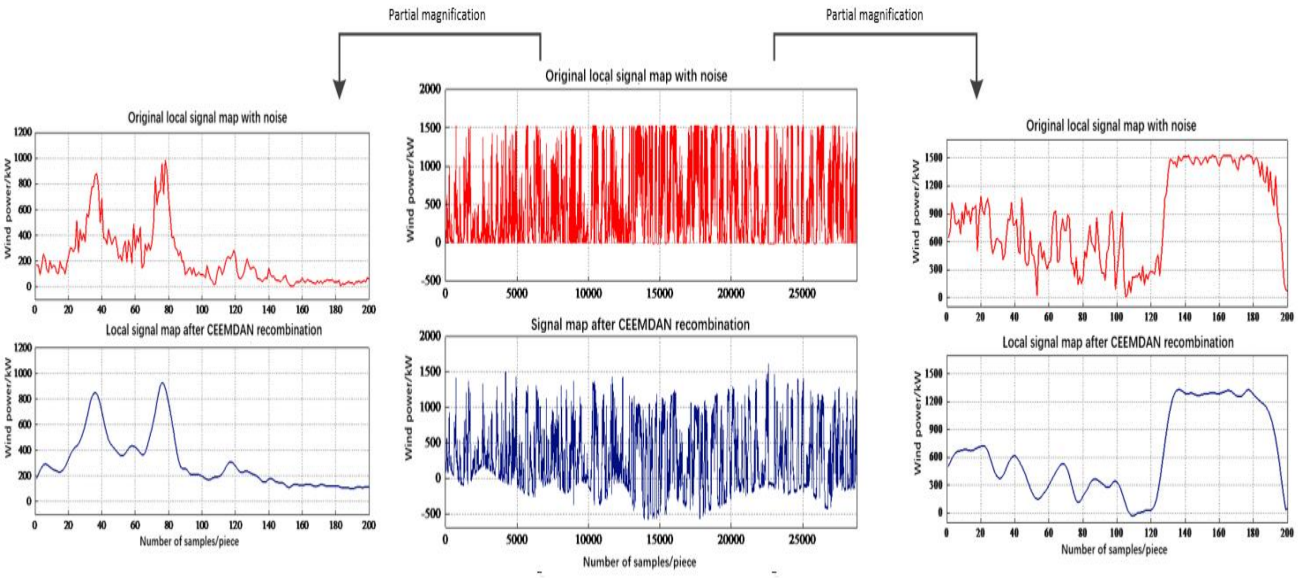


FIGURE 6 Overall and Partial comparison chart

According to the overall and local comparative analysis, after CEEMDAN processing, the change trend of sample data is smoother, and the burr is significantly reduced. In view of the influence of prediction time on the accuracy, the prediction accuracy of the model under different time scales is verified. Sample data processed by CEEMDAN is taken as input, and the relative error between prediction results and model is shown in Figure 7.

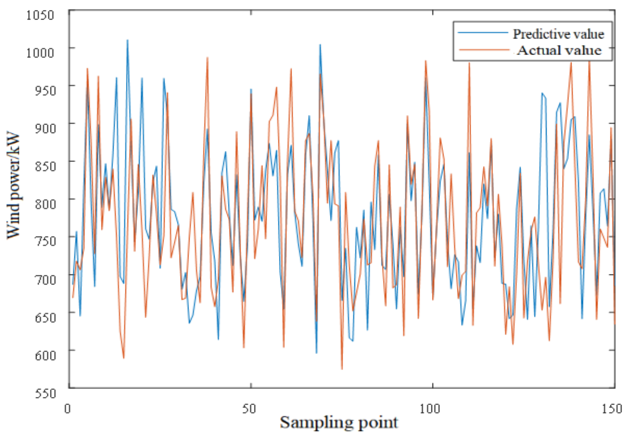


FIGURE 7(a) Sample interval of 5 minutes predicted results

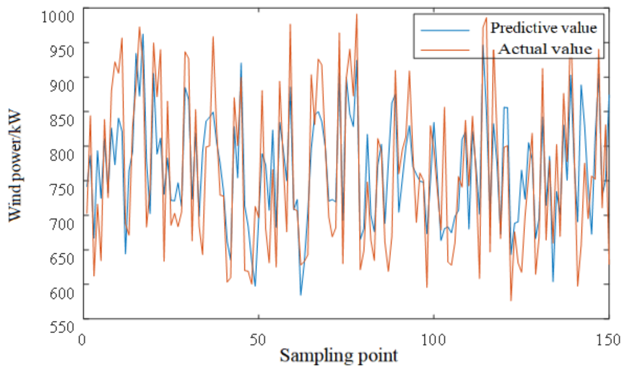


FIGURE 7(b) Sample interval of 10 minutes predicted results

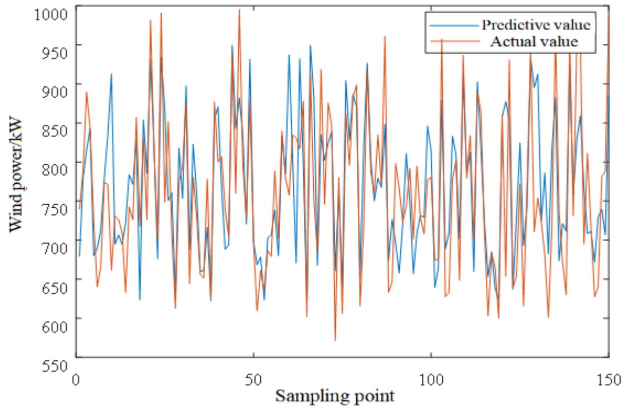


FIGURE 7(c) Sample interval of 20 minutes predicted results

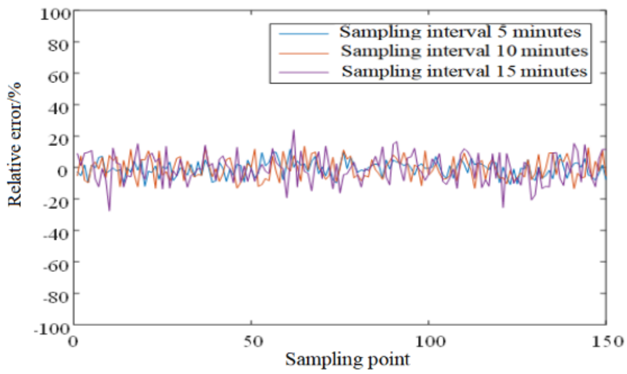


FIGURE 7(d) Relative error of prediction at different sampling intervals

In order to better verify the prediction effect of the model, LSTM, PSO- LSTM, CEEMDAN- LSTM, CEEM DAN-PSO- BP, CEEMDAN-PSO-SVM, and CEEMDAN-PSO-LSTM prediction models are constructed respectively, and the prediction effects of the models were compared. The results are shown in Figure 8.

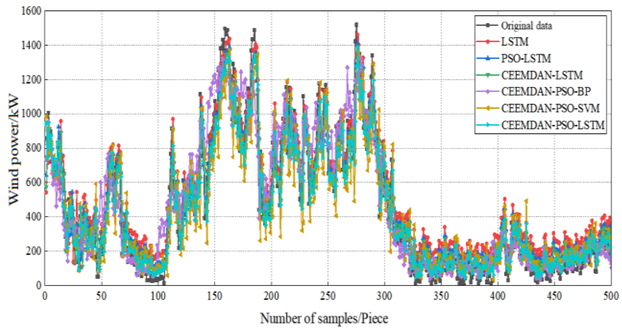


FIGURE 8 Comparison of forecast result

In order to compare and analyze the prediction effects of the above prediction models more clearly, the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Per- centage Error (MAPE) and R^2 perform ance index of each model are calculated respectively. The calculation results are shown in Table 2.

Table 2 Comparison table of prediction performance of corresponding models

Prediction models	MAE (kW)	RMSE (kW)	MAPE(%)	R2
LSTM	140.71	164.11	10.18	0.8286
PSO-LSTM	113.31	138.90	9.15	0.8772
CEEMDAN-LSTM	106.71	135.14	6.76	0.8837
CEEMDAN-PSO-BP	97.1431	134.5271	7.0511	0.8848
CEEMDAN-PSO-SVM	122.6931	152.9798	10.5934	0.8267
CEEMDAN-PSO-LSTM	74.9627	110.3304	2.7488	0.9686

From the analysis of the above results, it can be concluded that:

1) The prediction accuracy of CEEMDAN-PSO-LSTM model fluctuates slightly with different degree of data fluctuation. When the sampling interval is 5 minutes, the relative error of prediction results is small. When the sampling interval is 10 minutes, the relative error of prediction results is about 6% on average. When the sampling interval is 20 minutes, the relative error of prediction results is large. Therefore, different sampling intervals have certain influence on the prediction accuracy of the prediction model, and the prediction error increases with the increase of sampling intervals.

2) Compared with the pre-optimization and post-optimization prediction models, CEEMDAN-PSO-LSTM model has advantages in short-term wind power prediction. The MAE, RMSE, and MAPE evaluation indexes of CEEMDAN-LSTM compared with LSTM model decreased by 34.00, 28.97 and 3.42% respectively, and R^2 increased by 0.0551, which verified the necessity of CEEMDAN data preprocessing in wind power prediction. Compared with CEEMDAN-LSTM model, MAE, RMSE and MAPE evaluation indexes of CEEMDAN-PSO-LSTM model decreased by 31.75, 24.81 and 4.01% respectively, and R^2 increased by 0.0849. It is proved that PSO optimization algorithm can effectively improve the accuracy of prediction model.

3) In the same sample data set, the prediction performance of different prediction models is different. Compared with CEEMDAN-PSO-BP neural network model, MAE, RMSE and MAPE of CEEMDAN-PSO-LSTM model decreased by 22.1804, 24.1967 and 4.30% respectively, and R^2 increased by 0.0838. Compared with CEEMDAN-PSO-SVM model, MAE, RMSE and MAPE decreased by 47.7304, 42.6494 and 7.84%, respectively, and R^2 increased by 0.1419.

To sum up, according to the comprehensive analysis of MAE, RMSE, MAPE and R2 prediction evaluation indexes of the prediction model. The CEEMDAN-PSO-LSTM combined prediction model proposed in this paper has a prediction accuracy of 97.25%, which can better complete short-term wind power prediction under different time scales.

5 Conclusion

The combined CEEMDAN-PSO-LSTM wind power prediction model is proposed for solving the wind speed changes, volatility, and less controllability. The preprocess CEEMDAN decomposes wind power and eliminates abnormal data to improve the applicability of input data. The LSTM model optimized by PSO algorithm has avoided falling into the local optimal characteristics effectively and improve the accuracy further. The CEEMDAN-PSO-LSTM combined prediction model has been validated by comparative analysis of the prediction results at different time scales. The calculation speed and inputs data simplification should also be also considered to satisfy the online wind power prediction in the future.

ACKNOWLEDGEMENTS

This work is supported by S&T Program of Hebei (203145 01D); Science and Technology Project of Hebei Education Department(ZD2022030);Overseas Expertise Introduction Project of Hebei(2023); Science and Technology Project of Hebei Education Department(QN2021222)

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

None

DATA AVAILABILITY STATEMENT

The author has provided the required Data Availability State-ment, and if applicable, included functional and accurate links to said data therein.

References

1. Wang, Y., Zou, R.M., Liu, F., Zhang, L.J., Liu, Q.Y.: A review of wind speed and wind power forecasting with deep neural network. Applied Energy 304, 117766, (2021)
2. Wan, C., Song, Y.H.: Probability prediction theory and method of new energy power system and its application. Automation of Electric Power Systems 45,2-16, (2021)
3. Huang, W.C., Pan, F. Yang, Z.X. Chang, Y.F.: Short-term prediction of wind power based on improved kernel extrem e learning machines. Journal of Chongqing University of Technology (Natural Science) 37,241-250, (2023)
4. Zhai T.: Ultra-short-term prediction of wind power output based on data-driven. Shenyang: Shenyang University of Technology, (2020)
5. Wu Z., Luo G., Yang Z.L., Guo Y.J., Li K., Xue Y.S.: A comprehensive review on deep learning approaches in wind forecasting applications. CAAI Transactions on Intelligence Technology 7(2),129-143, (2022)
6. Soman, S.S., et al.: A review of wind power and wind speed forecasting methods with different time horizons. In: North American Power Symposium 2010, IEEE 1– 8, (2010)
7. Gu, B., Hu, H., Zhao, J, Zhang, H.T., Liu, X.Y.: Short-term wind power forecasting and uncertainty analysis based on FCM–WOA–ELM–GMM, Energy Reports 807-81 (2023)
8. Thi Hoai Thu Nguyen, Quoc Bao Phan: Hourly day ahead wind speed forecasting based on a hybrid model of EEMD, CNN-Bi-LSTM embedded with GA optimization, Energy Reports, 53-60, (2022)
9. Yang, J.X.: A novel short-term multi-input – multi-output prediction model of wind speed and wind power with LSSVM based on improved ant colony algorithm optimization. Cluster Computing 22(2), (2019)
10. Neeraj, K., Sudha K., Kusum, T.: Wind power prediction analysis by ANFIS, GA-ANFIS and PSO-ANFIS. Journal of Information and Optimization Sciences, 43(3), (2022)
11. Wang, L., Tao, R., Hu H.L, et al.: Effective wind power prediction using novel deep learning network: Stacked independently recurrent autoencoder. Renewable Energy 164(C): 642-655, (2021)
12. Banik, A., Behera, C., Sarathkumar, T.V. and Goswami, A.K., Uncertain wind power forecasting using LSTM-based prediction interval. IET Renew. Power. Gener. 14, 2657-2667, (2020)
13. Semero, Y.K., Zhang, J.H., Zheng, D.H.: EMD – PSO – ANFIS-based hybrid approach for short-term load forecasting in microgrids. IET Generation, Transmission & Distribution 14(3), (2022)
14. Hu, C.J., Zhao, Y., Jiang, H., Jiang, M.K., You, F.C., Liu, Q.: Prediction of ultra-short-term wind power based on CEEMDAN- LSTM- TCN, Energy Report 483-49, (2022)
15. Kamani, D, Ardehali, M.M., Long- term forecast of electrica l energy consumption with considerations for solar and win d energy sources, Energy 126617, (2023)
16. Liu, H., Chen D.H., Lin F., Wan Z.L.: Wind Power Short-Term Forecasting Based on LSTM Neural Network With Dragonfly Algorithm[J]. Journal of Physics: Conference Series 1748(3), 1-11, (2021)
17. Wang, H., Li, Y., Xiong, M., Chen, H.F.: A combined wind speed prediction model based on data processing, multi-objective optimization and machine learning, Energy Reports 413- 421, (2023)
18. Guo, C., Kang, X., Xiong, J., Wu, J.: A New Time Series Forecasting Model Based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Temporal Convolutional Network. Neural Process Lett. (2022)
19. Kumar, M., Tyagi, B.: Multi-variable constrained non-linear optimal planning and operation problem for isolated microgrids with stochasticity in wind, solar, and load dema nd data. IET Gener. Transm. Distrib. 14, 2181-2190, (2020)
20. Garg, S., Krishnamurthi, R.: A CNN encoder decoder LSTM model for sustainable wind power predictive analytics, Sust ainable Computing: Informatics and Systems 100869, (2023)
21. Li, J., Deng, D.Y., Zhao, J.B., Cai, D.S., Hu, W.H., Zhang, M., Huang, Q.: A Novel Hybrid Short-Term Load Forecasting Method of Smart Grid Using MLR and LSTM Neural Network. IEEE Transactions on Industrial Informatics 17,2443-2452, (2021)
22. Kuang, H.H., Guo, Q., Li, S.Q., Hao, Z.: Short-term wind power forecasting model based on multi-feature extraction and CNN-LSTM. IOP Conference Series: Earth and Environmental Science 702(1): 1-6, (2021)
23. Li, R., Ma, T., Zhang, X., et al.: Prediction of Short-term Wind Power based on convolutional long short-term memory neural network. Acta Solar Energy Sinica 42(06): 304-311, (2021)
24. Karan, S., Ketan, P. B., Tushar, S., Rajneesh, S.: An imputation and decomposition algorithms based integrated approach with bidirectional LSTM neural network for wind speed prediction. Energy 278, (2023)