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Research of Short-Term Wind Power Generation Forecasting Based on mRMR-PSO-LSTM Algorithm

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Abstract: A novel short-term wind power forecasting method called mRMR-PSO-LSTM was proposed to address the limitations of traditional methods in ignoring the redundancy and temporal dynamics of meteorological features. The methods employed the Minimum Redundancy Maximum Relevance (mRMR) algorithm to select relevant meteorological features while minimizing redundancy. Additionally, the Particle Swarm Optimization (PSO) algorithm was utilized to optimize the parameters of the Long Short-Term Memory (LSTM) network, thereby enhancing its forecasting accuracy. Experimental results demonstrated that the proposed mRMR-PSO-LSTM outperforms FNN, GRU, and PSO-LSTM in four key evaluation metrics.

Keywords: short-term wind power forecasting; feature selection; long short-term memory network



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1. Introduction

With the continuous development of society, the application of new energy is increasingly becoming an important pathway to address energy issues and environmental pollution [1–4]. Among clean energy sources, wind power generation has drawn widespread attention due to its pollution-free and renewable characteristics, and is considered the most promising new energy source in China's power generation sector [5,6]. However, due to the strong stochastic nature of wind speed, wind power generation exhibits significant fluctuations in power output, posing challenges to the stable operation and reliability of the power system [7]. Although there is a significant correlation between wind power generation and meteorological data, accurately predicting short-term power generation based on meteorological data remains a challenging problem due to the uncertainty of factors such as wind speed and direction [8–10].

Currently, researchers have successfully developed various models to address the issue of wind power prediction. A series of machine learning methods have been applied to this field [11–14]. Kramer et al. used support vector regression as a forecasting method for wind energy time series [11]. Yesilbudak et al. proposed an ultra-short-term wind power prediction model based on the k-nearest neighbors classifier, using wind speed, wind direction, air pressure, and temperature parameters as multivariate meteorological inputs [12]. Men et al. integrated hybrid density neural networks for short-term wind speed and power prediction [13]. Sharifian et al. combined expert knowledge of fuzzy systems with the learning capability of neural networks to achieve accurate wind power prediction [14]. However, applying machine learning techniques to the field of wind power prediction faces challenges such as significantly long computational times and the need for further improvement in predictive performance [15].

With the rapid development of deep learning, it is increasingly being used for short-term wind power prediction [16,17]. Abou Houran et al. combined Long Short Term

Memory (LSTM) and Swarm Intelligence optimization algorithms to generate a framework, the Coati optimization algorithm-Convolutional Neural Network-LSTM (COA-CNN-LSTM), which can accurately estimate the short-term output of offshore wind power [18]. Zhang et al. proposed a wind power output prediction model by combining multivariate time series clustering algorithms with deep learning networks based on numerical weather forecast data [19]. While recent advancements have marginally enhanced prediction accuracy, significant potential for improvement remains in wind power prediction. This is primarily attributed to the inadequacy of existing methods in concurrently accounting for the redundancy and temporal dynamics of meteorological features. Therefore, it is necessary to explore more advanced methods to comprehensively and accurately capture the correlation between wind power generation and meteorological data.

The Minimum Redundancy Maximum Relevance (mRMR) algorithm is a feature selection method based on mutual information, which can be used to address redundancy issues among meteorological features. It aims to maximize the correlation between features and the target variable while minimizing redundancy among features, thereby improving the quality of the feature subset [20]. Therefore, when applied to meteorological data, the mRMR algorithm can extract the most representative meteorological features closely related to wind power generation. Considering the temporal nature of meteorological data, LSTM effectively addresses issues such as local minima, vanishing gradients, and explosions commonly encountered by traditional neural networks, particularly exhibiting strong modeling and analytical capabilities for time series data [21]. When LSTM is applied to meteorological data, it can more effectively capture the temporal patterns of meteorological features [22]. Additionally, Particle Swarm Optimization (PSO) algorithm, as a global stochastic search algorithm, is introduced to optimize the weights and parameters of LSTM, further enhancing the model's generalization performance [23].

Combining the advantages of these three methods, this paper aims to effectively address the redundancy and temporality of meteorological features. By utilizing the mRMR algorithm to extract representative meteorological features, integrating LSTM networks to handle temporal information, and then globally optimizing model parameters through the PSO algorithm, we have developed a more accurate and robust short-term wind power prediction model, mRMR-PSO-LSTM. The application of this comprehensive approach is expected to not only enhance model performance but also better meet the requirements of wind power generation systems for reliable prediction.

2. Materials and Methods

With the widespread application of clean energy, wind power generation, as an essential component of renewable energy, plays a critical role in the stable operation of power systems. In the research on wind power generation systems, researchers generally recognize the significant correlation between meteorological data and wind power generation, thus extensively employing meteorological data and historical power generation data to forecast short-term wind power generation. However, despite the improvement in prediction accuracy to some extent, this approach still faces challenges. This is mainly due to the stochastic, redundant, and time-dependent nature of meteorological data, making accurate short-term wind power generation prediction still an urgent scientific challenge to be addressed.

2.1. Data Preparation and Preprocessing

To evaluate the performance of the model, over five months of meteorological data and historical wind power generation data were collected. The meteorological data include 31 features, which can be categorized into four classes as shown in Table 1, with a sampling interval of 1 h. Meteorological conditions describe the fundamental attributes of weather; cloud cover and radiation depict the atmospheric conditions of clouds and the intensity of solar radiation; hydrological conditions describe the flow and distribution of surface and groundwater, and atmospheric instability indices describe the stability of the atmosphere

and potential convective activity. The historical wind power generation data were sampled at 5-min intervals, resulting in a total of 39,454 data points after excluding any missing values. To ensure data consistency, the historical power generation for each hour was taken as the target variable. Specifically, the 5-min interval was converted to a 1-h interval by averaging the remaining data within each hour after removing missing values.

Table 1. The collected 31 original features.

Category	Feature
Meteorological conditions	Atmospheric pressure
	Air temperature
	Precipitation
	Snowfall
	Snow depth
	Snow density
	Snow layer temperature
	Surface temperature
	Dew point temperature
	Humidity
	Evaporation
	Potential evaporation
	Wind speed
	Wind direction
Cloud cover and radiation	Visibility
	Sunshine duration
	Cloud base height
	Low cloud cover
	Medium cloud cover
	High cloud cover
	Total cloud cover
	Total solar radiation
Hydrological conditions	Net solar radiation
	Direct radiation
	UV index
	Runoff
Atmospheric instability indices	Surface runoff
	Subsurface runoff
	Thunderstorm probability
	K index
	Convective available potential energy

Prior to model construction, the box plot method was initially executed to remove outliers beyond the upper and lower bounds. The principle of the box plot method is to arrange a set of data in ascending order and divide it into four equal parts. Let U represent the upper quartile, L represents the lower quartile, and $IQR = U - L$ represents the interquartile range. Points falling outside the interval $[U - 1.5 * IQR, L + 1.5 * IQR]$ are considered outliers. Subsequently, 3663 data points were obtained for simulation experiments. Additionally, considering the short-term continuity of meteorological data, a strategy based on neighboring data was adopted. Specifically, missing values were filled by utilizing the average of their adjacent data points to better preserve the temporal relationships in the data. Finally, the min-max normalization method was applied to each meteorological feature to eliminate the dimensional differences among different features. Through the aforementioned data preprocessing steps, the data quality and consistency for model construction were ensured, providing a reliable foundation for subsequent analysis and experiments.

2.2. Construction of mRMR-PSO-LSTM Model

In order to more effectively utilize wind energy resources and enhance the predictability and stability of wind power generation systems, the mRMR-PSO-LSTM model has been developed for short-term wind power generation prediction. The research framework is illustrated in Figure 1, which not only encompasses data preparation and preprocessing processes but also fully leverages feature selection methods based on mutual information and deep learning prediction models based on time-series modeling, aiming to maximize the extraction of relevant information from meteorological data to better adapt to the task of wind power generation prediction. These steps are designed and executed reasonably to contribute effectively to improving the predictive performance of wind power generation systems. The process of feature selection and power generation prediction implementation is detailed in the following sections.

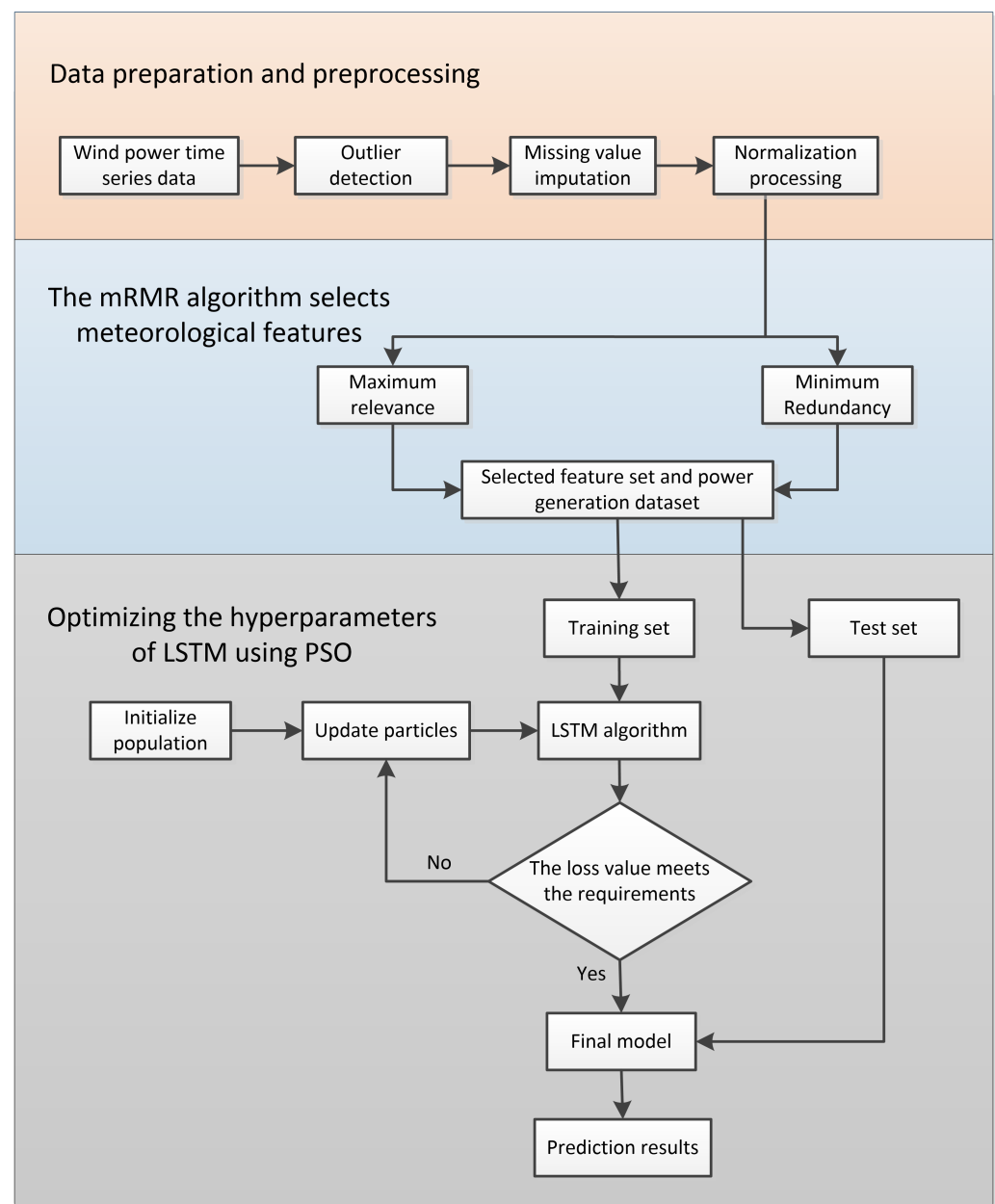


Figure 1. Flowchart of the mRMR-PSO-LSTM model.

2.3. Meteorological Feature Selection Based on mRMR Method

The primary issue with using meteorological data is the redundancy of features, which directly affects the stability of prediction models. After preprocessing meteorological data and historical power generation data, 3563 data points were selected for model training, and the remaining 100 data points were used for model testing. Let $y = (y_1, \dots, y_k, \dots, y_{3563})^T$ be the data of 3563 power generation units, and $C = (c_1, \dots, c_i, \dots, c_j, \dots, c_{31})$ be the matrix composed of 31 meteorological features, where c_i and c_j are the column vectors of the i -th and j -th meteorological features, respectively. To find the feature set C_5 containing five meteorological features, first, maximize the average mutual information between the features and the power generation:

$$\max D(C_5, y) = \frac{1}{5} \sum_{c_i \in C_5} MI(c_i; y),$$

where $MI(c_i; y) = \sum_y \sum_{c_i \in C_5} p(c_i, y) \log(\frac{p(c_i, y)}{p(c_i)p(y)})$ represents the mutual information between meteorological features c_i and power generation y , $p(c_i, y)$ represents the joint probability distribution of the i -th meteorological feature and power generation y , and $p(c_i)$ and $p(y)$ represent their respective marginal probability distributions. Secondly, it is necessary to minimize the average mutual information between meteorological features:

$$\min R(c_i, c_j) = \frac{1}{25} \sum_{c_i, c_j \in C_5} MI(c_i; c_j),$$

where $MI(c_i; c_j) = \sum_{c_i, c_j \in C_5} p(c_i, c_j) \log(\frac{p(c_i, c_j)}{p(c_i)p(c_j)})$ represents the mutual information between meteorological features c_i and c_j . By combining maximum correlation and minimum redundancy, the mRMR algorithm uses the following equation to find the optimal meteorological feature set:

$$\max \phi(D, R) = D - R,$$

where $\phi(D, R)$ represents the mRMR score, and D and R represent the correlation score and redundancy score between meteorological characteristics and power generation, respectively.

This paper is based on the mRMR algorithm, which accurately extracts the most representative meteorological feature set C_5 by maximizing the correlation between features and target variables while minimizing the redundancy between features. The number of features in the feature set is determined based on an analysis of experimental results. When more than five features are selected using mRMR, the scores of the top five features are significantly higher than those of the remaining features.

2.4. PSO Optimization of Hyperparameters in LSTM Models

To overcome the limitations of traditional models in handling long sequence data, the LSTM network, known for its outstanding performance, is introduced to more effectively capture the temporal patterns of wind power generation. As a variant of recurrent neural networks, the core idea of LSTM involves the incorporation of gate mechanisms, aiding the network in managing and utilizing long-term memory more effectively. The specific structure of the forget gate, input gate, and output gate in the LSTM model is illustrated in Figure 2. By employing LSTM, the model's ability to model the complex temporal relationships of wind power generation is enhanced, thereby enabling more accurate prediction of future power generation changes.

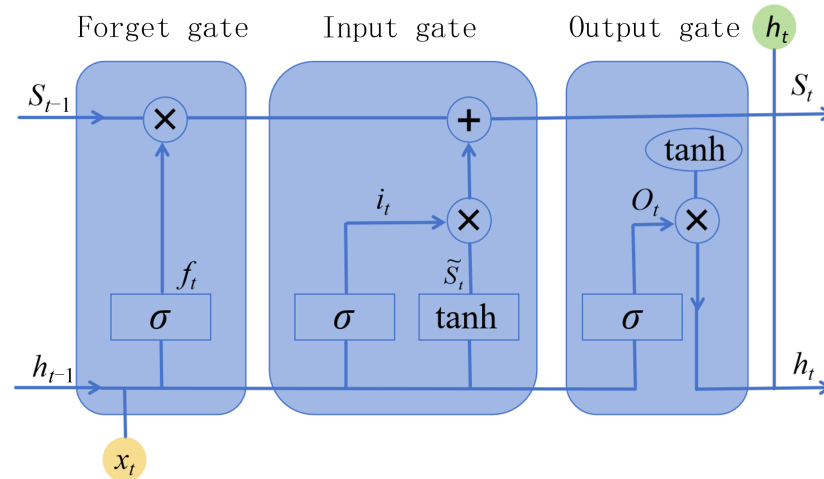


Figure 2. Figure of the unit structure of an LSTM network.

In meteorological data forecasting, the forget gate helps the network to disregard past meteorological conditions as not all past information is crucial for predicting the current moment. At each time step t , the forget gate f_t is a value constrained between 0 and 1, achieved through a Sigmoid function:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f).$$

The input gate assists the network in determining the importance of current meteorological information (such as wind speed, temperature, etc.) for predicting wind power generation, thus better adapting to varying meteorological conditions. Similarly, the input gate i_t is constrained through a Sigmoid function:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i).$$

The cell state update enables the LSTM network to capture long-term dependencies within the input meteorological data. $\tilde{S}_t$ represents the candidate cell state, constrained through a hyperbolic tangent function:

$$\tilde{S}_t = \tanh(W_s \cdot [h_{t-1}, x_t] + b_s).$$

Subsequently, S_t denotes the new cell state, obtained through element-wise multiplication and addition operations between the input gate and the candidate cell state:

$$S_t = f_t S_{t-1} + i_t \tilde{S}_t.$$

The output gate aids the LSTM network in determining which information within the cell states is useful for the final prediction, thereby generating the ultimate output. O_t represents the output gate, constrained through a Sigmoid function. This gate determines how much of the current cell state is to be outputted to the hidden state:

$$O_t = \tanh(W_o \cdot [h_{t-1}, x_t] + b_o).$$

The hidden state h_t encompasses the network's cumulative memory of past temporal information from the input sequence, reflecting which information from the current moment's cell state is selectively outputted through element-wise multiplication between the output gate and the cell state:

$$h_t = O_t \tanh S_t.$$

In the formulas for f_t , i_t , and O_t , W represents weights, and b denotes bias terms.

Additionally, the PSO algorithm is employed to optimize the parameters of LSTM, aiming to enhance the model's generalization performance. PSO simulates the collaborative behavior among individuals within a flock of birds or a school of fish. In PSO, individuals (particles) move in the search space and update their positions and velocities by learning from both their neighbors and the global optimum position. In PSO-LSTM, each particle represents a parameter vector, specifically the hyperparameters of LSTM such as learning rate, number of hidden units, etc. The update rule of PSO is defined as follows:

$$\begin{cases} v_{mn}^{t+1} = \omega v_{mn}^t + k_1 r_1 (p_{mn} - x_{mn}^t) + k_2 r_2 (g_n - x_{mn}^t); \\ x_{mn}^{t+1} = x_{mn}^t + v_{mn}^{t+1}. \end{cases}$$

where v_{mn} represents the velocity of particle m in dimension n , ω is the inertia weight, k_1 and k_2 are acceleration constants, r_1 and r_2 are random numbers, p_{mn} is the individual best position of particle m in dimension n , g_n is the global best position, and x_{mn} is the current position of particle m in dimension n .

2.5. Comparative Methods and Evaluation Metrics

To validate the effectiveness of the mRMR-PSO-LSTM model in addressing the redundancy and temporality of meteorological features, PSO-LSTM, Gate Recurrent Unit (GRU), and feedforward neural network (FNN) are employed as comparative methods. The performance of each method is comprehensively evaluated by calculating the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The formulas for calculating each evaluation metric are as follows:

$$MAPE = \frac{1}{100} \sum_{k=1}^{100} \frac{|y_k - \hat{y}_k|}{y_k} \times 100\%,$$

$$MAE = \frac{1}{100} \sum_{k=1}^{100} |y_k - \hat{y}_k|,$$

$$RMAE = \sqrt{\frac{1}{100} \sum_{k=1}^{100} (y_k - \hat{y}_k)^2},$$

$$R^2 = 1 - \frac{\sum_{k=1}^{100} (y_k - \hat{y}_k)^2}{\sum_{k=1}^{100} (\hat{y}_k - \bar{y})^2},$$

where y_k represents the actual power generation data, $\hat{y}_k$ denotes the model-predicted power generation data, $\bar{y}$ denotes the mean of the actual power generation, and R^2 is a metric used to assess the model's representation of the actual data. The closer its value to 1, the better the predicted data reflects the actual data, indicating a more effective performance.

3. Results

The mRMR-PSO-LSTM, FNN, mRMR-GRU, mRMR-LSTM, and PSO-LSTM algorithms were separately applied to datasets containing all 31 meteorological features, as well as datasets containing only the five meteorological features selected through the mRMR algorithm. Following the principle of controlled variables, the superiority of the selected feature sets was displayed based on the performance of the models when the same method was applied to different datasets. Meanwhile, the difference in model performance was induced when the FNN, mRMR-GRU, mRMR-LSTM, and PSO-LSTM were applied to the same dataset, depending on whether the model effectively handled temporal data. Specifically, the mRMR algorithm was applied to preprocessed meteorological data and historical wind power generation data. Through this algorithm, a feature set C_5 containing wind direction, wind speed, atmospheric pressure, air temperature, and humidity was

selected. Wind direction affects whether a wind turbine can effectively capture wind energy, with wind speed being the most critical parameter for wind power generation [24,25]. Atmospheric pressure, temperature, and humidity directly influence air density which, in turn, affects the amount of wind energy that a wind turbine can capture [26]. These five features exhibited the highest correlation with wind power generation, with minimal redundancy among them. Subsequently, the first 3563 data points containing the feature set C_5 and historical power generation data were used for model training, while the remaining 100 data points were reserved for model testing. In the LSTM model, both the input layer and the output layer are set to time steps of 24 h. The multi-step prediction value is set to 24. Each data point represents an hourly measurement, so a 24-h window corresponds to a full day, capturing daily patterns and trends effectively. The parameters of the FNN, PSO algorithm, and LSTM model optimized through the PSO algorithm are listed in Table 2. The Levenberg–Marquardt (LM) algorithm is employed for training FNN, which combines the advantages of Newton’s method and gradient descent, demonstrating rapid convergence.

Table 2. Model parameter settings.

Method	Parameter
FNN	Activation function: tansig (Hidden layer) purelin (Output layer)
	Training method: LM algorithm
	Learning rate: 0.01
	Training goal: 1×10^5
	Maximum training times: 1000
PSO	Population size: 20
	Maximum number of iterations: 200
	Acceleration constants k_1, k_2 : 1.5
	Inertia weight: 0.5
	The maximum value of particle velocity: 10 The minimum value of particle velocity: -10
PSO-LSTM	numHiddenUnits1: 67
	numHiddenUnits2: 138
	maxEpochs: 150
	learning_rate: 0.0095

After training, the four models were utilized to predict the wind power generation for the next 100 h. These predicted curves are depicted in Figure 3, where the red dashed lines represent the model predictions, while the blue solid lines represent the actual wind power generation. From the fluctuation trends observed in the six subplots of Figure 3, it is evident that the predictions generated by the PSO-LSTM model closely resemble the actual wind power generation, indicating that LSTM is better at capturing the temporal characteristics of meteorological data, thus enabling more accurate predictions of future wind power generation. Furthermore, regarding the fluctuation amplitudes observed in the six subplots of Figure 3, the models based on the mRMR algorithm exhibit smaller fluctuations around the actual wind power generation. This suggests that the mRMR algorithm effectively filters out redundant meteorological features, enhancing the robustness of the model’s predictive performance. It is noteworthy that the proposed mRMR-PSO-LSTM model achieves the most accurate predictive performance among the six models, considering the comprehensive consideration of the temporal and redundancy aspects of meteorological features. This indicates that the model effectively addresses the issues of redundancy and temporality in meteorological features, significantly improving the accuracy of wind power generation prediction.

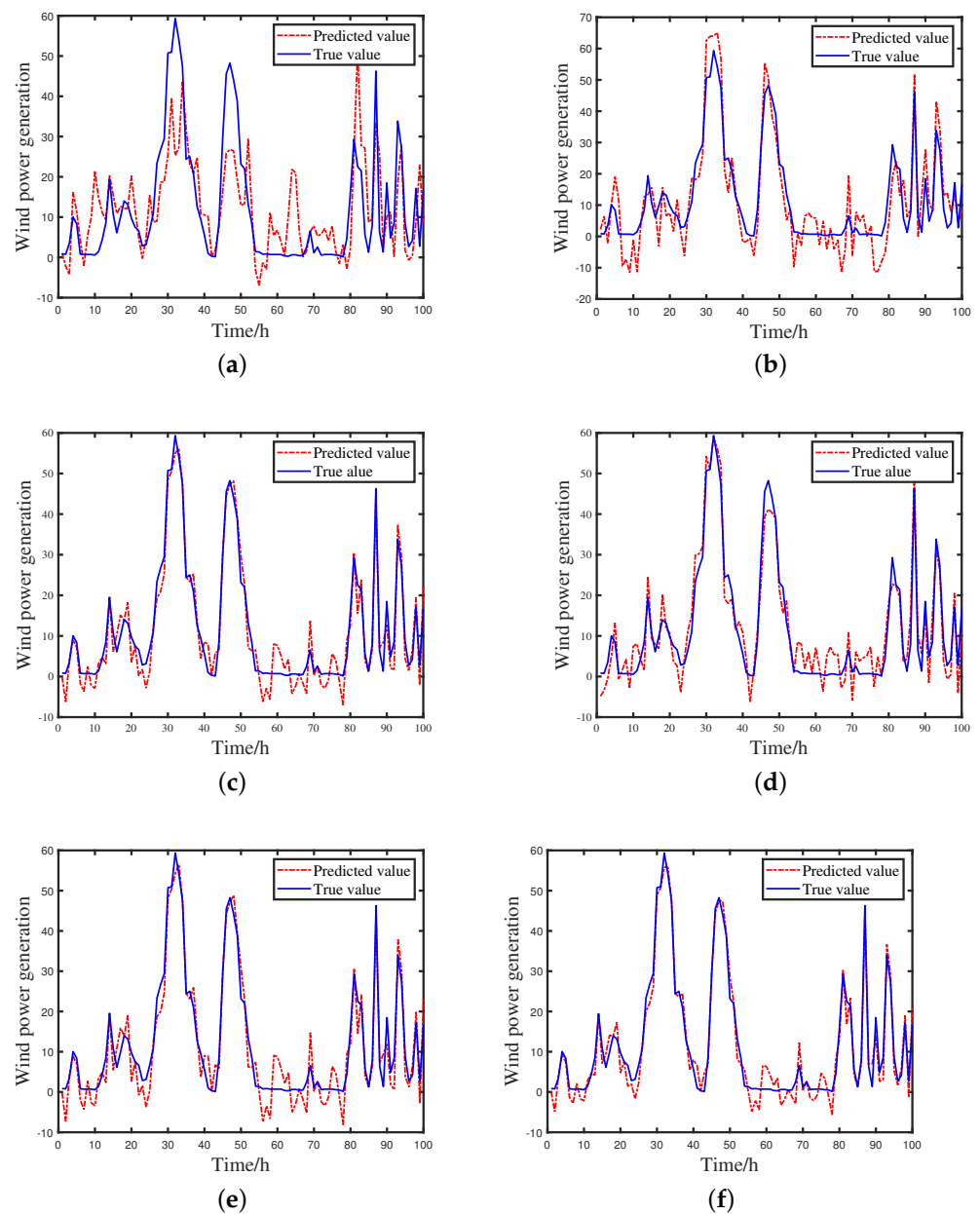


Figure 3. Curves of wind power generation prediction by four methods. (a) FNN; (b) mRMR–FNN; (c) mRMR–GRU; (d) mRMR–LSTM; (e) PSO–LSTM; (f) mRMR–PSO–LSTM.

To quantify the differences in predictive accuracy among the four models, their performance results under four evaluation metrics are displayed in Table 3. Consistent with expectations, the mRMR-PSO-LSTM model achieves the best results in terms of MAPE, MAE, and RMSE, with values of 2.1328, 2.9038, and 3.3819, respectively, while also exhibiting the highest value for R^2 : 0.9785. Specifically, compared to FNN, mRMR-FNN, mRMR-GRU, mRMR-LSTM, and PSO-LSTM, the mRMR-PSO-LSTM model reduces MAPE by 2.5994, 2.3647, 0.518, 0.4538, and 0.9141, respectively. Its MAE decreases by 6.9851, 3.6986, 0.7052, 0.8548, and 1.2445, respectively, relative to FNN, mRMR-FNN, mRMR-GRU, mRMR-LSTM, and PSO-LSTM. Additionally, the RMSE of mRMR-PSO-LSTM decreases by 9.6574, 4.2966, 0.8214, 0.9431, and 1.4494, respectively, compared to FNN, mRMR-FNN, mRMR-GRU, mRMR-LSTM, and PSO-LSTM. The R^2 of mRMR-PSO-LSTM increases by 0.29, 0.0892, 0.0117, 0.0136, and 0.0223, respectively, compared to FNN, mRMR-FNN, mRMR-GRU, mRMR-LSTM, and PSO-LSTM.

Most notably, the accuracy of mRMR-FNN predictions is superior to that of FNN, and the accuracy of mRMR-PSO-LSTM predictions is superior to that of PSO-LSTM, indicating that mRMR effectively addresses meteorological feature redundancy. Compared to the results of mRMR-LSTM, mRMR-GRU showed slightly better performance in terms of MAPE and R^2 but was slightly inferior in MAE and RMSE. This indicates that while mRMR-GRU requires fewer hyperparameters, the overall performance of the two models is comparable. Given that LSTM excels at handling long-term dependencies in sequences, it is incorporated into the proposed model. Furthermore, the experimental results of mRMR-LSTM and mRMR-PSO-LSTM demonstrate that the PSO algorithm effectively optimizes the parameters within the LSTM model. This refinement results in improved performance and validation of the PSO's effectiveness in tuning LSTM networks. On the same dataset, PSO-LSTM predictions are more accurate than those of FNN, demonstrating that PSO-LSTM effectively captures the temporal characteristics of the data. In a word, the mRMR-PSO-LSTM model has significant advantages in wind power prediction, offering not only lower average errors but also more accurate fitting of overall trends. These findings provide strong support for the reliability of the mRMR-PSO-LSTM model in practical applications for wind power generation prediction.

While the proposed mRMR-PSO-LSTM outperforms the other five methods in all four evaluation metrics, it requires a relatively longer computational time due to the utilization of the PSO algorithm to optimize the parameters in the LSTM network. Table 4 shows that while the proposed mRMR-PSO-LSTM model has the longest training time compared to the other five methods, its prediction time is not more than two seconds longer than FNN, mRMR-FNN, and mRMR-GRU. In practical applications, for the sake of efficiency, it is common to complete the model training process ahead of time and save the trained model. When predictions are required, it only needs to apply the already trained model for prediction without having to undergo the entire training process again. Although the prediction time may be slightly longer compared to the other five models, considering the significant improvement in prediction accuracy achieved, such a time cost is well worth it.

Table 3. Comparison of prediction accuracy of six models.

Prediction Model	MAPE	MAE	RMSE	R^2
FNN	4.7322	9.8889	13.0393	0.6885
mRMR-FNN	4.4975	6.6024	7.6785	0.8893
mRMR-GRU	2.6508	3.6090	4.2033	0.9668
mRMR-LSTM	2.5866	3.7586	4.3250	0.9649
PSO-LSTM	3.0469	4.1483	4.8313	0.9562
mRMR-PSO-LSTM	2.1328	2.9038	3.3819	0.9785

Table 4. The training time and prediction time of six models.

Prediction Model	Training Time	Prediction Time
FNN	31.21s	1.05 s
mRMR-FNN	45.86 s	0.97 s
mRMR-GRU	68.94 s	2.32 s
mRMR-LSTM	85.20 s	3.41 s
PSO-LSTM	100.45 s	3.52 s
mRMR-PSO-LSTM	146.75 s	3.34 s

4. Conclusions

Based on the characteristics of meteorological data, the proposed mRMR-PSO-LSTM method in this paper demonstrates superior performance in short-term wind power generation prediction, significantly outperforming traditional FNN and single PSO-LSTM methods. Through the mRMR algorithm for feature selection, we successfully reduced

the redundancy of meteorological features, making the selected features more representative. Additionally, by introducing the PSO algorithm for parameter optimization of the LSTM network, we effectively improved the model's generalization performance and accuracy. Compared to FNN, the mRMR-PSO-LSTM method has made significant progress in handling temporal data and considering feature redundancy. This study provides a more intelligent and accurate prediction model for wind power generation systems, which is expected to enhance system operational efficiency and the utilization of clean energy. The successful application of this method also provides valuable references for future research on meteorological data processing, deep learning, and optimization algorithms.

One of the main findings is that the integration of mRMR for feature selection and PSO for LSTM parameter optimization not only reduces computational complexity but also enhances prediction accuracy, showcasing the synergy between feature selection and parameter optimization techniques. Moreover, the contribution of this study lies in its use of the mRMR algorithm to remove redundant features and the LSTM model to capture the temporal characteristics of the features, thereby producing an accurate model for short-term wind power generation prediction. However, a limitation of this study is that it does not consider the robustness of the model to noise or a significant amount of missing data. Therefore, future work will focus on enhancing the model's robustness by incorporating techniques to handle noisy and incomplete data, ensuring its reliability in diverse conditions. In summary, this study not only advances the state of wind power generation prediction by integrating mRMR and PSO-LSTM but also lays the foundation for future meteorological data processing and optimization algorithms.

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Conflicts of Interest: Author Xuanmin Huo, Hao Su, Pu Yang, Cangzhen Jia, Ying Liu and Juanjuan Wang were employed by the company State Grid Xinxiang Electric Power Supply Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

mRMR	minimum Redundancy Maximum Relevance
LSTM	Long Short-Term Memory
COA-CNN-LSTM	Coati optimization algorithm-Convolutional Neural Network-LSTM
PSO	Particle Swarm Optimization
GRU	Gate Recurrent Unit
FNN	Feedforward Neural Network
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
LM	Levenberg-Marquardt

References

1. Demirbas, A. Potential applications of renewable energy sources, biomass combustion problems in boiler power systems and combustion related environmental issues. *Prog. Energy Combust. Sci.* **2005**, *31*, 171–192. [[CrossRef](#)]
2. Panwar, N.L.; Kaushik, S.C.; Kothari, S. Role of renewable energy sources in environmental protection: A review. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1513–1524. [[CrossRef](#)]

3. Bukhari, S.M.S.; Moosavi, S.K.R.; Zafar, M.H.; Mansoor, M.; Mohyuddin, H.; Ullah, S.S.; Alroobaea, R.; Sanfilippo, F. Federated transfer learning with orchard-optimized Conv-SGRU: A novel approach to secure and accurate photovoltaic power forecasting. *Renew. Energy Focus* **2024**, *48*, 100520. [\[CrossRef\]](#)
4. Hameed, M.Z.; Lamichhane, B. Transductive-Transfer Learning Based Deep Neural Networks for Day-Ahead PV Power Forecasting in Smart Grid Application: A Comparative Analysis. In Proceedings of the 2023 North American Power Symposium (NAPS), Asheville, NC, USA, 15–17 October 2023; pp. 1–6.
5. Wu, G.; Zeng, M.; Peng, L.; Liu, X.; Li, B.; Duan, J. Role of renewable China's new energy development: Status, constraints and reforms. *Renew. Sustain. Energy Rev.* **2016**, *53*, 885–896.
6. Shokrieh, M.M.; Rafiee, R. Simulation of fatigue failure in a full composite wind turbine blade. *Compos. Struct.* **2006**, *74*, 332–342. [\[CrossRef\]](#)
7. Zhang, Y.; Wang, J.; Wang, X. Review on probabilistic forecasting of wind power generation. *Renew. Sustain. Energy Rev.* **2014**, *32*, 255–270. [\[CrossRef\]](#)
8. Hu, S.; Xiang, Y.; Zhang, H.; Xie, S.; Li, J.; Gu, C.; Sun, W.; Liu, J. Hybrid forecasting method for wind power integrating spatial correlation and corrected numerical weather prediction. *Appl. Energy* **2021**, *293*, 116951. [\[CrossRef\]](#)
9. Vladislavleva, E.; Friedrich, T.; Neumann, F.; Wagner, M. Predicting the energy output of wind farms based on weather data: Important variables and their correlation. *Renew. Energy* **2013**, *50*, 236–243. [\[CrossRef\]](#)
10. Okumus, I.; Dinler, A. Current status of wind energy forecasting and a hybrid method for hourly predictions. *Energy Convers. Manag.* **2016**, *123*, 362–371. [\[CrossRef\]](#)
11. Kramer, O.; Gieseke, F.; Satzger, B. Wind energy prediction and monitoring with neural computation. *Neurocomputing* **2013**, *109*, 84–93. [\[CrossRef\]](#)
12. Yesilbudak, M.; Sagioglu, S.; Colak, I. A novel implementation of kNN classifier based on multi-tupled meteorological input data for wind power prediction. *Energy Convers. Manag.* **2017**, *135*, 434–444. [\[CrossRef\]](#)
13. Men, Z.; Yee, E.; Lien, F.; Wen, D. Short-term wind speed and power forecasting using an ensemble of mixture density neural networks. *Renew. Energy* **2016**, *10*, 203–211. [\[CrossRef\]](#)
14. Sharifian, A.; Ghadi, M.J.; Ghavidel, S.; Li, L.; Zhang, J. A new method based on Type-2 fuzzy neural network for accurate wind power forecasting under uncertain data. *Renew. Energy* **2018**, *120*, 220–230. [\[CrossRef\]](#)
15. Heinermann, J.; Kramer, O. Machine learning ensembles for wind power prediction. *Renew. Energy* **2016**, *89*, 671–679. [\[CrossRef\]](#)
16. Buestán-Andrade, P.A.; Peñacoba-Yagüe, M.; Sierra-García, J.E.; Santos, M. Wind Power Forecasting with Machine Learning Algorithms in Low-Cost Devices. *Electronics* **2024**, *13*, 1541. [\[CrossRef\]](#)
17. Lu, P.; Ye, L.; Zhao, Y.; Dai, B.; Pei, M.; Tang, Y. Review of meta-heuristic algorithms for wind power prediction: Methodologies, applications and challenges. *Appl. Energy* **2021**, *301*, 117446. [\[CrossRef\]](#)
18. Abou Houran, M.; Bukhari, S.M.S.; Zafar, M.H.; Mansoor, M.; Chen, W. COA-CNN-LSTM: Coati optimization algorithm-based hybrid deep learning model for PV/wind power forecasting in smart grid applications. *Appl. Energy* **2023**, *349*, 121638. [\[CrossRef\]](#)
19. Zhang, Y.; Li, Y.; Zhang, G. Short-term wind power forecasting approach based on Seq2Seq model using NWP data. *Energy* **2020**, *213*, 118371. [\[CrossRef\]](#)
20. Peng, H.C.; Long, F.H.; Ding, C. Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. *IEEE Trans. Pattern Anal. Mach. Intell.* **2005**, *27*, 1226–1238. [\[CrossRef\]](#)
21. Ren, X.; Liu, S.; Yu, X.; Dong, X. A method for state-of-charge estimation of lithium-ion batteries based on PSO-LSTM. *Energy* **2021**, *234*, 121236. [\[CrossRef\]](#)
22. Liu, H.; Mi, X.W.; Li, Y.F. Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and Elman neural network. *Energy Convers. Manag.* **2018**, *156*, 498–514. [\[CrossRef\]](#)
23. Yuan, X.; Chen, C.; Jiang, M.; Yuan, Y. Prediction interval of wind power using parameter optimized Beta distribution based LSTM model. *Appl. Soft Comput.* **2019**, *82*, 105550. [\[CrossRef\]](#)
24. Song, M.; Chen, K.; Zhang, X.; Wang, J. Optimization of wind turbine micro-siting for reducing the sensitivity of power generation to wind direction. *Renew. Energy* **2016**, *85*, 57–65. [\[CrossRef\]](#)
25. Safari, B. Modeling wind speed and wind power distributions in Rwanda. *Renew. Sustain. Energy Rev.* **2011**, *5*, 925–935. [\[CrossRef\]](#)
26. Ulazia, A.; Sáenz, J.; Ibarra-Berastegi, G.; González-Rojí, S.J.; Carreno-Madinabeitia, S. Global estimations of wind energy potential considering seasonal air density changes. *Energy* **2019**, *187*, 115938. [\[CrossRef\]](#)

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