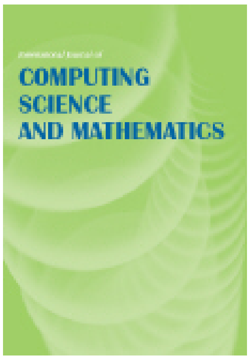

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Offshore wind power prediction based on chaotic optimisation PSO-SCN-LSTM model

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Abstract: Offshore wind power, as a clean energy source, is receiving increasing attention worldwide. To enhance the economic and safety performance of offshore wind power, short-term forecasting of wind power is essential. This paper proposes a model based on chaos optimisation integrated with particle swarm optimisation (PSO), stochastic configuration network (SCN), and long short-term memory (LSTM) algorithm. Firstly, leveraging the randomness and ergodicity of the complex logistic chaos system, the collected power data from wind turbines is utilised as the input data source for the PSO, enhancing the randomness of the data. Subsequently, the SCN is employed to optimise the PSO, increasing the variation in the hidden layer during iterations and mitigating the PSO's tendency to fall into local optima, thereby obtaining initial prediction values. Finally, the mechanism model of the LSTM is utilised for secondary prediction, further improving prediction accuracy. Compared with traditional algorithms, the optimised algorithm significantly reduces errors and enhances prediction precision.

Keywords: chaos theory; particle swarm optimisation algorithm; random configuration network; LSTM prediction model.

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1 Introduction

As an important component of clean energy, offshore wind farms have developed rapidly in recent years, and their position in the energy structure has become increasingly prominent. However, the volatility and uncertainty of offshore wind farm output pose challenges to the stable operation of the offshore wind farms. Therefore, accurate prediction of offshore wind power is particularly important. This can not only help the power system dispatch department make reasonable scheduling arrangements in advance, optimise resource allocation, but also effectively respond to fluctuations in wind farm output and ensure the stable operation of the power grid. Studying the power prediction of offshore wind farms can also help improve the safety and reliability of the entire energy system.

The research on wind power prediction has attracted the attention of many scholars. Especially based on computer data processing technology and machine learning algorithms, network modelling and simulation can be used to predict wind power across time and space (Wang et al., 2024). Mogos et al. (2022) proposes an effective short-term wind speed prediction method using a multiple regression model, which uses Pearson correlation coefficient (PCC) for feature selection and calculates error index to evaluate different algorithms. Sun et al. (2020) considers source correlation for short-term wind power prediction and proposes a combined forecasting method based on day ahead numerical weather forecast positioning technology. Zhang et al. (2019) improves the multi-objective interval prediction based on the conditional Copula function by utilising the correlation between variables for multi-objective interval prediction. An et al. (2021) proposes a method for multi-source wind speed fusion, which utilises the characteristics of three types of wind oscillators and uses weighted naive Bayes method to fuse the three types of wind oscillators to obtain accurate wind speed estimates. Ye et al. (2024) considers the impact of extreme weather and uses time series correction to improve prediction accuracy.

The various wind power prediction methods mentioned above also require the use of computer algorithms for implementation. After the particle swarm optimisation (PSO) algorithm was proposed in 1995, a large number of achievements have been made after years of research. Particle swarm optimisation algorithm is widely used in various fields due to its simple structure and strong global search ability. Huang and Li (2023) proposes a photovoltaic power generation prediction model that combines vector machine (SVM) with PSO algorithm. Han et al. (2023) combines simulated annealing algorithm (SA) with particle swarm optimisation algorithm (APSO) using adaptive coefficients instead of intrinsic coefficients, and introduces chaotic mapping strategy to propose a SA-CAPSO algorithm. Aurangzeb et al. (2021) introduces the application of PSO algorithm in deep learning, which has significant advantages for image processing.

Stochastic configuration network (SCN) is an incremental random weight neural network proposed by Wang et al. (2017). This network utilises the mechanism of increasing hidden layer nodes and adding forgetting factors to ensure the convergence of the algorithm, thereby achieving the goal of accelerating convergence speed. Wang et al. (2023) proposes a multi-objective SCN modelling method based on a stochastic configured network (SCN), introducing an alternating optimisation algorithm to calculate the structural matrix and output weights. Chen et al. (2021) associates the maximum correlation coefficient (mRMR) with the improved stochastic configuration network (CWCs SCN) for gear fault diagnosis, which can improve the accuracy of diagnosis. Li et al. (2019) combines dropout models with stochastic algorithms and applies dropout to SCN, providing new ideas for signal recognition using stochastic algorithms.

In order to improve the accuracy of prediction, by the use of a long short-term memory (LSTM) neural network structure proposed by Hochreiter et al. to ensure the temporal correspondence between auxiliary variables and dominant variables, through the dynamic information processing capability of LSTM neural network, achieving dynamic modelling. Bao et al. (2022) combines fuzzy logic with LSTM neural networks to propose an FLCNN-LSTM model for predicting air quality. Wang et al. (2021) combines convolutional neural networks (CNN) with LSTM for collaborative processing of spatiotemporal data. Dai et al. (2023) uses the integrated empirical mode decomposition (EEMD) method to decompose the original wind power sequence according to frequency, and then establishes an LSTM prediction model. Shu et al. (2021) uses LSTM network to divide into individual (P-LSTM) and population (G-LSTM) levels, and establishes a ‘host parasite’ structure to selectively integrate information from individuals into the population, which is a novel prediction model. Jyotishi and Dandapat (2020) applies the LSTM model to the recognition of electrocardiogram signals, and LSTM has superior performance in capturing changes in ECG signal segments. Dai et al. (2019) proposes a trajectory prediction model based on spatiotemporal LSTM (ST-LSTM) on the basis of the original LSTM, which embeds spatial interaction into the LSTM model and adds shortcut connections between the input and output layers to solve the problem of gradient vanishing. Kim and Cho (2019) combines PSO algorithm with LSTM neural network to optimise the hyperparameters of LSTM, enhance global search capability, and achieve perfect prediction performance.

Since the emergence of chaos theory, it has been widely applied in industrial fields, complex control, and other areas. Applying chaos theory to improve computer algorithms can enhance the performance of predictive models. Zhang et al. (2021) proposes a two-dimensional lagged complex logistic mapping that can ensure good security performance for cryptographic communication. Wang et al. (2023) uses chaotic systems to study pseudo-random sequences, analyses dynamic behaviour through the study of a two-dimensional CML model, and applies it to secure communication. Kou et al. (2024) combines chaos theory with genetic algorithm to propose a new model for planning inspection paths for offshore wind farms.

The remaining research content of this paper is arranged as follows. The chaotic reconstruction of the original dataset is presented in Section 2. Section 3 discusses the construction of prediction models. Section 4 uses data from previous years for prediction processing and analyses errors. Section 5 summarises the research content of this paper.

2 Dataset reconstruction based on chaotic sequences

For the selection of data for this prediction model, in order to ensure the reliability and timeliness of the prediction, selecting the wind turbine operation data of the wind farms from 2020 to 2023. Considering the computational power and running speed of the model, in order to ensure computational efficiency, a classification method of daily, monthly, and quarterly forecasting is adopted. The wind power data for the first quarter starts from 0:00 on January 1st and ends at 23:59:45 on March 31st. Collect data every 15 min. The collected data includes wind speed, wind direction, temperature, relative humidity, air pressure, and power generation at the hub of the wind turbine. A total of 96 datasets were collected on January 1st, 2260 datasets were collected for January, and 7842 datasets were collected for the first quarter.

Before initialising the dataset, it is necessary to preprocess the dataset. The dataset is reconstructed through mapping with chaos sequences. This project adopts a two-dimensional lagged complex Logistic chaos map with real parameters, which can be mathematically shown in equation (1):

$$\begin{cases} w_{n+1} = bw_n(1 - z_n) \\ z_{n+1} = ax_n{}^2 + y_n{}^2 \end{cases} \tag{1}$$

Among them $w_n = x_n + jy_n$ are complex state variables, x_n, y_n, z_n are real state variables, and a, b are real parameters. By analysing the dynamic characteristics of the chaotic system and calculating the Lyapunov exponent, selecting parameters $a = 2, b = 2$ can maintain good chaotic characteristics. After importing the dataset, it is necessary to reconstruct it, establish a mapping relationship between the data and the complex logistic sequence, and then perform normalisation processing. The initialisation process of the dataset is shown in Figure 1.

The normalised calculation formula is shown in equation (2):

$$z^* = \frac{z - z_{\min}}{z_{\max} - z_{\min}} \tag{2}$$

In the formula: z^* is the normalised data, z is the data that needs to be normalised, $z_{\min}$ is the smallest data value, $z_{\max}$ is the largest data value.

From Figure 2, it can be seen that after initialisation, the dataset undergoes chaotic mapping processing, and the data changes are relatively stable with small fluctuations, which can improve the stability of prediction.

Figure 1 Reconstruction process of chaotic mapping dataset (see online version for colours)

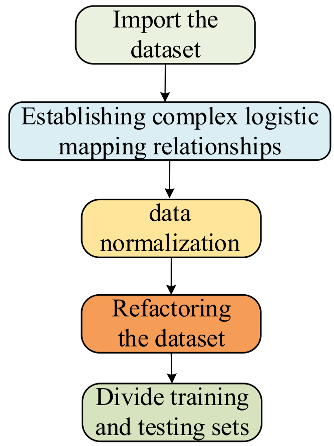
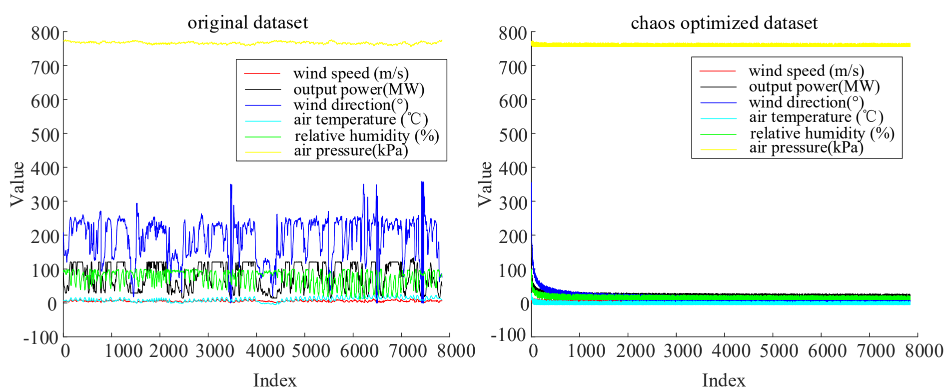


Figure 2 Comparison between chaotic dataset and original dataset (see online version for colours)



3 Construction of wind power prediction model

3.1 PSO-SCN prediction model

The basic principle of PSO algorithm is that a swarm of particles is given in a certain space, each particle has two attributes of velocity and position, and each particle also has memory function. Each particle updates its position and velocity in the space to perform the search. The quality of the position is judged by the fitness value of each particle. The search direction is adjusted according to the optimal position of the individual and the optimal position of the swarm until the stopping condition is reached and the update stops. This model has strong global search ability, but after a certain number of iterations, particles will gather and fall into the problem of local search optimisation.

The velocity update formula and position update formula in the PSO algorithm are shown in equation (3) and (4):

$$V_i(t+1) = V_i(t) + c_1 rand(P_i(t) - X_i(t)) + c_2 rand(P_g(t) - X_i(t)) \tag{3}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{4}$$

$V_i(t+1)$ is the velocity of the ith particle after the update, $V_i(t)$ is the velocity of the ith particle before the update, $X_i(t)$ is the position vector of the ith particle, $P_i(t)$ is the historical optimal position of the ith particle, $P_g(t)$ is the global optimal position of the population, c_1, c_2 is the acceleration factor, and $rand$ represents a random number between $[0,1]$.

After updating the speed and position, particles will have their individual historical optimal position and the global optimal position of the population updated.

Update of individual historical optimal position is shown in equation (5):

$$P_i(t+1) = \begin{cases} X_i(t+1) & \text{if } f(X_i(t+1)) < f(P_i(t)) \\ P_i(t) & \text{otherwise} \end{cases} \tag{5}$$

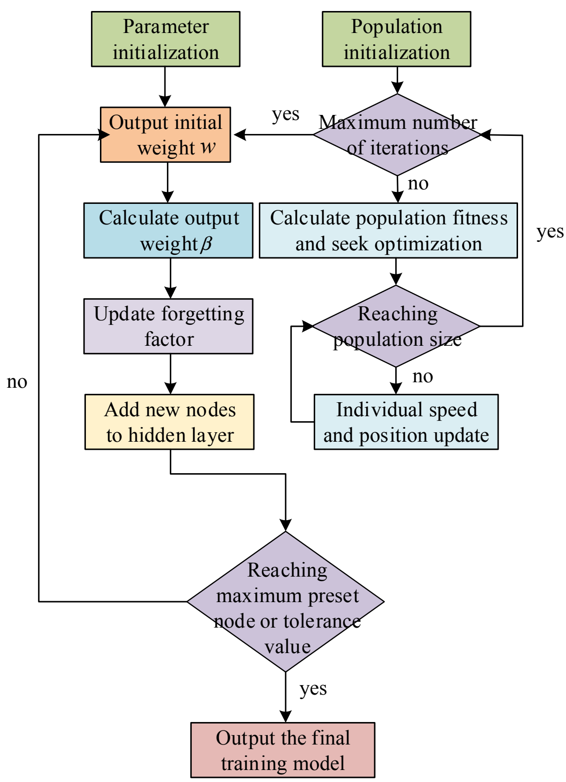
Updating the Global Optimal Position of the Population is shown in equation (6)

$$P_g(t) = \min\{X_1(t), X_2(t), X_3(t) \cdots X_n(t)\} \tag{6}$$

$f(X_i(t))$ represents the fitness value of each particle

Combining a SCN with PSO algorithm, utilising the characteristics of SCN network and the advantages of PSO algorithm, a new prediction model is established. The algorithm flow of the model is shown in Figure 3.

Figure 3 The algorithm flowchart of the PSO-SCN network (see online version for colours)



The PSO-SCN optimisation algorithm process is as follows:

1 Population initialisation (setting maximum population size, number of population updates, speed boundaries, weight boundaries, etc.).
2 Calculate the fitness value of the population, select the current optimal fitness value and its corresponding speed and position.
3 Update of individual speed and position.
4 Reaching the maximum number of iterations and outputting the optimal weight value.
5 Calculate output weights, update forgetting factors, and add new nodes to the hidden layer.
6 Reaching the maximum preset node, outputting the result to LSTM for temporal prediction.

3.2 Chaos particle swarm optimisation algorithm

The application of chaos theory can also be used to optimise the speed updating formula and position updating formula of PSO.

Add chaos factor L to inertia weight w and introduce a velocity update formula to adjust the search ability of the particle swarm. Optimised speed update formula is shown in equation (7):

$$V_i(t+1) = w_L(t)V_i(t) + c_1 rand(P_i(t) - X_i(t)) + c_2 rand(P_g(t) - X_i(t)) \tag{7}$$

The calculation formula for inertia weight w is shown in equation (8):

$$w(t) = w_{\max} - \frac{t(w_{\max} - w_{\min})}{\max\_iternum} \tag{8}$$

$w_{\max}$ is the maximum limit of inertia weight, $w_{\min}$ is the minimum limit of inertia weight, t is the current iteration number, $\max\_iternum$ is the maximum iteration number.

The weight coefficients optimised by adding chaotic sequences are shown in equation (9):

$$\begin{aligned} w_L(t) &= w_{\max} - \frac{tL(w_{\max} - w_{\min})}{\max\_iternum} \\ L &= \frac{chaos_n - \min(chaos)}{\max(chaos) - \min(chaos)} \end{aligned} \tag{9}$$

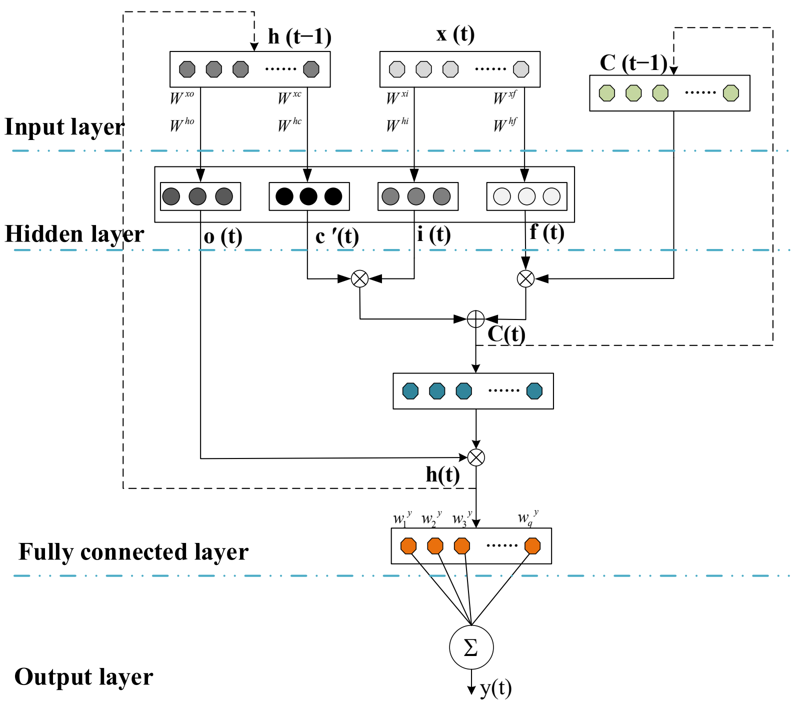
$chaos_n$ is the value of the generated two-dimensional complex logistic chaotic sequence, which $\min(chaos)$ is the minimum value in the chaotic sequence and $\max(chaos)$ is the maximum value in the chaotic sequence.

By introducing chaos factors to optimise the velocity update formula of particle swarm, the overall search capability and local search capability can be adjusted to maintain a balance, thus achieving a more stable optimisation process.

3.3 LSTM time series prediction model

The LSTM model is a special form of recurrent neural network (RNN). By introducing a gating mechanism, LSTM enables the model to more effectively capture and store long-term dependencies in sequences. LSTM's unique network structure makes it more effective in time series modelling. Combining artificial intelligence algorithms with time series forecasting models for ensemble forecasting can improve forecasting results. Figure 4 is a framework diagram of an LSTM unit.

Figure 4 LSTM unit structure (see online version for colours)



The LSTM neural network structure achieves information memory by using memory units and three nonlinear gates instead of its basic hidden neurons. LSTM units typically contain three inputs, namely the previous unit state $C_{(t-1)}$, the previous implicit state $h_{(t-1)}$ and the current input variable $x_{(t)}$. In each step, LSTM updates its internal state based on the current input and the previous state.

The relationship between the updated unit state $C_{(t)}$ and unit output $h_{(t)}$ are shown in equation (10):

$$\begin{aligned} C_{(t)} &= f_{(t)} \otimes C_{(t-1)} \oplus i_{(t)} \otimes c'_{(t)} \\ h_{(t)} &= o_{(t)} \otimes \tanh(C_{(t)}) \end{aligned} \tag{10}$$

$f_{(t)}$ is the forget gate used to control $C_{(t-1)}$ the useless information before forgetting, $i_{(t)}$ is the input gate used to control the retention of important information in $c'_{(t)}$, $o_{(t)}$ is the output gate used to determine which information $C_{(t)}$ outputs to $h_{(t)}$, $c'_{(t)}$ is the candidate cell state, W, b is the weight matrix and bias vector corresponding to each gate unit, p, q is the network input dimension and the number of hidden layer nodes, $\sigma(\cdot)$ is the sigmoid activation function, and $\tanh(\cdot)$ is the hyperbolic tangent activation function.

The relationship formula for network output $y_{(t)}$ is shown in equation (11):

$$y_{(t)} = g\left(\sum_{k=1}^{q} W_k^y (o_{(t)} \otimes \tanh(f_{(t)} \otimes C_{(t-1)} \oplus i_{(t)} \otimes c'_{(t)})\right) + b^y) \tag{11}$$

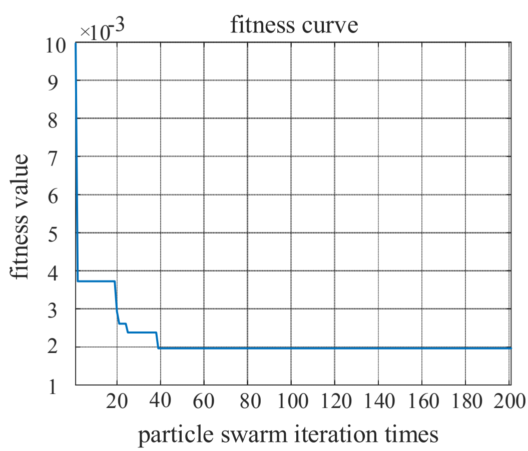
LSTM controls the flow of information through its carefully designed gating mechanism. This continuously updated mechanism enables LSTM to selectively retain and update information, thus effectively capturing long-term dependencies in the sequence.

4 Experimental results and analysis

Utilise the reconstructed dataset after chaos transformation as prediction samples for predictive analysis. Initialise the PSO algorithm and perform population initialisation: set the individual acceleration coefficient to 2, the global acceleration coefficient to 2, the number of population updates to 200, the maximum population size to 50, the maximum velocity to 0.5, the minimum velocity to 1.0, the maximum weight boundary to 0.9, and the minimum weight boundary to 0.3. Set the training parameters: set the number of training iterations to 200, the target error to 1e-5, and the learning rate to 0.02.

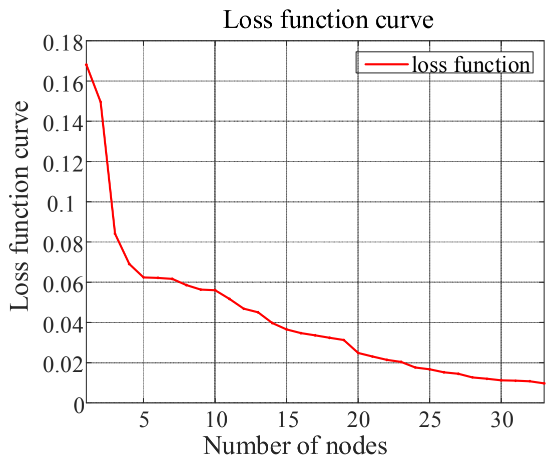
When the population is iterated 93 times, the fitness value reaches its minimum, and the optimal particle is selected. The population fitness curve is shown in Figure 5.

Figure 5 Population fitness curve of PSO-SCN algorithm (see online version for colours)



The loss function curve is typically used to demonstrate the performance changes of the model during the training process. As can be seen from the figure, before increasing to 5 nodes, the loss function decreases rapidly, indicating that the model is quickly learning and adapting to the training data. Afterward, the model has basically learned the distribution and patterns of the training data and is further fine-tuning parameters to optimise performance. The loss function curve is shown in Figure 6.

Figure 6 Loss function curve of PSO-SCN algorithm (see online version for colours)



To verify the optimisation effect of the PSO-SCN algorithm, simulations were conducted separately for the PSO and PSO-SCN models. Figure 7 show the comparison between the PSO algorithm and PSO-SCN algorithm and the actual output values of the training and testing sets using data from January 1st. It can be clearly seen that the PSO-SCN algorithm is more similar to the actual output and has better prediction performance.

Figure 7 Training set and test set prediction results on January 1st (see online version for colours)

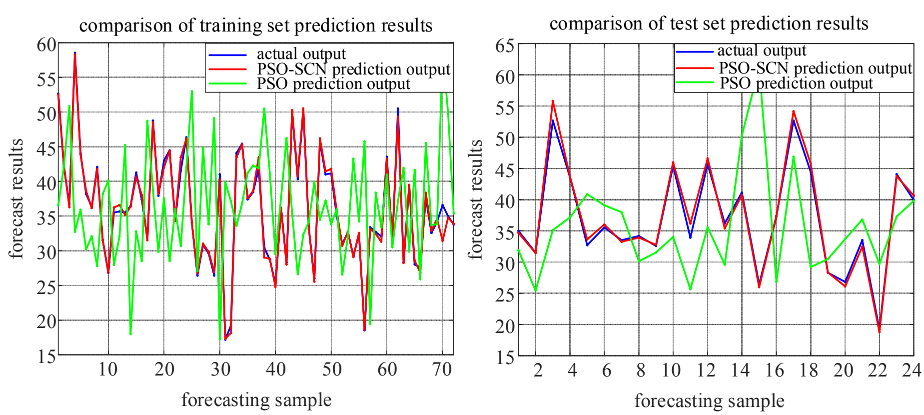


Figure 8 show a comparison of the prediction results of PSO algorithm and PSO-SCN algorithm in January. Due to the large amount of data, using scatter plots to display the root mean square error (RMSE) of the two algorithms. Using 2260 sets of data from January, the training set and test set are divided in a ratio of 3 : 1.

Figure 9 show a comparison of the prediction results of PSO algorithm and PSO-SCN algorithm in the first quarter of 2023. Using 7784 sets of data from first quarter, the training set and test set are divided in a ratio of 3 : 1.

Figure 8 Training set and test set prediction results in January (see online version for colours)

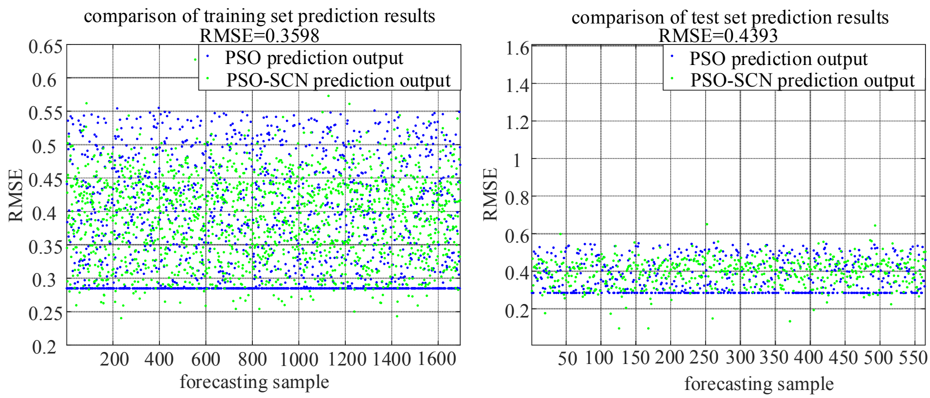
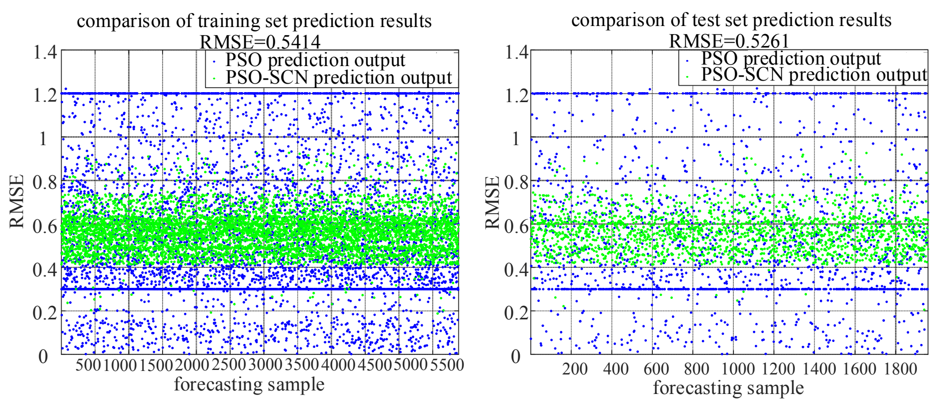


Figure 9 Training set and test set prediction results in the first quarter (see online version for colours)



Using the PSO-SCN optimisation algorithm to predict the data, import a new dataset as the input source for the LSTM network for secondary prediction. The dataset for secondary prediction is still divided into daily, monthly, and quarterly data volumes.

Figure 10 show the comparison chart of prediction results after secondary prediction between the predicted and actual values by using data from January 1st.

Figure 11 show the comparison chart of prediction results after secondary prediction between the predicted and actual values by using data from January.

Figure 10 The training and test set prediction results of LSTM secondary prediction on January 1st (see online version for colours)

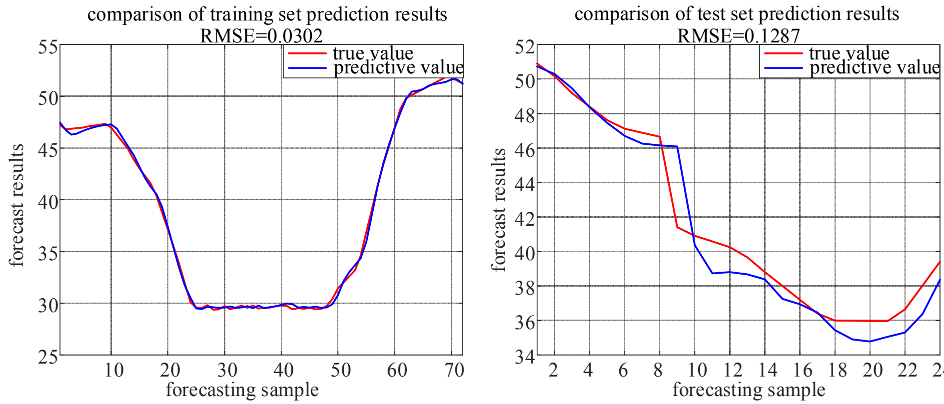


Figure 11 The training set and test set prediction results of LSTM secondary prediction in January (see online version for colours)

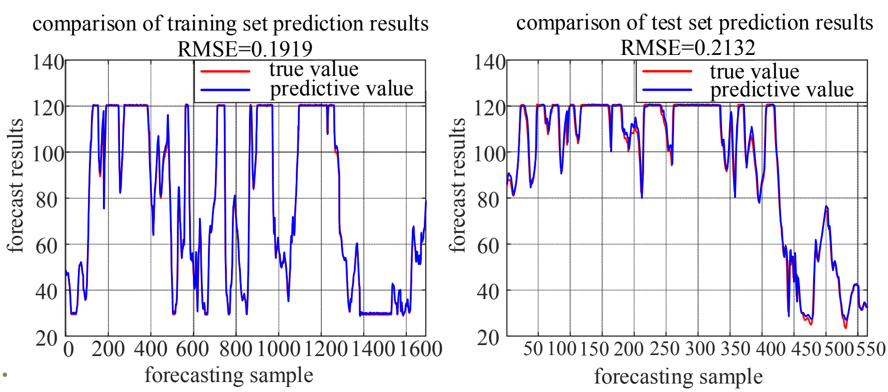
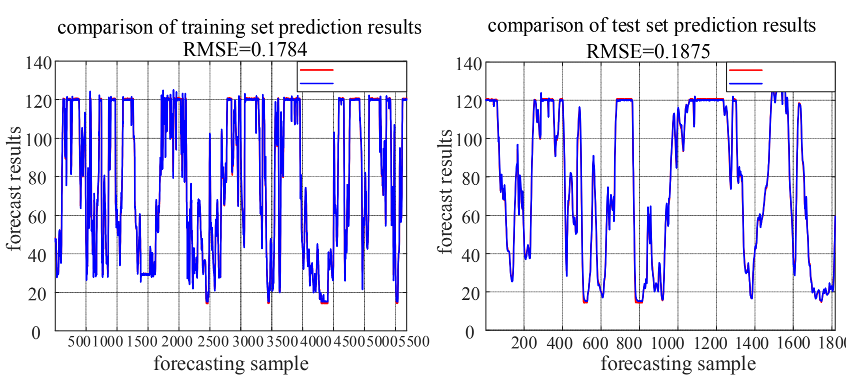


Figure 12 show the comparison chart of prediction results after secondary prediction between the predicted and actual values by using data from the first quarter.

Figure 12 The training set and test set prediction results of LSTM secondary prediction in the first quarter (see online version for colours)



In order to facilitate the exploration of prediction accuracy and analyse the performance of the model, the RMSE is used to measure the quality of the prediction results.

The RMSE represents the deviation between the predicted values and the actual values, and its calculation formula is shown in equation (12):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(u_{actual}^{t} - u_{predict}^{t})^2} \tag{12}$$

Table 1 shows the RMSE of three algorithms on different datasets.

Table 1 The RMSE comparison of three algorithms

Data	*Types of algorithms*	*Training set RMSE*	*Test set RMSE*
January 1st. data (96)	PSO algorithm	1.1238	1.5589
	PSO-SCN algorithm	0.3665	0.7445
	PSO-SCN-LSTM algorithm	0.0302	0.1287
January data (2260)	PSO algorithm	0.4633	0.4777
	PSO-SCN algorithm	0.3596	0.4393
	PSO-SCN-LSTM algorithm	0.1919	0.2132
First quarter data (7842)	PSO algorithm	0.6285	0.6427
	PSO-SCN algorithm	0.5414	0.5261
	PSO-SCN-LSTM algorithm	0.1784	0.1875

From Table 1, when the sample size is 96 (for daily prediction), the training set RMSE of PSO algorithm is 1.1238, the training set RMS of PSO-SCN model is 0.3665, and the training set RMSE of PSO-SCN-LSTM model is 0.0302, showed that a significant improvement in the prediction accuracy of the model. When the sample size is 2260 (for monthly prediction), the training set RMSE of PSO algorithm is 0.4633, the training set RMS of PSO-SCN model is 0.3596, and the training set RMSE of PSO-SCN-LSTM model is 0.1919. The prediction accuracy is improved by 23% and 47% respectively. When the sample size is 7842 (for seasonal prediction), the training set RMSE of PSO algorithm is 0.6285, the training set RMS of PSO-SCN model is 0.5414, and the training set RMSE of PSO-SCN-LSTM model is 0.1784. The prediction accuracy is improved by 16% and 67% respectively. The test set showed the same results.

5 Conclusion

To achieve more accurate power prediction of offshore wind farms, this paper designs a new prediction model. By improving the dataset, network parameters, and model structure, more accurate prediction results have been achieved. In response to the problem of complex and diverse offshore wind power data with high volatility. Proposed incorporating chaos theory into the optimisation of the initial dataset. Propose a novel data preprocessing method for datasets. In response to the problem of global optimisation in traditional PSO algorithms, chaotic sequences and SCN network architecture are utilised to improve the predictive ability of the model. To address the issue of low prediction accuracy, combined with time series prediction models, a combination prediction is conducted to improve prediction accuracy. Therefore, by solving the existing problems, this paper designs an offshore wind power prediction model based on chaos optimisation PSO-SCN-LSTM. The simulation results show that the model has achieved significant improvement in prediction accuracy, meeting the expectations of designing this model.

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References

An, J., Yin, F., Wu, M., She, J. and Chen, X. (2021) 'Multisource wind speed fusion method for short-term wind power prediction', *IEEE Transactions on Industrial Informatics*, Vol. 17, No. 9, September, pp.5927–5937.

Aurangzeb, K., Aslam, S., Alhussein, M., Naqvi, R.A., Arsalan, M. and Haider, S.I. (2021) 'Contrast enhancement of fundus images by employing modified PSO for improving the performance of deep learning models', *IEEE Access*, Vol. 9, pp.47930–47945.

Bao, R., Zhou, Y. and Jiang, W. (2022) 'FL-CNN-LSTM: indoor air quality prediction using fuzzy logic and CNN-LSTM model', *2022 2nd International Conference on Electrical Engineering and Control Science (IC2ECS)*, Nanjing, China, pp.986–989.

Chen, Y., Jiang, T., Liu, H., Li, Y. and Yu, Z. (2021) 'Event recognition system based on fiber Bragg grating and mRMR-CWCs-SCN', *IEEE Sensors Journal*, Vol. 21, No. 22, 15 November, pp.26132–26139, doi: 10.1109/JSEN.2021.3119993.

Dai, Q., Qi, W., Hao, Y., Che, J. and Li, Z. (2023) 'A short-term hybrid prediction model for offshore wind power based on EEMD and LSTM', *2023 6th International Conference on Energy*, *Electrical and Power Engineering (CEEPE)*, Guangzhou, China, pp.1225–1229.

Dai, S., Li, L. and Li, Z. (2019) 'Modeling vehicle interactions via modified LSTM models for trajectory prediction', *IEEE Access*, Vol. 7, pp.38287–38296.

Han, X., Zhang, J., Fan, Y., Wu, Z. and Xie, X. (2023) 'Research on USV route planning based on simulated annealing-chaos adaptive particle swarm optimization algorithm', *2023 35th Chinese Control and Decision Conference (CCDC)*, Yichang, China, pp.4554–4559.

Huang, C. and Li, Y. (2023) 'A short-term prediction method for PV power generation based on SVM weather classification and PSO-BP neural network', *2023 IEEE 2nd International Power Electronics and Application Symposium (PEAS)*, Guangzhou, China, pp.2544–2549, doi: 10.1109/PEAS58692.2023.10394800.

Jyotishi, D. and Dandapat, S. (2020) 'An LSTM-based model for person identification using ECG signal', *IEEE Sensors Letters*, Vol. 4, No. 8, August, pp.1–4, Art No. 6001904.

Kim, T-Y. and Cho, S-B. (2019) 'Particle swarm optimization-based CNN-LSTM networks for forecasting energy consumption', *2019 IEEE Congress on Evolutionary Computation (CEC)*, Wellington, New Zealand, pp.1510–1516, doi: 10.1109/CEC.2019.8789968.

Kou, L., Wang, Y., Zhang, F., Yuan, Q., Wang, Z., Wen, J. and Ke, W. (2024) 'A chaotic simulated annealing genetic algorithm with asymmetric time for offshore wind farm inspection path planning', *International Journal of Bio-Inspired Computation*, in press, DOI: 10.1504/IJBIC.2024.10066897.

Li, W., Zeng, Z., Qu, H. and Sun, C. (2019) 'A novel fiber intrusion signal recognition method for OFPS based on SCN with dropout', *Journal of Lightwave Technology*, Vol. 37, No. 20, 15 October, pp.5221–5230, doi: 10.1109/JLT.2019.2930624.

Mogos, A.S., Salauddin, M., Liang, X. and Chung, C.Y. (2022) 'An effective very short-term wind speed prediction approach using multiple regression models', *IEEE Canadian Journal of Electrical and Computer Engineering*, Vol. 45, No. 3, Summer, pp.242–253, doi: 10.1109/ICJECE.2022.3152524.

Shu, X., Zhang, L., Sun, Y. and Tang, J. (2021) 'Host–parasite: graph LSTM-in-LSTM for group activity recognition', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 32, No. 2, February, pp.663–674.

Sun, Y., Li, Z., Yu, X., Li, B. and Yang, M. (2020) 'Research on ultra-short-term wind power prediction considering source relevance', *IEEE Access*, Vol. 8, pp.147703–147710.

Wang, Q., Bu, S., He, Z. and Dong, Z.Y. (2021) 'Toward the prediction level of situation awareness for electric power systems using CNN-LSTM network', *IEEE Transactions on Industrial Informatics*, Vol. 17, No. 10, October, pp.6951–6961.

Wang, Q., Hong, Q., Wu, S. and Dai, W. (2023) 'Multitarget stochastic configuration network and applications', *IEEE Transactions on Artificial Intelligence*, Vol. 4, No. 2, April, pp.338–348, doi: 10.1109/TAI.2022.3162570.

Wang, Y., Liu, Z., Zhang, L.Y., Pareschi, F., Setti, G. and Chen, G. (2023) 'From chaos to pseudorandomness: a case study on the 2-D coupled map lattice', *IEEE Transactions on Cybernetics*, Vol. 53, No. 2, February, pp.1324–1334, doi: 10.1109/TCYB.2021.3129808.

Wang, Z., Wang, Y., Zong, F., Yan, X., Ke, W., Kou, L., Yu, Z., Wan, J., Zhang, F., Sun, G. and Hu, Z. (2024) 'Offshore booster station site selection based on an immune optimisation algorithm', *International Journal of Computing Science and Mathematics*, Vol. 19, No. 4, pp.339–354.

Ye, W., Yang, D., Tang, C., Wang, W. and Liu, G. (2024) 'Combined prediction of wind power in extreme weather based on time series adversarial generation networks', *IEEE Access*, Vol. 12, pp.102660–102669.

Zhang, F., Zhang, X., Cao, M., Ma, F. and Li, Z. (2021) 'Characteristic analysis of 2D lag-complex logistic map and its application in image encryption', *IEEE MultiMedia*, Vol. 28, No. 4, 1 October-December, pp.96–106, doi: 10.1109/MMUL.2021.3080579.

Zhang, G., Li, Z., Zhang, K., Zhang, L., Hua, X. and Wang, Y. (2019) 'Multi-objective interval prediction of wind power based on conditional copula function', *Journal of Modern Power Systems and Clean Energy*, Vol. 7, No. 4, July, pp.802–812.