Short-Term Wind Speed Forecasting Based on Singular Spectrum Analysis, Fuzzy C-Means Clustering and Improved SSABP

Gonggui Chen, Bangrui Tang, Zhizhong Zhang*, Xianjun Zeng and Shuaiyong Li

Abstract—**Overuse of non-renewable energy has seriously affected environment, wind power is of vital significance to alleviate the energy crisis and protect the environment. The forecasting accuracy of wind speed has a positive correlation with the effective utilization rate of wind energy. BP neural network has advantages over traditional prediction models in dealing with nonlinear problems, but it has different generalization ability to different data. Therefore, we proposed a hybrid forecasting model based on singular spectrum analysis (SSA), fuzzy c-means clustering (FCM) and improved sparrow search algorithm (ISSA-BP). Firstly, after the raw wind speed data are obtained, singular spectrum analysis is employed to de-noise, so as to improve the data quality. Secondly, the input dataset of BP is divided into several categories using FCM, and the number of classifications for two different datasets is obtained through multiple experiments. Thirdly, since the selection of parameters largely determines the performance of BP neural network, the improved sparrow search algorithm (ISSA) is adopted to optimize the weights and thresholds. Then different ISSA-BP models are built for each class of input datasets. Finally, the class of forecasting input is determined and the corresponding ISSA-BP is used for forecasting. The experimental results of two cases showed that the proposed model was not only suitable for one-step forecasting, but also improved the accuracy of multi-step forecasting. The ultimate experimental results, in comparison with other six different models, demonstrate that the proposed model can acquire higher prediction precision.**

Index Terms—**Wind Speed Forecasting, Singular Spectrum Analysis (SSA), Fuzzy C-means Clustering (FCM), Improved Sparrow Search Algorithm-BP (ISSA-BP).**

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I. Introduction

UNCERTAINTY of wind power output affects the robustness of power system. Wind energy is a clean and renewable energy, but its utilization rate is low because of the intermittent and volatility of wind energy [1-4].

Considering the intermittency and volatility of wind power, the power system is faced with a series of effects brought by wind power generation. Moreover, the use of energy is close to our everyday life, meanwhile it reflects the strength of national economy as well. So, reliable and precise wind speed forecasting is of great importance to both wind power system and electrical power system [5, 6].

For improving the precision of wind speed forecasting, lots of wind speed prediction methods have been put forward over the previous few decades by many scholars. Wind speed prediction models could be divided into four sorts, which are physical models, statistical models, artificial intelligence models, and hybrid models [7-9].

The physical models, which are also called weather forecasting system, establishes equations through information such as a variety of meteorological factors named air pressure, temperature, humidity, and then solving the equations to forecast wind speed.

The statistical models are divided into linear and non-linear forecasting models. The statistical models are mainly reflected in the linear model, including auto regressive (AR), auto-regressive moving average (ARMA) and auto regressive integrated moving average (ARIMA) [10-12]. For example, Grigonyte and Butkeviciute [13] used ARIMA model to predict short-term wind speed. Torres *et al.* [14] utilized ARMA model in Navarre (Spain) to forecast the average hourly wind speed. Nevertheless, considering the fluctuation and intermittent characteristics of wind speed series, only grasping its simple linear relationship may lack a certain degree of confidence, so a more complex function is needed to capture the non-linear relationship.

The artificial intelligence models are mainly embodied in the nonlinear model, for instance the artificial neural network (ANN) and the support vector machine (SVM) [15-17]. For example, Griorgi *et al.* [18] selected the ANN to forecast short-term wind speed; compared with the linear correlation model, the ANN provides a great approach for the study of wind forecasting. Zhou *et al.* [19] showed a prediction model on account of the SVM, which has great precision of prediction in the short-term wind speed prediction.

The hybrid models considering data quality and internal relationship, intelligent optimization algorithm and prediction model is the mainstream prediction method at present. Such as Wang *et al.* [20] used the ensemble empirical mode decomposition (EEMD) to divide the original data into signals of different frequencies, and used the decomposed signals as the input of GA-BP. Zhang *et al.* [21] adopted the wavelet transform (WT) which united phase space reconstruction and variation mode decomposition to forecast wind speed ending up with a good result. Reference [22] had established SAM-ESM-RBFN hybrid model by combining SAM, ESM and RBFN, after that applied the novel model to predict the wind speed.

Singular spectrum analysis (SSA), which proposed by Colebrook, is a powerful technique to study nonlinear time series data in recent years. Due to its powerful signal processing ability, it has been selected by many scholars for data pretreatment. Ding *et al.* [23] combined the SSA and neural network which optimized by particle swarm optimization algorithm (PSO) to study wind speed prediction. Wang *et al.* [24] proposed a novel flutter detection method on account of WPD, SSA and SVM-PSO.

BP neural network has been widely used since it was proposed in 1986, especially in prediction models. Considering that its main feature is the error back propagation, so there will be different prediction accuracy for different input datasets. Reference [25] had clarified that the BP neural network obtains low prediction accuracy when input data with large volatility, and high prediction accuracy for input data with low volatility. Hence, to maximize the prediction accuracy, we used FCM to divide the input data of BP neural network into different categories according to the similarities, and then to establish different BP neural network prediction models on this account. In this paper, the improved sparrow search algorithm with BP neural network (ISSA-BP), which is a novel swarm intelligence optimization algorithm to optimize the weight of combined model.

The main work accomplished in this paper is shown as following: (1) Considering the characteristics of strong intermittence and randomness of wind, for improving the data quality and prediction accuracy, singular spectrum analysis (SSA) method is selected to de-noise the data as data preprocessing. (2) Divide the de-noised wind speed data into multiple categories on the basis of FCM and establish corresponding prediction models respectively. (3) To solve the trouble that BP neural network may fall into local optimum, the improved sparrow search algorithm is introduced to optimize the weights and thresholds of it. (4) In order to verify the performance of the improved algorithm, a comparative experiment of benchmark function is designed. (5) So as to reflect the performance of the proposed method and the workload of each section, other six different models are tested on two wind speed datasets with a sampling interval of 15 minutes. For each different model, four commonly used error evaluation indexes are selected for comparison, and finally the conclusion is drawn.

Fig. 1 shows two sets of wind speed data with the sampling interval of 15 minutes, which is the real wind speed data measured by a real wind power plant in China. Among them, the first 2900 data of each set are regarded as training set, and the last 100 data are regarded as testing set for simulation verification.

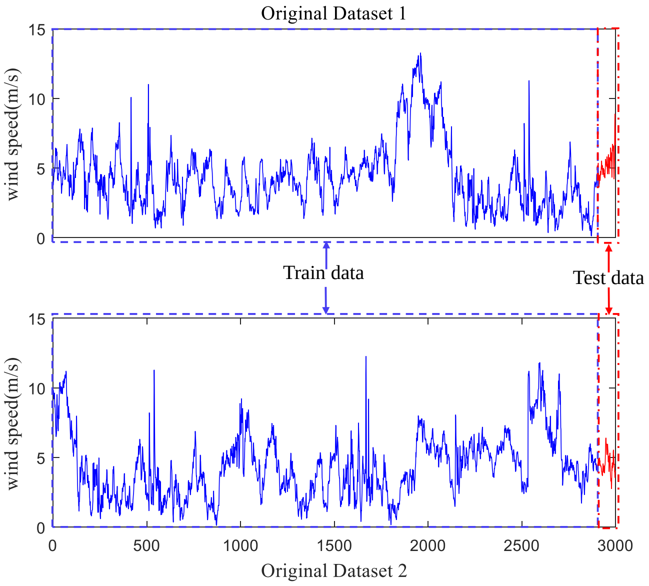

Fig. 1. Two original wind speed datasets

II. METHODOLOGY

As noted above, the proposed model in this paper is constituted by three parts, namely data pretreatment, data clustering processing, and establishment and implementation of the prediction model. In this part, the relevant theoretical knowledge and implementation process of the model proposed in this paper will be introduced in detail below.

A. Singular Spectrum Analysis (SSA)

The generation, acquisition and transmission of signals are inevitably disturbed by noise, so it is necessary to de-noise in signal preprocessing. The SSA method on account of singular value decomposition (SVD) was first proposed and used in Oceanography Research by Colebrook in 1978. Now this technique has been applied to signal de-noising and has good effect in noise reduction [26, 27]. The implementation steps of SSA are detailed as following:

a: Embeding

The embedding operation can be regarded as the mapping process from one-dimensional sequence to multi-dimensional sequence. $F_N = (f_1, \cdots; f_N)$, expressed the time series of raw wind speed, is shifted to a trajectory matrix X which is consisted of L-dimensional vector $x_i = (f_1, \cdots; f_{i+L-1})^T$.

$$X = \begin{pmatrix} f_1 & f_2 & \cdots & f_K \\ f_2 & f_3 & \cdots & f_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ f_L & f_{L+1} & \cdots & f_N \end{pmatrix} \quad (1)$$

where, L means window length, and $2 \le L \le N$, $K = N\text{-}L\text{+}1$.

b: SVD Decomposition

The eigenvalues λ_i ($\lambda_i \geq 0$, i = 1, 2, ⋯; L), left singular vector (U_i) and right singular vector (R_i) of XX^T are calculated. After that, the matrix X and x_i can be also described as below:

$$X = X_1 + X_2 + \cdots + X_d \tag{2}$$

$$x_i = \sqrt{\lambda_i} U_i R_i^T \tag{3}$$

where, $d = max(i, \lambda_i > 0) = Rank(XX^T)$, U_i and R_i represent the left and right singular vectors of X respectively.

c: Grouping

Grouping is mainly to separate the target signal component from the original signal component, that is, to filter out the noise signal. Combined with the empirical formula, the first R larger singular values are generally selected as the main components of the signal [28].

Divide the matrix X which is obtained above into several different parts, and m matrixes in d are selected as trend elements. Delimit the sub-matrix of Rth part as R= {r_1, ⋯; r_m}, and $F_R = F_{r1} + \cdots + F_{rm}$, F_R means the main trend segment of raw wind speed series. Hence, the rest are considered noise elements that need to be filtered out.

d: Reconstructing

Through the above processing, the corresponding wind speed data will be converted from the group X_R and described as trend segment F_{trend} = {F_{r1}, ⋯; F_{rm}} and noise segment F_{noise}. In summary, the original wind speed data can be expressed by the following formula:

$$F_N = F_{trend} + F_{noise} = F_{r1} + F_{r2} + \cdots + F_{rm} + F_{noise} \tag{4}$$

In the above steps, two undetermined parameters are involved, that is to say the length L of window and the number of singular values r of the reconstructed signal. The selection of parameters is also important for data pretreatment. Combining the previous experience formula and the actual data structure of this article, the parameters and corresponding values selected in this article are listed in Fig. 2 and TABLE I below.

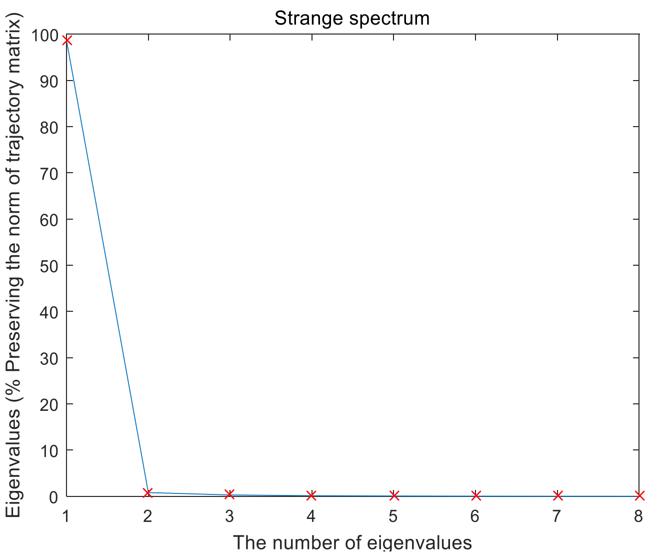

Fig. 2. Singular spectrum analysis graph

TABLE I
SSA PARAMETERS AND VALUES

Parameter name	Value
Window length L	8
singular values number r	4
characteristic value r_1	98.64%
characteristic value r_2	0.8038%
characteristic value r_3	0.2931%
characteristic value r_4	0.1263%

The comparison between the original wind speed data and the data after SSA de-noising is shown in Fig. 3.

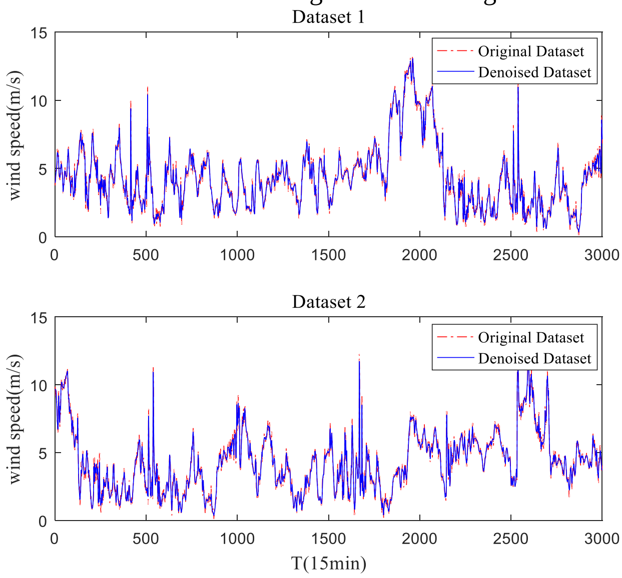

Fig. 3. Data comparison before and after de-noising

B. Fuzzy C-Means Clustering (FCM)

The fuzzy c-means clustering algorithm, which combined fuzzy logic method and k-means, was proposed by Dunn in 1973 and improved by Bezdek in 1984 [29, 30].

The data is clustered into k-cluster by measuring the distance between the cluster center and each sample data with the membership matrix. The data matrix X consists of p variables of n samples.

$$H = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1p} \\ h_{21} & h_{22} & \cdots & h_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ h_{n1} & h_{n2} & \cdots & h_{np} \end{bmatrix} \tag{5}$$

This algorithm divides n data samples into c classes, and $V=(v_1,v_2,\cdots,v_c)$ is the cluster center, where $v_i=(v_{i1}, v_{i2}, \cdots, v_{ip})$, $i=(1,2,\cdots c)$.

The target function of FCM is given by:

$$J(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^m d_{ik}^2 \tag{6}$$

where, u_{ik} is degree of membership for data point, $U=(u_{ik})_{c\times n}$ is the membership matrix, and d_{ik} is the distance between data point and cluster center $d_{ik} = \|h_k - v_i\|$.

The clustering criterion of FCM algorithm aims to find U and V to minimize $J(U,V)$. The specific steps for FCM are as following:

(i) First, a series of parameters such as the number of clusters c, the initial membership matrix $U^{(0)}=(u_{ik}^{(0)})$ and the number of iterations l are initialized.

(ii) The calculation formula of cluster center $V^{(l)}$ in the lth iteration is given by calculation 7.

$$v_i^{(l)}=\frac{\sum_{k=1}^{n}(u_{ik}^{(l-1)m}h_k)}{\sum_{k=1}^{n}(u_{ik}^{l-1})^m},i=1,2,\cdots c \tag{7}$$

(iii) Modify the current membership matrix $U^{(l)}$ and calculate the objective function value $J^{(l)}$.

$$u_{ik}^{(l)}=\frac{1}{\sum_{j=1}^{n}\left(\frac{d_{ik}^{(l)}}{d_{jk}^{(l)}}\right)^{\frac{2}{m-1}}},i=1,2,\cdots c;k=1,2\cdots n \tag{8}$$

$$J^{(l)}(U^{(l)},V^{(l)})=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik}^{(l)})^m(d_{ik}^{(l)})^2 \tag{9}$$

where, $d_{ik}^{(l)}=\|h_k-v_i^{(l)}\|$.

(iv) Eventually, the iteration will end when the condition $\max\{|u_{ik}^{(l)}-u_{ik}^{(l-1)}|\}<\varepsilon_n$ is met. Otherwise, $l=l+1$, then *step* (ii) is performed. Where ε_n is a constant greater than zero.

Through the above four steps, the ultimate membership matrix U and the cluster center V could be obtained to minimize J.

The selection of the number of clustering categories c would have a great influence on the final forecasting results. It's crucial for each set of data to find the optimal number of clustering categories. For the two sets of data used in this paper, we set c to 1, 2, 3, 4, 5, 6 respectively, and then conducted 10 experiments using BP neural network. The average error criteria for the number of different categories of experiments are shown in TABLE II.

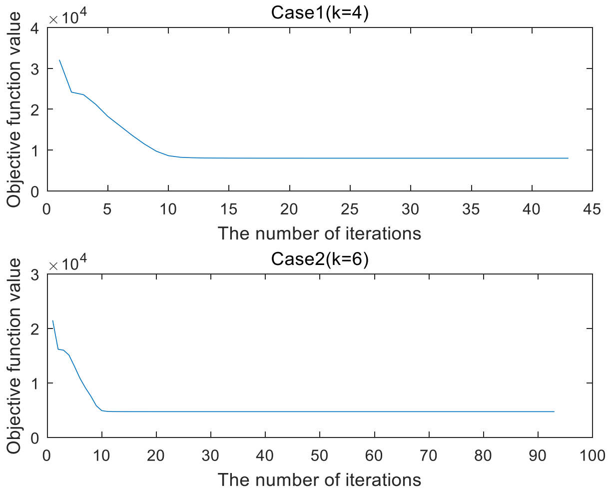

Fig. 4. FCM iteration process

As can be seen from TABLE II, for dataset 1 and dataset 2, when c is 4 and 6 respectively, the evaluation index of prediction results is the best. Therefore, this paper selects the number of clustering categories as 4 and 6 for dataset 1 and 2, and then carries out subsequent modeling and prediction. The proposed FCM iteration process for two datasets is shown in Fig. 4.

TABLE II
AVERAGE ERROR CRITERIA OF DIFFERENT CLASSES

		MAE	RMSE	MAPE(%)
	1	0.272	0.364	5.435
	2	0.280	0.344	5.542
	3	0.307	0.391	5.780
Case1	4	**0.259**	**0.324**	**5.175**
	5	0.268	0.336	5.542
	6	0.260	0.327	5.320
	1	0.317	0.415	5.891
	2	0.314	0.421	5.625
	3	0.324	0.417	5.869
Case2	4	0.325	0.418	5.958
	5	0.328	0.423	6.014
	6	**0.304**	**0.401**	**5.578**

C. *Sparrow Search Algorithm (SSA)*

Sparrow search algorithm, a novel swarm intelligence optimization approach, is proposed in 2020, primarily inspired by sparrow's foraging behavior and anti-predatory behavior [31]. Sparrow search algorithm mainly simulates the foraging process of sparrows. The foraging process of sparrows is also a kind of discoverer follower model, and the detection and the warning mechanism is superimposed. In the process of sparrow foraging, they are divided into producers and scroungers. The producers are in charge of finding food in the population and provide foraging area and direction for the whole sparrow population, while the scroungers obtain food by the information supplied by producers. In order to get as much food as possible, sparrows can usually adopt two behavioral strategies: producer and scrounger. Individuals in the population supervise the behavior of other individuals in the population, and the attackers in the population compete for food resources with their high ingestion peers in order to improve their predation rate. Additionally, when the sparrow population is aware of danger, it will make anti-predatory behavior timely [32, 33].

In conclusion, we idealize sparrow behavior and formulate corresponding rules for simplicity when using sparrow search algorithm, as shown below:

(1) Producers often have the highest energy reserve levels and are in charge of providing information including foraging areas and directions for all scroungers. It is in charge of identifying areas where plentiful food sources could be discovered. The amount of energy stored depends on depends on the fitness value of the individual.

(2) Only if the sparrow finds the predator, it would start to chirp regarding as a warning signal. While the warning value is larger than the security threshold, the producers require leading all scroungers to a more secure area.

(3) The identity of sparrow can be changed between producer and scrounger. On condition that a better food source is found, each sparrow can become a producer, but the proportion of producer and scrounger in the sparrow population will not change.

(4) Individual sparrows with higher energy will serve as producers, and a few starving scroungers are more prone to move to other areas in search of food.

(5) The main way scroungers get their food is by following the producers who could provide the food information. At the same time, some scroungers pay attention to producers and contend for food for the sake of raising their own predation rate.

(6) When the sparrow on the fringes of the population senses danger, it will rapidly fly to a safe area to get a better place, while the others who are occupied in the middle of the population will walk randomly to get close to others.

According to the above definitions and rules, the place of the sparrow can be expressed as follows:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1d} \\ w_{21} & w_{22} & \cdots & w_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nd} \end{bmatrix} \tag{10}$$

where, n represents size of the population and d refers to the dimension of the variables to be optimized. What is more, the fitness values of sparrow individuals could be conveyed by the below vectors:

$$f_W = \begin{bmatrix} f\left(\left[w_{11} & w_{12} & \cdots & w_{1d}\right]\right) \\ f\left(\left[w_{21} & w_{22} & \cdots & w_{2d}\right]\right) \\ \vdots & \vdots & \ddots & \vdots \\ f\left(\left[w_{n1} & w_{n2} & \cdots & w_{nd}\right]\right) \end{bmatrix} \tag{11}$$

where, the each row in f_W means the individual's fitness value. In this algorithm, the producer with better fitness value will get food first in the search process.

Additionally, the producer is responsible for finding food for the entire sparrow population and providing direction for all participants. Therefore, producers can obtain a larger range of foraging search than the scroungers. In each iteration, the producer's location update is described as following:

$$W_{ij}^{t+1} = \begin{cases} W_{ij}^{t} \cdot exp\left(\dfrac{-i}{\alpha \cdot iter_{max}}\right) & if\ R_2 < ST \\ W_{ij}^{t} + Q \cdot L & if\ R_2 \geq ST \end{cases} \tag{12}$$

where, t shows the number of current iteration, j=1, 2, $\cdots$; d, W_{ij}^{t} indicates the value of the jth dimension of the ith sparrow at the tth iteration, $iter_{max}$ represents the maximum number of iterations. α is a random digit belonging to (0, 1]. Q is a random number obeying normal distribution. L is a $1 \times d$ matrix with element values of 1. $R_2 \in [0, 1]$ and $ST \in [0.5, 1.0]$ remark the warning value and the safety threshold, respectively.

About the scroungers, they require to follow regulations 4 and 5 setting out above. As stated above, some scroungers notice producers more repeatedly. The situation update formula of scroungers is expressed as following:

$$W_{ij}^{t+1} = \begin{cases} Q \cdot exp\left(\dfrac{W_{worst}^{t} - W_{ij}^{t}}{i^2}\right) & if\ i > \dfrac{n}{2} \\ W_{p}^{t+1} + \left|W_{ij}^{t} - W_{p}^{t+1}\right| \cdot A^{+} \cdot L & otherwise \end{cases} \tag{13}$$

where, W_p is the optimal position currently occupied by the producer, and W_{worst} indicates the current worst place globally. A shows a $1 \times d$ matrix which each element is randomly appointed a value of 1 or -1, and $A^+ = A^T(AA^T)^{-1}$.

While the sparrow is aware of the danger in the process of foraging, the sparrow population will make anti-predatory behavior, which is to abandon the current food and move to a new location. The mathematical expression of the position update is as following.

$$W_{ij}^{t+1} = \begin{cases} W_{best}^{t} + \beta \cdot \left|W_{ij}^{t} - W_{best}^{t}\right| & if\ f_i \neq f_g \\ W_{ij}^{t} + K \cdot \left(\dfrac{\left|W_{ij}^{t} - W_{worst}^{t}\right|}{(f_i - f_w) + \varepsilon}\right) & if\ f_i = f_g \end{cases} \tag{14}$$

where, W_{best} is the current global optimal place. As a step size parameter, β is a random number which abides by normal distribution of mean value 0 and variance 1. $K \in [-1, 1]$ is a random digit and f_i means the fitness value of the current individual. f_g and f_w represent the present global best and worst fitness values. ε is a smallest constant greater than 0 to avert falling into a denominator of 0.

Combining the rules defined above and the location update formula in each case, the general steps of sparrow search algorithm (SSA) could be represented as following pseudo code:

Title The structure of the sparrow search algorithm.

Input:
M: the largest iteration number
PN: the total number of producers
SN: the number of sparrows who are aware of the danger
R_2: the warning value
N: the size of the sparrow population
Output: W_{best}, f_g
1: **while** ($t < M$)
2: Sort the fitness values of all sparrows to find the current best individual and the worst individual.
3: $R_2 = rand(1)$
4: **for** i = 1: PN
5: Employing formula (12) update the producer's position;
6: **end for**
7: **for** $i = (PN + 1) : N$
8: Employing formula (13) update the scrounger's position;
9: **end for**
10: **for** i = 1: SN
11: Employing formula (14) update the sparrow's position;
12: **end for**
13: Obtain the current novel position;
14: As long as the novel position is better than before, update it;
15: $t = t + 1$;
16: **end while**
17: **return** W_{best}, f_g

D. Improved Sparrow Search Algorithm (ISSA)

Although the sparrow is small and has all the internal organs, each sparrow in this paper has only one attribute: location, which represents the location of the food it finds. Each sparrow has three possible behaviors: 1. as a producer, it requires going on searching for food; 2. as a scrounger, follows a producer for food; 3. alert detection, and give up food provided that there is danger.

According to the analysis of the three update formulas, it can be concluded that the position update method of the sparrow search algorithm can be roughly divided into two types: the first is to close the current optimal position; another situation is to close the origin. In the meantime, each sparrow of the sparrow search algorithm converges to the current optimal solution by jumping directly to the current optimal solution, instead of moving to the optimal solution like the particle swarm algorithm, which also causes the sparrow search algorithm to be caught in the local optimal easily, the capability of global search is weak. Consequently, this paper proposes improvements to the sparrow search algorithm as following:

(1) The operation of convergence to the origin is removed, and the jump operation to the optimal position is replaced by the movement to the optimal position. The specific implementation formula is modified as follows:

$$W_{ij}^{t+1} = \begin{cases} W_{ij}^{t} \cdot (1+Q) & if \ R_2 < ST \\ W_{ij}^{t} + Q & if \ R_2 \geq ST \end{cases} \tag{15}$$

where, Q is a standard normal distribution random number.

(2) If the sparrow is in the optimal position, it will escape to the random location between the optimal location and the worst location according to Levy flight strategy, otherwise, it will escape to the random location between itself and the optimal location. The specific implementation formula is reformed as follows:

$$W_{ij}^{t+1} = \begin{cases} W_{ij}^{t} + Le \cdot (W_{ij}^{t} - W_{best}^{t}) & if \ f_i \neq f_g \\ W_{ij}^{t} + Le \cdot (W_{worst}^{t} - W_{best}^{t}) & if \ f_i = f_g \end{cases} \tag{16}$$

where, Le represents the Levy flight strategy, which is a decent way for organisms to find food in unknown environments, it can be described by the following formula [34, 35].

$$Le = \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \cdot \frac{1}{s^{1+\lambda}} \tag{17}$$

where, $\Gamma(\lambda)$ means the standard gamma function, and this distribution is valid for large steps $s > 0$.

E. *Comparative Experiment of Benchmark Functions*

The above two sections describe the original sparrow search algorithm and the improved sparrow search algorithm in this paper respectively. In order to verify the performance of ISSA algorithm, benchmark function comparison experiment is designed [36]. The four different types of test functions used in this article are shown in TABLE III.

The benchmark function $F1$-$F4$ has different features in function: $F1$ and $F2$ are unimodal variable separable and non-separable functions respectively; $F3$ and $F4$ are multimodal variable separable and non-separable functions respectively. As a unimodal test function, $F1$ and $F2$ are used to verify the optimization accuracy of algorithms, while $F3$ and $F4$ are multimodal test functions, which are selected to verify the global optimization capability of algorithms due to their non-linear nature and the existence of many local extreme points. In this part, the general parameters of algorithms are setting as follows: the population size $PN = 30$, the largest number of iterations $MaxIteration = 100$, and the number of producers and the number of sparrows who are aware of danger is both 20% of the population size. Through the simulation experiment of test function, the iteration comparison diagram of each test function is obtained respectively, as shown in Fig. 5, Fig. 6, Fig. 7 and Fig. 8.

Considering the randomness of ISSA in the search strategy, for the sake of quantitatively analyzing the performance of ISSA, the four benchmark functions listed above were run independently for 30 times, and the mean value, standard deviation, worst value and best value of each function optimization results were obtained as shown in TABLE IV. According to the convergence curves of SSA and ISSA in four different types of benchmark functions, it can be intuitively seen that ISSA is superior to SSA in both convergence speed and convergence accuracy. At the same time, it can be concluded from TABLE IV that ISSA has improved 42.5% in terms of optimization accuracy and 48.5% in terms of stability compared with the initial sparrow search algorithm.

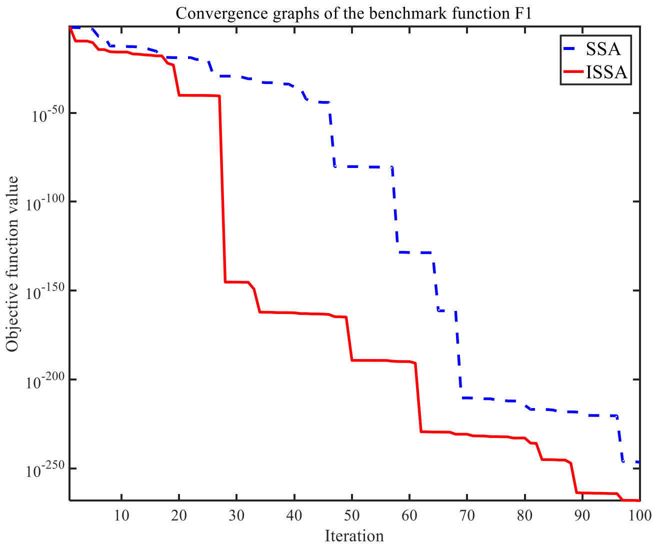

Fig. 5. Convergence graphs of the benchmark function *F*1

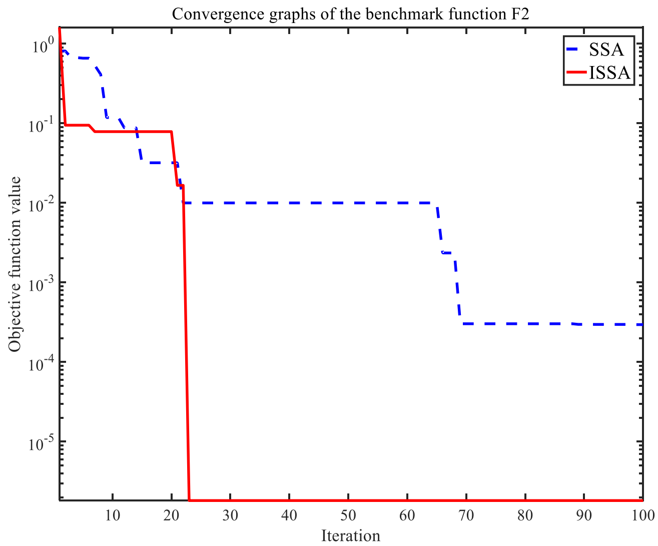

Fig. 6. Convergence graphs of the benchmark function *F*2

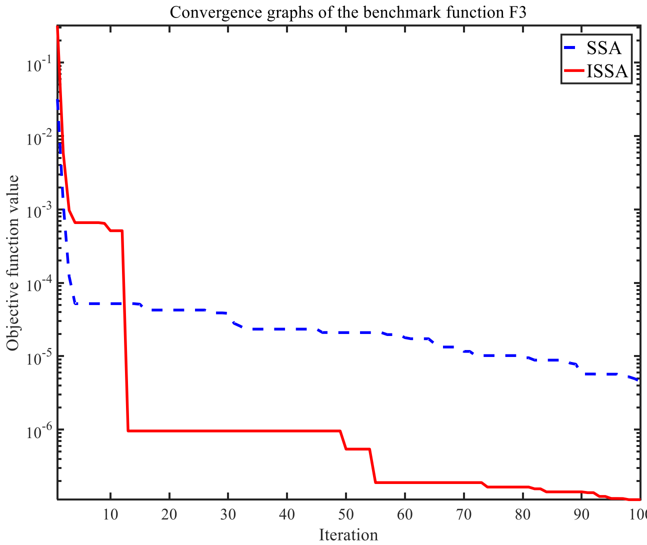

Fig. 7. Convergence graphs of the benchmark function *F*3

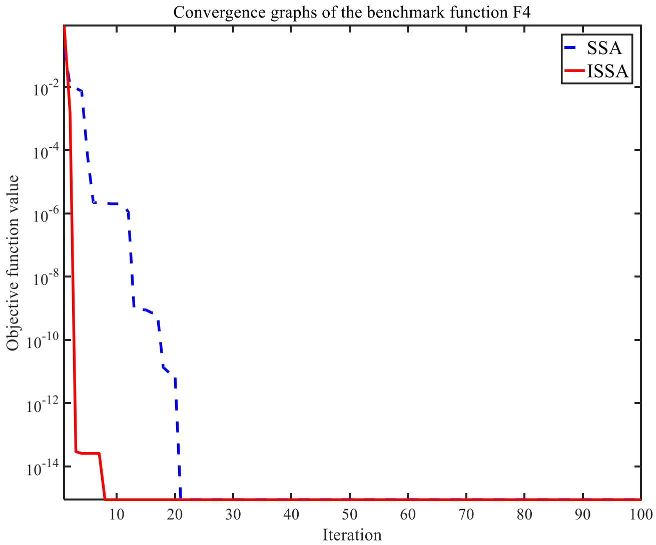

Fig. 8. Convergence graphs of the benchmark function *F*4

TABLE III
BENCHMARK FUNCTIONS

Function	Feature	Functional expression	Boundary	Dim
$F1$	US	$f_1(x) = \max\{\lvert x_i\rvert, 1 \le i \le D\}$	$[-100,100]^D$	30
$F2$	UN	$f_2(x) = \sum_{i=1}^{D-1}\left[100\left(x_{i+1} - x_i^2\right) + \left(x_i - 1\right)\right]$	$[-30,30]^D$	30
$F3$	MS	$f_3(x) = 0.1\{\sin^2(3\pi x_1) + \sum_{i=1}^{D}(x_i-1)^2[1+\sin^2(3\pi x_i+1)] + (x_n-1)^2[1+\sin^2(2\pi x_n)]\} + \sum_{i=1}^{D} u(x_i,5,100,4)$	$[-50,50]^D$	30
$F4$	MN	$f_4(x) = -20\exp\left(-0.2\sqrt{D^{-1}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(D^{-1}\sum_{i=1}^{D}\cos 2\pi x_i\right) + 20 + e$	$[-32,32]^D$	30

TABLE IV
PERFORMANCE COMPARISON OF ALGORITHMS

Benchmark function simulation results					
Function	Algorithm	*MEAN*	*STDEV*	*BEST*	*WORST*
*F*1	SSA	3.3541E-04	4.4652E-05	2.5601E-47	0.0308
	ISSA	**3.2631E-07**	**7.2654E-11**	**6.1395E-69**	**0.0106**
*F*2	SSA	0.0651	0.0290	2.9529E-04	0.8090
	ISSA	**0.0321**	**0.0143**	**1.8172E-06**	**0.5624**
*F*3	SSA	3.5499E-04	0.0232	4.5332E-04	0.0318
	ISSA	**5.2643E-12**	**0.0178**	**1.1126E-07**	**0.0154**
*F*4	SSA	2.6584E-03	7.992E-04	8.8817E-16	0.0562
	ISSA	**5.1256E-07**	**6.605E-07**	**3.5648E-25**	**0.02541**

F. ISSA-BP

Sparrow search algorithm (SSA) is a sort of swarm intelligence optimization algorithm on account of the behavior of sparrows in foraging and escaping predators. It can find the optimal individual by changing the identity of sparrows and updating the position of fleeing predators. Nevertheless, the algorithm has some limitations on global search. Taking this issue into account, the corresponding improvement measures are put forward.

At the same time, BP neural network is very sensitive to the initial connection weights between the input layer and the hidden layer, the hidden layer and the output layer neurons, and the initial thresholds the initial thresholds between the hidden layer and the output layer [37]. However, the initial weights and thresholds of BP neural network are given randomly, so the prediction precision of the model depends on the selection of incipient weights and thresholds. To improve the limitation of BP neural network and the accuracy of the prediction model, the incipient weights and thresholds of BP neural network are optimized by ISSA, afterward adopt the optimized result of ISSA as the incipient weights and thresholds of BP neural network. The structure of ISSA-BP is shown in Fig. 9.

In other word, the prediction precision is also determined by the parameters to a certain extent, for that reason the selection of parameters is also very important. After repeated tests and previous empirical formulas, the parameters used in the proposed model are shown in TABLE V.

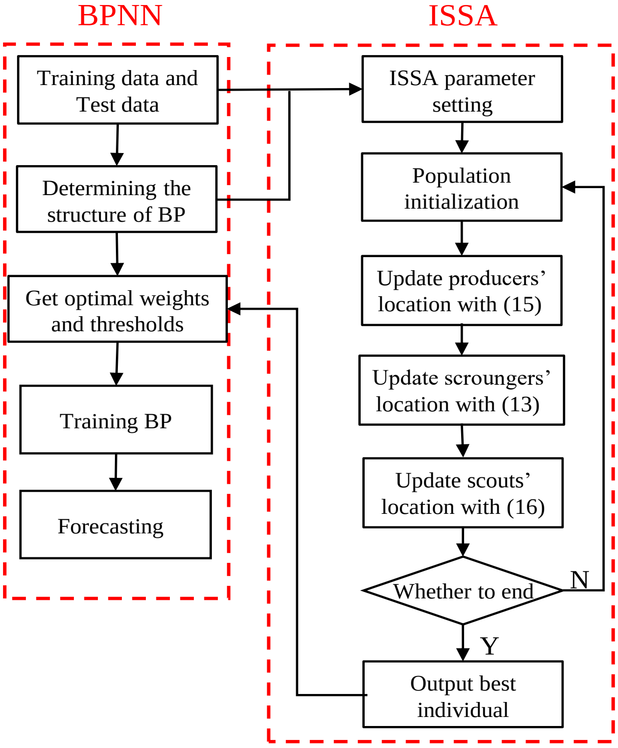

Fig. 9. The structure of ISSA-BP

TABLE V
PARAMETER INITIALIZATION

Parameter name	Value
Number of iterations	200
Population size	30
Evolution times	30
Proportion of producers	0.2
Security threshold	0.8
Number of input layer nodes	5
Number of hidden layer nodes	11
Number of output layer nodes	1

III. FRAMEWORK OF HYBRID MODEL

Combining all the methods and models mentioned above, the hybrid prediction model framework proposed in this paper is shown in Fig. 10. For dataset 1, singular spectrum analysis is adopted to de-noise firstly, and then FCM is used to classify the input data into 4 categories. For dataset 2, the de-noising process is also performed firstly, secondarily the input dataset is divided into 6 categories using FCM. Finally, according to different types of input data, different ISSA-BP models are used for training and prediction verification. Many of the parameters used are shown in TABLE V above.

IV. RESULT ANALYSIS

A. Performance evaluation index

Many performance evaluation indexes have been proposed and adopted by many scholars in their papers. Similarly, the following four error criteria, named MAE, MSE, RMSE, and MAPE, are selected to measure the precision of wind speed forecasting. Their meanings and specific calculations are shown in TABLE VI.

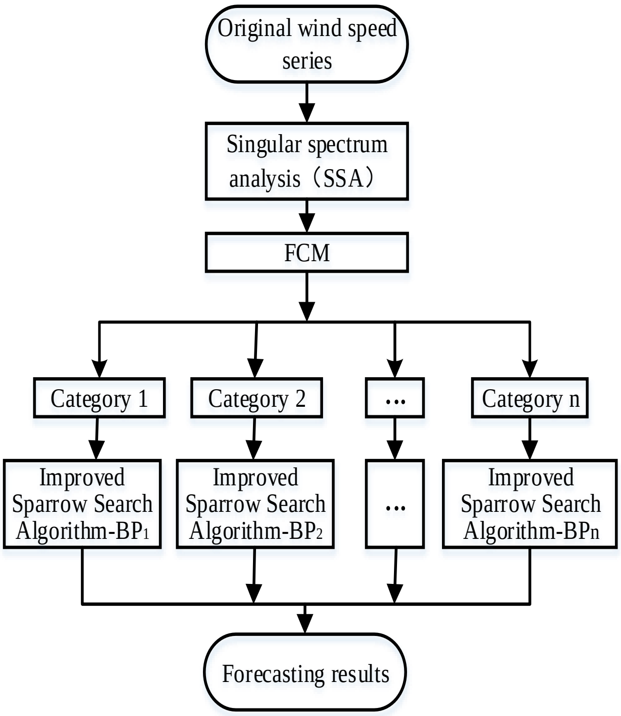

Fig. 10. The framework of hybrid model

TABLE VI
THE PERFORMANCE EVALUATION INDEX

Index	Significance	Formula
MAE	Mean Absolut Error	$MAE=\frac{1}{n}\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert$
MSE	Mean Square Error	$MSE=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
RMSE	Root Mean Squared Error	$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$
MAPE	Mean Absolute Percentage Error	$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{\hat{y}_i-y_i}{y_i}\right\rvert\times 100\%$

where, y_i denotes the true wind speed; $\hat{y}_i$ denotes the predicted wind speed, and n is the number of wind speed forecasting. MAE and RMSE with the equal amplitude can avoid the mutual cancellation of positive and negative prediction errors. MSE could evaluate the degree of change in data. The smaller the MSE value is, the more stable the degree of change in data is, what is more the higher the prediction accuracy is. MAPE plays an important role in reflecting the prediction error. It could not only reflect the relationship between the true wind speed and the predicted wind speed, but also reflect the deeper relationship between the error and the true wind speed to a certain extent.

In order to further verify that the proposed model has better performance, the one-step forecasting, the two-step forecasting and the three-step forecasting are used in this paper to verify [38]. The schematic diagram of multi-step prediction is shown in Fig. 11.

At the same time, as mentioned above, for showing the performance of the proposed model in this paper, seven different forecasting models, which namely SSA-PSOBP, SSA-ARIMA, SSA-BP, SSA-Elman, SSA-FCMBP, SSA-FCM-SSABP and the proposed model, respectively, are evaluated and analyzed. Four various performance evaluation indexes are selected to testify the prediction precision of the proposed model. The specific evaluation index data of each model is compared and analyzed in combination with different datasets below.

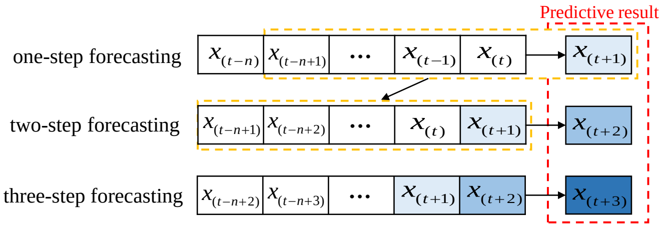

Fig. 11. Multi-step forecasting diagram

It should be noted that the abbreviations of singular spectrum analysis and sparrow search algorithm are the same, so we should pour attention into differentiation when writing. Here, the abbreviation pronoun of singular spectrum analysis should be put in front.

B. Prediction results and comparative analysis

The wind speed datasets used in this paper whose collection interval is 15 minutes are all from a real wind farm in Jiangsu Province, China. In this paper, two sets of wind speed data of the wind farm in different months are selected, each of which contains 3000 real wind speed values. The first 2900 wind speed data is regarded as the training set of the model, and the last 100 wind speed data is used as the testing set prediction, and the performance of the proposed model is evaluated by the results. The analysis of the results obtained for different datasets and models is shown as follows.

a: Dataset 1

The four performance indicators and their corresponding values of the proposed model and the other six models for dataset 1 are listed in TABLE VII. For seven different models, the approaches of one-step forecasting, two-step forecasting and three-step forecasting are used, and the results are shown in Fig. 14, Fig. 15 and Fig. 16, respectively.

By analyzing these data in TABLE VII, for one-step forecasting, the proposed model has higher prediction accuracy than the other six models, with MSE, MAE, RMSE, and MAPE values of 0.020, 0.102, 0.118, and 1.801%, respectively. Meanwhile, it is noted that MAE, MSE and RMSE of the proposed model are slightly smaller than those of SSA-PSOBP model, while MAPE is little bigger than that of SSA-PSOBP model. Moreover, in order to more intuitively display the results of each evaluation index for different models, one-step forecasting is selected as the representative to make histogram as shown in Fig. 12. This indicates that the proposed method is similar to SSA-PSOBP model in one-step forecasting. For the two-step forecasting and the three-step forecasting, the four evaluation indexes obtained by the proposed model in this paper are optimal compared with the other six models, so the prediction accuracy is the highest. In addition, compared with ARIMA, a typical model for linear problems, the proposed model in this paper has evident advantages.

By comparison to SSA-FCM-SSABP model, the values of the four evaluation indexes can be reflected. The improved algorithm can seek out more suitable incipient weights and thresholds of BP neural network. Therefore, the prediction precision of the proposed model is higher than others. By comparing to the prediction results of SSA-BP and SSA-ARIMA, it is evident that BP is more suitable to tackle the nonlinear problems than ARIMA. Similarly, comparing the prediction results of SSA-BP and SSA-Elman model, we can know that BP is better than Elman model in this wind speed dataset. By longitudinal comparison of the prediction results of each model in multi-step prediction, it could be concluded clearly that the prediction accuracy decreases with the increase of prediction step size.

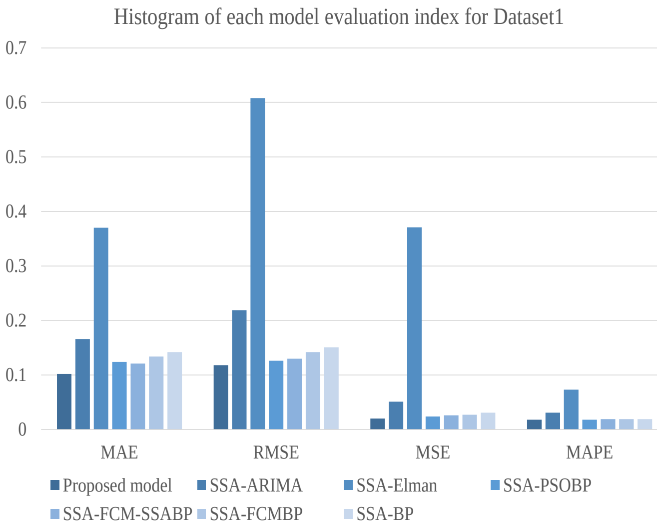

Fig. 12. The histogram of each model evaluation index for Dataset1

b: Dataset 2

The four performance indicators and their corresponding values of the proposed model and the other six models for dataset 2 are listed in TABLE VIII. For seven different models, the methods of one-step forecasting, two-step forecasting and three-step forecasting are used, and the results are shown in Fig. 17, Fig. 18 and Fig. 19, respectively. Compared with wind speed dataset 1, wind speed dataset 2 is not only different in data, but also has different number of clusters using FCM.

By analyzing the relevant index data in TABLE VIII, it is evident that the MAE, MSE, MAPE and RMSE obtained by the proposed model in this paper are better than those of the other six models， with MSE, MAE,RMSE, and MAPE values of 0.011, 0.102, 0.092, and 1.642%, respectively， whether in one-step forecasting, two-step forecasting or three-step forecasting. Moreover, with the increase of prediction step size, the proposed model has evident advantages compared to other models.

Compared with the previous wind speed dataset 1, no matter which prediction model is selected, the error criterion is larger than the former. It could know that for different wind speed series, BP neural network has different adaptability, which leads to different performance of prediction model. In the same way, in order to more intuitively display the results of each evaluation index for different models, one-step forecasting is selected as the representative to make histogram as shown in Fig. 13. It is universally acknowledged that the smaller the value of the evaluation index means the higher the prediction accuracy of the model.

For the wind speed series with high volatility, the final results are generally poor, while for the wind speed series with small volatility, the final results are often better. To be specific, ARIMA, as a typical model for dealing with linear problems, has obvious disadvantages when applied to unsteady, intermittent and fluctuating wind speed series. Likewise, Elman model is very unstable in dealing with the problems in this paper, and there is a big deviation in the prediction, which is obviously reflected in the two-step forecasting and the three-step forecasting. Compared with the classical PSO model, the prediction accuracy of the proposed model in this paper is almost higher than the former in one-step forecasting, two-step forecasting or three-step forecasting. In comparison with other models, the proposed model is more stable and has more advantages in dealing with complex nonlinear problems.

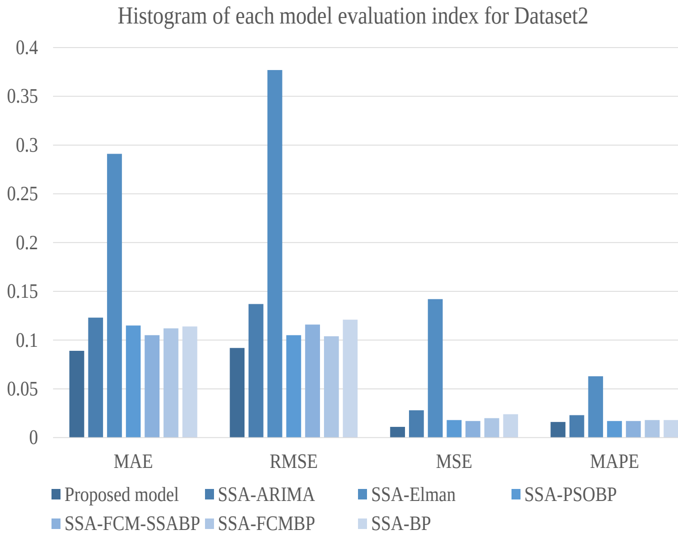

Fig. 13. The histogram of each model evaluation index for Dataset2

TABLE VII
FORECASTING ERROR CRITERIA OF DIFFERENT MODELS FOR DATASET 1

	MAE			RMSE			MAPE (%)			MSE		
	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
Proposed Method	**0.102**	**0.181**	**0.268**	**0.118**	**0.243**	**0.387**	1.801	**3.152**	**5.102**	**0.020**	**0.074**	**0.154**
SSA-ARIMA	0.166	0.586	0.912	0.219	0.841	1.061	3.093	12.99	16.91	0.051	0.731	1.130
SSA-Elman	0.370	0.442	0.509	0.608	0.681	0.723	7.316	7.976	9.413	0.371	0.472	0.522
SSA-PSOBP	0.124	0.184	0.292	0.126	0.283	0.453	**1.772**	3.504	5.231	0.024	0.081	0.161
SSA-FCM-SSABP	0.121	0.192	0.281	0.130	0.263	0.408	1.864	3.201	5.187	0.026	0.081	0.166
SSA-FCMBP	0.134	0.209	0.299	0.142	0.286	0.441	1.816	3.933	5.545	0.027	0.082	0.194
SSA-BP	0.142	0.192	0.284	0.151	0.298	0.412	1.945	3.560	5.204	0.031	0.089	0.167

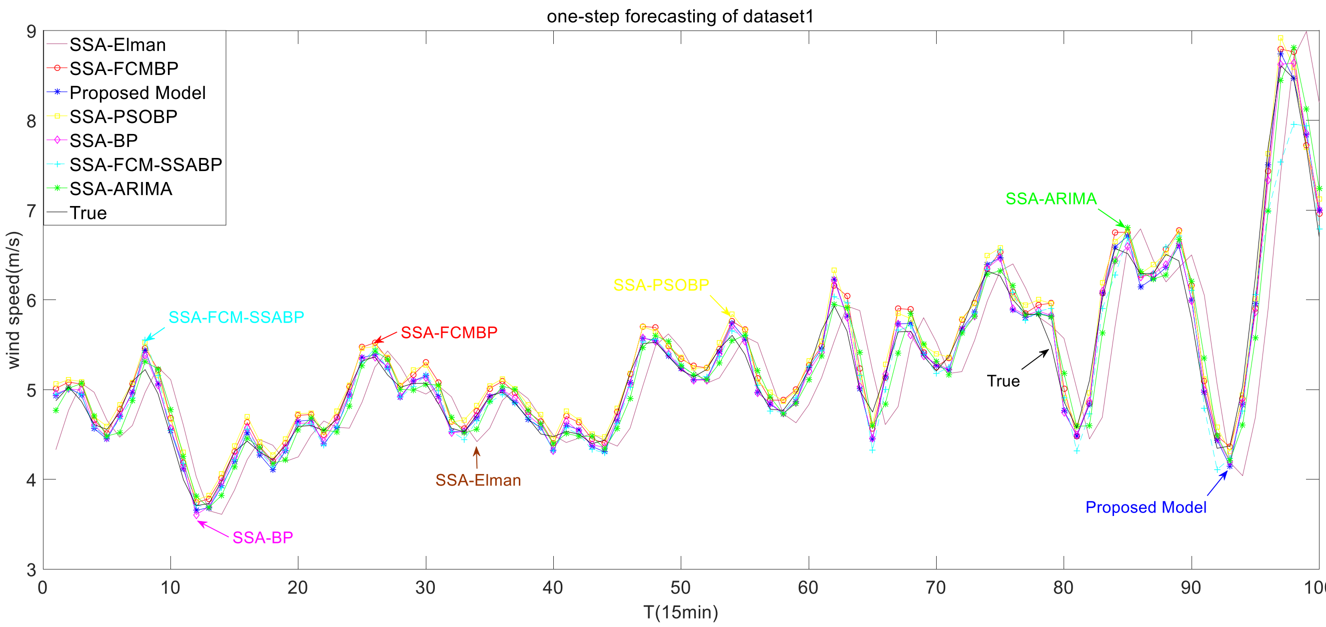

Fig. 14. One-step forecasting of Dataset 1

TABLE VIII
FORECASTING ERROR CRITERIA OF DIFFERENT MODELS FOR DATASET 2

	MAE			RMSE			MAPE (%)			MSE		
	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
Proposed Method	**0.089**	**0.134**	**0.241**	**0.092**	**0.205**	**0.380**	**1.642**	**3.194**	**5.214**	**0.011**	**0.036**	**0.145**
SSA-ARIMA	0.123	0.381	0.442	0.137	0.483	0.576	2.332	8.352	9.653	0.028	0.231	0.332
SSA-Elman	0.291	0.306	0.447	0.377	0.395	0.591	6.337	6.884	9.710	0.142	0.156	0.349
SSA-PSOBP	0.115	0.146	0.252	0.105	0.219	0.401	1.720	3.265	5.301	0.018	0.048	0.134
SSA-FCM-SSABP	0.105	0.147	0.256	0.116	0.221	0.397	1.747	3.310	5.370	0.017	0.048	0.150
SSA-FCMBP	0.112	0.157	0.257	0.104	0.243	0.394	1.751	3.482	5.314	0.020	0.059	0.152
SSA-BP	0.114	0.150	0.260	0.121	0.223	0.402	1.784	3.348	5.351	0.024	0.051	0.142

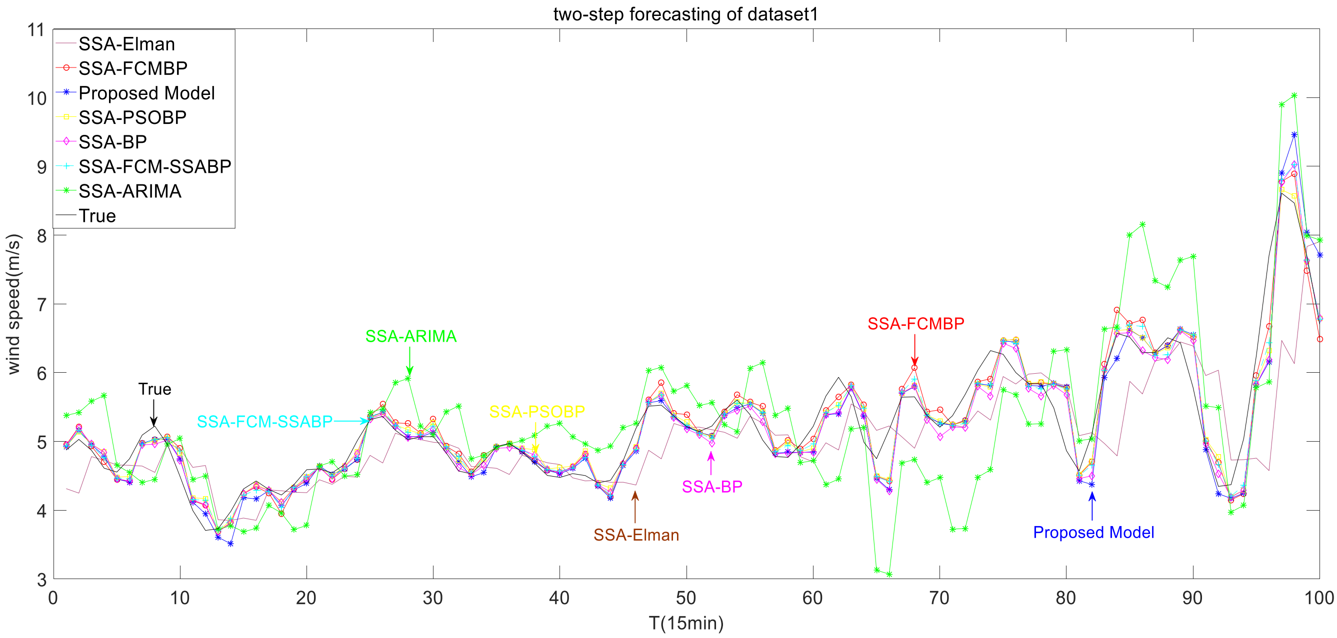

Fig. 15. Two-step forecasting of Dataset 1

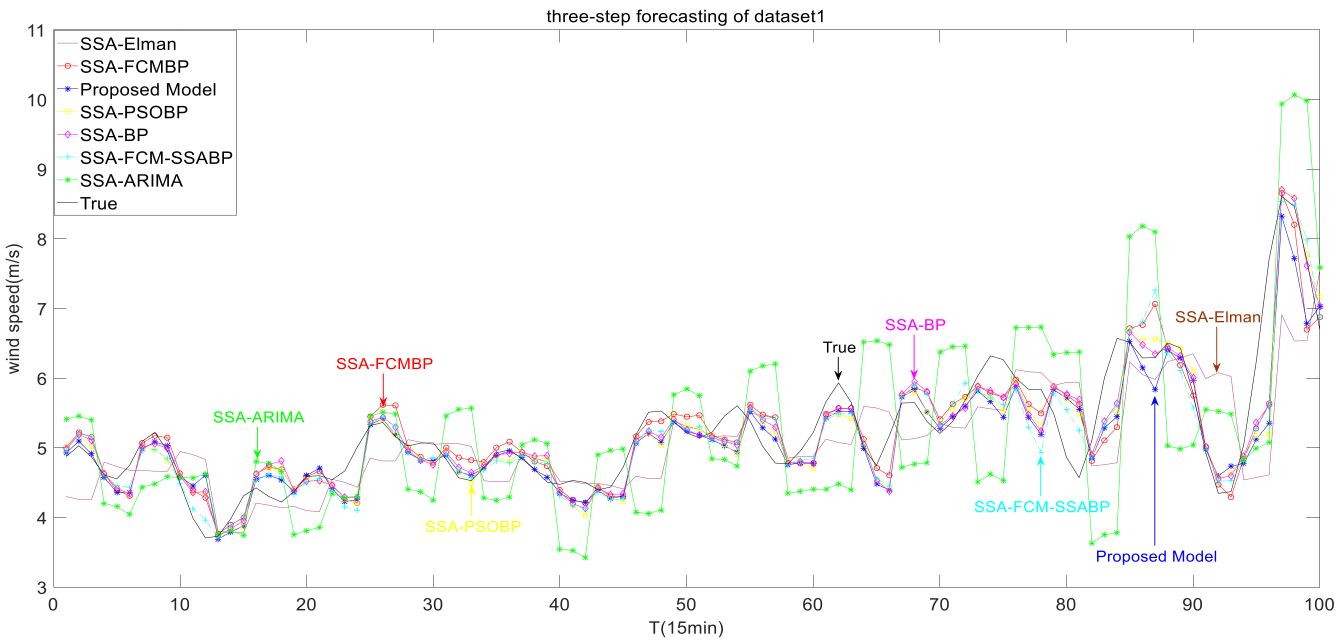

Fig. 16. Three-step forecasting of Dataset 1

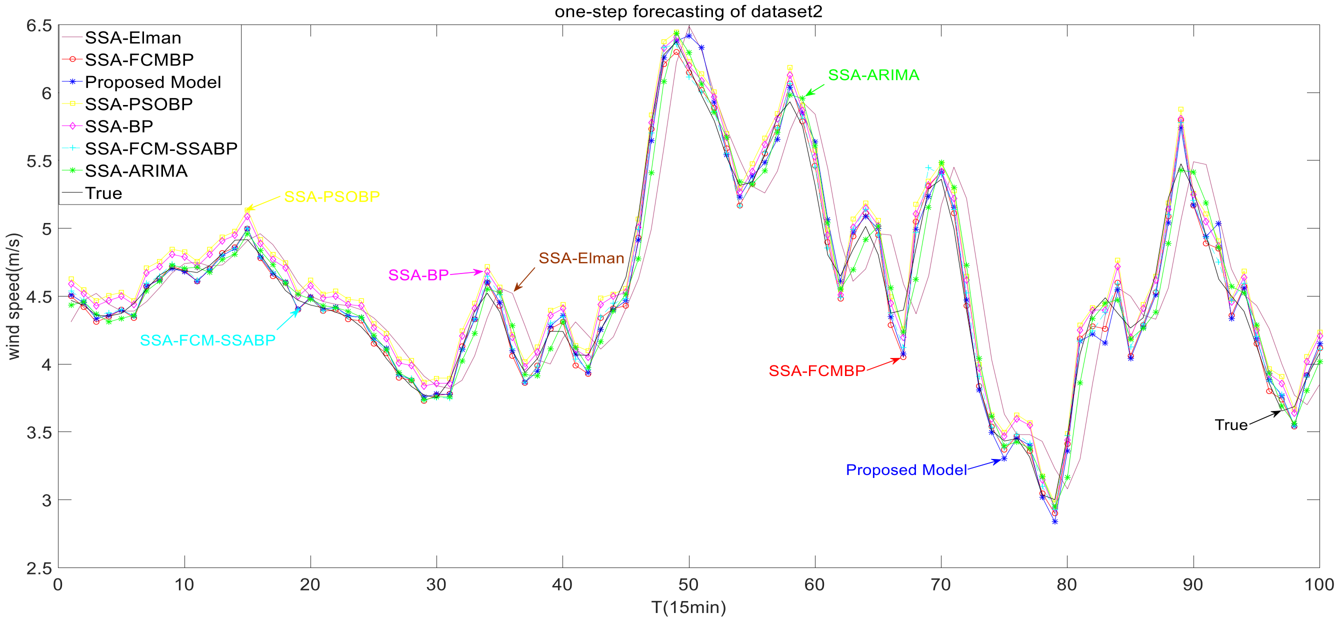

Fig. 17. One-step forecasting of Dataset 2

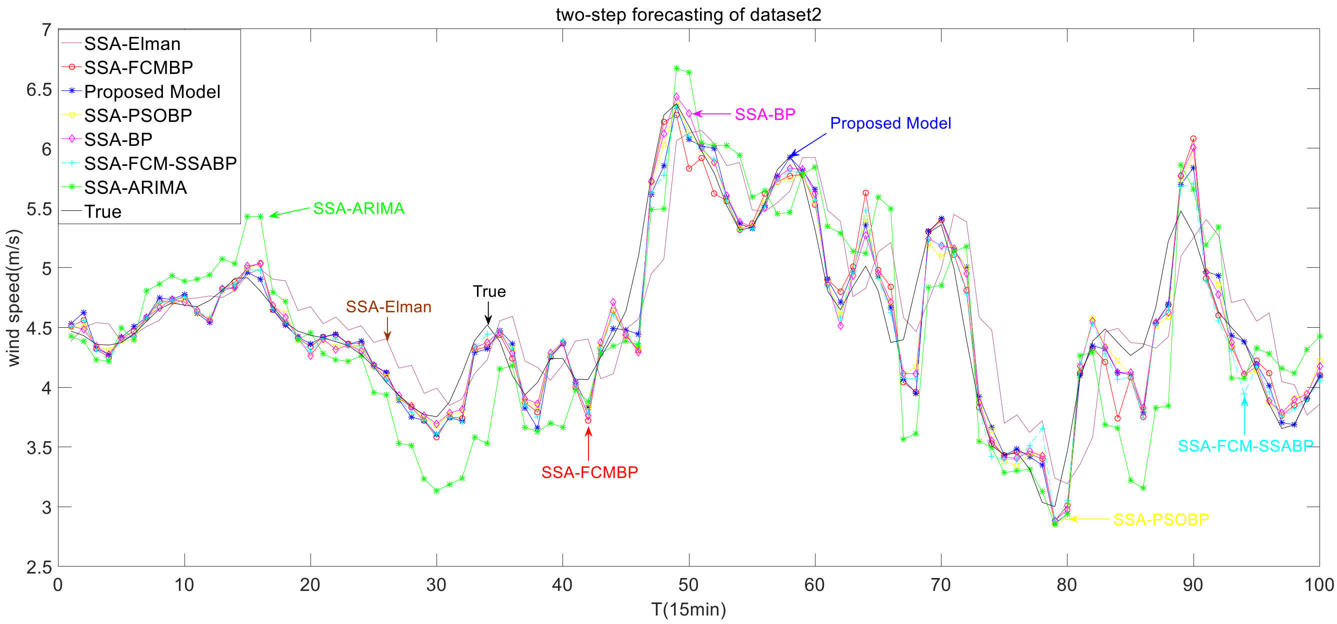

Fig. 18. Two-step forecasting of Dataset 2

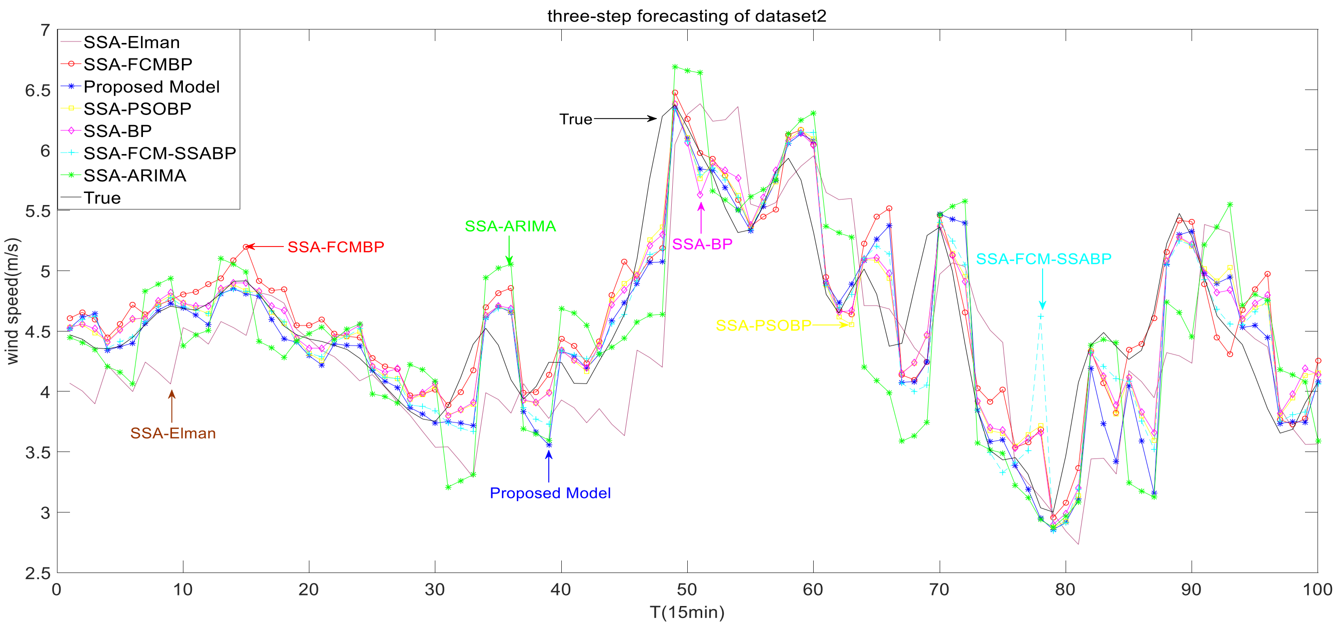

Fig. 19. Three-step forecasting of Dataset 2

V. Conclusion

In this paper, a novel hybrid forecasting model is proposed by combining singular spectrum analysis (SSA), fuzzy c-means clustering (FCM) and improved sparrow search algorithm nested BP neural network. In this model, singular spectrum analysis is adopted as the data pretreatment method to de-noise the original wind speed data including select appropriate parameters to filter the noise components in the original wind speed data, and retain the real and effective wind speed data information for improving the data quality. Then, the de-noised real wind speed data are processed by FCM and clustered into corresponding categories. Compared with the traditional k-means clustering, high-dimensional data processing has more advantages, and has good scalability. However, the number of clustering categories c should vary with the different datasets processed. In addition, this paper also puts forward the improvement of sparrow search algorithm which is caught in the local optimum easily. The local optimal solution can be avoided by eliminating the convergence to the origin and reducing the jump to the optimal position by using Levy flight strategy. ISSA not only enhances the capability of local search of the algorithm, but also avoids the trouble of falling into the local optimal solution. It can quickly and effectively seek out the optimal initial weights and thresholds of BP neural network. It is necessary that, to verify the effectiveness and stability of the improved sparrow search algorithm in this paper, four different types of benchmark functions are selected to design a comparative experiment, and the conclusion is drawn clearly that the improved algorithm is superior to the original sparrow search algorithm in both convergence speed and convergence accuracy. Finally, seven different models are compared on two different wind speed datasets, including the proposed model, SSA-Elman model, SSA-FCMBP model, SSA-PSOBP model, SSA-FCM-SSABP model, SSA-BP model and SSA-ARIMA model. Through the analysis of two different datasets, it could be clearly seen that the prediction accuracy of the proposed model has been improved. However, the prediction precision of multi-step prediction needs to be further improved.

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