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FOA-ESN in tourism demand forecasting from the perspective of sustainable development

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Abstract: Nowadays, the tourism industry has made significant contributions to the national economy, and accurately predicting tourism demand is a necessary step to promote the rational allocation of tourism resources and sustainable development. Echo state network (ESN) is an algorithmic model that can effectively handle nonlinear problems. This study first adaptively adjusts the fruit fly optimisation algorithm (FOA) method and obtains the improved fruit fly optimisation algorithm (IFOA). Then, integrate IFOA with ESN (IFOA-ESN). IFOA-ESN mainly utilises IFOA to obtain key parameters of ESN, improving the overall performance. Finally, the simulation results of IFOA-ESN on tourism demand show that the average absolute percentage error (MAPE) and normalised root mean square error (NRMSE) values of IFOA-ESN are 0.40% and 0.61%, respectively, and their prediction accuracy is higher than other models. The predicted results obtained can serve as a reference for resource allocation and related policy decisions in the tourism industry.

Keywords: FOA; fly optimisation algorithm; ESN; echo state networks; tourism demand forecast; tourism sustainable development.

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1 Introduction

Tourism has become one of the emerging pillar industries in the national economy, with a significant market space in the 21st century. However, it is an unstable industry due to multiple factors such as weather and holidays impacting tourism demand. The non-linear characteristics of tourism products also add to the complexity of forecasting demand. Accurately predicting tourism demand is crucial for the rational allocation of resources and promoting sustainable tourism development (Mondal and Samaddar, 2021). On the topic of using machine learning algorithms to predict nonlinear problems, many researchers have contributed to this topic, and their prediction results are also different. Echo state networks (ESN) can handle nonlinear problems very well, and its operation is simple and efficient, so it has great application prospects. However, when faced with different types of data, the parameter setting of the ESN network is prone to non-optimal problems, resulting in uncertainty in its output results (Alizamir et al., 2020). As a consequence, increasing numbers of researchers choose parameter optimisation techniques to enhance the functionality of the ESN model (Kim and King, 2020; Mansoor et al., 2021). FOA is a new type of global search optimisation algorithm, which has the advantages of strong convergence and high execution efficiency (Liu et al., 2020). Currently, some scholars have used the FOA algorithm to optimise the parameters of other target algorithms and obtained considerable research results. This research innovatively integrates FOA and ESA and applies them to the forecast of tourism demand, aiming to provide a reference value for the rational allocation of tourism resources to promote sustainable development. The specific innovations of this study are as follows:

1 In view of the shortcomings of the FOA algorithm, such as low convergence efficiency and easy falling into local optimal, an adaptive improvement strategy is proposed to improve the global search ability and local foraging ability of the algorithm.

2 In view of the shortage of the traditional ESN network relying on manual debugging parameters, the improved FOA is introduced into ESN to improve the parameter optimisation efficiency and optimisation effect of ESN.

3 The construction of the IFOA-ESN method is applied to tourism demand forecasting to make tourism demand forecasting more intelligent and convenient.

2 Related works

Numerous researchers have become interested in the ESN algorithm due to its benefit of making the network training process simpler. It also has a wide range of applications in prediction. To avoid the problem of over-fitting, Yang et al. (2019) used the SRLS to optimise the existing ESN network and used the sub-gradient technique to estimate the output weight matrix. The final simulation results showed that the constructed model had a good advantage in network compactness, and its estimation accuracy in time series prediction was improved. Researchers such as Liu et al. (2020) proposed a new hybrid model of BGWO-ESN, which optimised the output connection of ESN through a feature selection scheme. It can reduce redundant reservoir output features to a certain extent, thereby improving the generalisation ability of ESN. The verification results of the model on the financial dataset showed that compared with other models, its generalisation error was the smallest and had stronger effectiveness. Scholars such as Zhang et al. (2020) conducted research on the topic of short-term traffic forecasting, and chose to use the improved FOA algorithm to optimise the ESN algorithm. The constructed model mainly used the IFOA algorithm to improve the five main parameters in ESN to improve its performance. The final experimental findings demonstrated that the ESN-IFOA model had a strong capacity for predicting traffic volume for the next 5 min. Öztürk et al. (2020) aimed to enhance the performance of the ESN network by proposing a hyperparameter optimisation approach using the SGD algorithm to optimise the model's parameters. They compared the effectiveness of this technique with the grid search method and determined that the SGD algorithm improved the accuracy of the ESN model's parameter estimation. The final experiment confirmed the success of this approach in enhancing the ESN network's performance. Researchers such as Hu et al. (2021) presented a hybrid model of VMD-DE-ESN to properly anticipate the wind speed and assist the steady operation of the power system. The model first employed the VMD method to break down the wind speed and mined its primary properties before using the DE algorithm to optimise the three key ESN model parameters. The hybrid model's average error was small across the four datasets, and it had a strong application for predicting wind speed.

FOA algorithm has a simple and easy-to-understand operating principle and strong local search capabilities. Researchers in various scientific fields will consider using it to optimise the target algorithm to improve model performance. Peng et al. (2020) believed that the performance and accuracy of the model were significantly influenced by the LSTM network's parameters. The FOA method was proposed to find the best LSTM network parameters in order to improve this scenario. After verification, the new model constructed reduced the error level by 11.44% and had a good experimental performance. Scholars such as Bhatt et al. (2020) proposed a FFOA algorithm for the vulnerability of WSN to external attacks. The algorithm captured attacks with the goal of maximum node contribution, maximum key contribution and finding the optimal node. Simulation results showed that the constructed model obtained the largest proportion of damaged traffic, lower number of attack rounds, and less energy cost. Huang et al. (2021) researchers introduced the FOA to optimise the low efficiency of the OTSU algorithm for image segmentation. To increase the effectiveness of the model, the newly developed FOA-OTSU model employed the FOA algorithm to look for the best segmentation threshold. The evaluation results of SNR and PSNR showed that the improved model reduced the segmentation time by about 50% under the condition of ensuring the segmentation effect, and had a faster convergence speed. Scholars such as Xiong and Lian (2021) proposed an improved FOA algorithm to effectively locate structural damage and judge its degree of damage. The population was initially divided into positive and negative subgroups using the model, and then the IFOA and FOA algorithms were used to perform global searches on them, respectively. Simulation results showed that IFOA had better recognition effect and performance than FOA. Researchers such as Yang et al. (2020) designed an evolutionary FOA to overcome the shortcomings of traditional FOA such as local optimisation difficulties, slow convergence, and insufficient robustness. The algorithm used an evolutionary mechanism to retain the superior population and filter out the inferior population. The performance of EFOA and other swarm intelligence algorithms was evaluated in experiments, and it was discovered that EFOA had a clear edge in terms of global search ability and resilience, and that its convergence speed also increased.

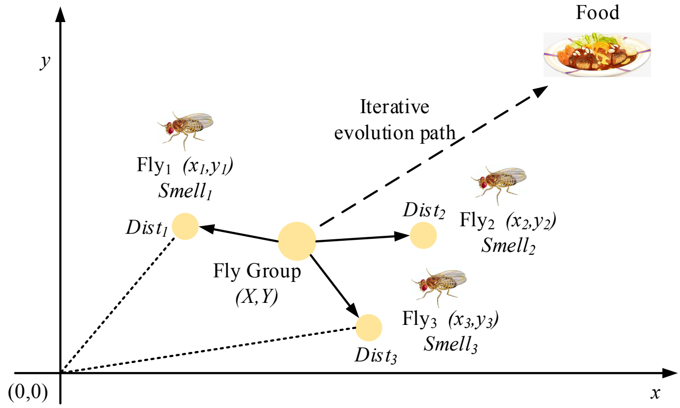
To sum up, the ESN and FOA algorithms are favoured by researchers in various scientific fields. Scholars from all walks of life have used different methods to innovate and improve it to be more suitable for the research object. The methods and means have their own characteristics and are quite effective, and the harvested research results lay the foundation for further model exploration. In this experiment, on the topic of tourism demand forecasting, a hybrid model combining adaptive FOA and ESN is proposed to explore its predictive performance on tourism demand. Compared with the traditional model, the IFOA-ESN method has higher parameter optimisation efficiency and optimisation effect, which can greatly enhance the intelligence of tourism demand forecasting.

3 Construction of tourism demand forecasting model based on IFOA-ESN algorithm

3.1 Model research and improvement of FOA algorithm

FOA algorithm was first proposed in 2012, and its main principle is to find the optimal solution of the target algorithm by simulating the physiological process of drosophila foraging (Li et al., 2019). Based on the study of Drosophila foraging behaviour through bionic simulation, the algorithm uses the Drosophila movement pattern to find the optimal solution of a certain target, which is a novel heuristic algorithm. FOA algorithm has a strong global search ability and fast convergence performance. Compared with other population optimisation algorithms, FOA has a faster convergence speed and fewer parameter Settings. FOA also has operability and optimisation ability for parameter optimisation of ESN (Li et al., 2019). FOA includes five steps: population initialisation, random flight, determination of taste concentration judgement value, determination of taste concentration, and location marking. Figure 1 depicts the FOA algorithm's optimisation process.

Figure 1 The process of drosophila group iterative search for food (see online version for colours)



FOA algorithm first initialises the population, the population size is defined as $Popsize$, and the initial position of the population as $\left(X_c, Y_c\right)$. Each fruit fly in the group is given a random flight direction, and its position information can be expressed as $\begin{cases} X_i = X_c + R \\ Y_i = Y_c + R \end{cases}$ $i = 1, 2, 3, \ldots, n$, then there is a formula:

$$\begin{cases} X_i = X_c + R \\ Y_i = Y_c + R \end{cases} \qquad i = 1, 2, 3, \ldots, n \tag{1}$$

In formula (1), X_i and Y_i represent the position of the i th fruit fly, and $S_i = \frac{1}{\sqrt{X_i^2 + Y_i^2}}$ represents the step value. Next, the judgement value of the taste concentration is calculated, and its specific formula can be expressed as:

$$S_i = \frac{1}{\sqrt{X_i^2 + Y_i^2}} \tag{2}$$

In formula (2), the flavour concentration's evaluation value is represented by S_i. The location of the fruit fly cannot be correctly represented by its horizontal and vertical coordinates, so the inverse of the distance formula is used here. Therefore, the taste concentration value can be determined according to the taste concentration judgement value, and its specific function expression is:

$$Smell_i = F\left(S_i\right) \tag{3}$$

In formula (3), the i th fruit fly's taste concentration value is represented by $Smell_i$, and its fitness function is represented by F. After that, the location can be determined according to the magnitude of the taste concentration value. The place where the fruit fly group flies together and the starting position of the next iteration are both indicated by $Smell_{best}$, which stands for the person with the best flavour concentration value, or the greatest taste concentration value. If the current fruit fly is in the best position, its position coordinate is $\left(X_{best}, Y_{best}\right)$, and the corresponding taste concentration value is $\begin{cases} Smell_i = Smell_{best} \\ X_i = X_{best} \\ Y_i = Y_{best} \end{cases}$. Then the fruit fly group flies to this position, then there is a formula:

$$\begin{cases} Smell_i = Smell_{best} \\ X_i = X_{best} \\ Y_i = Y_{best} \end{cases} \tag{4}$$

The technique of designating the location of the fruit fly population is shown in formula (4). The stages of formulae (3) to (4) are repeated until the maximum iteration frequency is attained if the current optimum flavour concentration value is better than the ideal value in the preceding phase. At this time, the current is $Smell_{best}$ the global optimal solution found in the fruit fly swarm search process The FOA method has several obvious advantages and is easy to use, but due to its set step size, it has poor convergence performance and is more likely to encounter local optima (Ding et al., 2021; Zhang et al., 2020). To better solve this problem, this experiment chooses to make adaptive improvement to the traditional FOA algorithm, that is, to construct the IFOA algorithm. IFOA has the ability to adaptively change the population size and random search step based on the location's flavour concentration value. First a variable random search step size is introduced as R_{step}, and the standard step size as $R_{step}\left(t+1\right) = \frac{F(t)}{F(target)} * R_{standard}$. Then there is the formula:

$$R_{step}\left(t+1\right) = \frac{F\left(t\right)}{F\left(target\right)} * R_{standard} \tag{5}$$

In formula (5), $R_{step}\left(t+1\right)$ indicates the maximum search step size for the next iteration. $F\left(t\right)$ represents the current local optimal solution, and $F\left(target\right)$ represents the target average absolute percentage error value, and the ratio of the two can be used as an adjustment factor for the random search step size. When $F\left(t\right)$ is poor, jump out of the range quickly by increasing the fruit fly step size. When $F\left(t\right)$ is good, strengthen the local search ability by reducing the fruit fly step size. The random step size has good flexibility and can be adjusted adaptively according to the specific situation of the local optimal solution. Then a variable population size is introduced, and its function expression is:

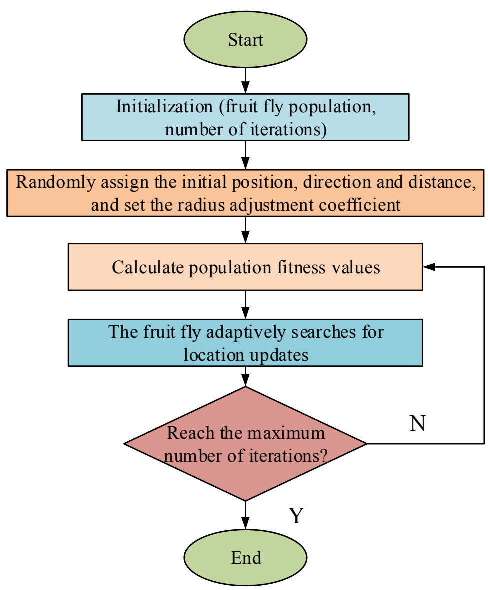
$$Popsize\left(t+1\right) = \frac{F\left(target\right)}{F\left(t\right)} * Popsize_{standard} \tag{6}$$

In formula (6), $Popsize\left(t+1\right)$ represents the population size of the next iteration, and $Popsize_{standard}$ represents the standard population size. The ratio of $F\left(target\right)$ and $\begin{cases} X_i = X_c + R_{step}\left(t\right) * \left(Rand - 0.5\right) \\ Y_i = Y_c + R_{step}\left(t\right) * \left(Rand - 0.5\right) \end{cases} i = 1, 2, 3, \ldots, n$ is used as an adjustment factor for the population size. The variable population size also has good flexibility. When the location is good, the population of fruit flies increases by the stimulation of the odour concentration, and vice versa. This strategy can reduce the search ability of the fruit fly when it is in a better position of the current solution, and weaken its search ability when the solution is worse. The operation efficiency and optimisation impact of the FOA method may be somewhat enhanced following the addition of random step size and variable population size. Then in the improved IFOA algorithm, the position formula of the randomly generated population size is updated as:

$$\begin{cases} X_i = X_c + R_{step}(t) * (Rand - 0.5) \\ Y_i = Y_c + R_{step}(t) * (Rand - 0.5) \end{cases} \quad i = 1, 2, 3, \ldots, n \tag{7}$$

In formula (7), $Rand$ represents a random number, and its value range is between 0 and 1. The formula for calculating the taste concentration value remains unchanged. Next, the population size and search step size of the subsequent iteration are adaptively modified in accordance with formulas (5) and (6). The steps up to the maximum number of iterations are repeated until the global optimal solution is output. The IFOA method has a quick convergence rate and also has adaptive step size and population size adjustments. It not only increases the FOA algorithm's capacity for global search across a wider area, but it also strengthens the model's capacity for local foraging. The flow of the IFOA algorithm is shown in Figure 2.

Figure 2 IFOA algorithm flow (see online version for colours)

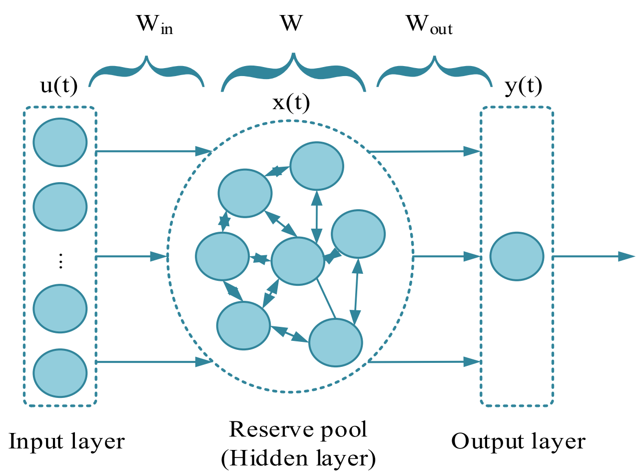


3.2 Construction of tourism demand forecasting model combined with IFOA-ESN hybrid algorithm

Compared with the traditional algorithm, the ESN training process is simple and efficient and can approach dynamic systems infinitely under normal conditions. It is widely used in various prediction problems. However, ESN also has its own shortcomings and limitations. For example, the parameters and connection weights of ESN are randomly set, and only the weights of the output layer are adjusted during the training process, which is easy to fall into the local optimal solution. At present, the common method used is to construct the ESN model when the network selects the optimal output many times or to select parameters according to experience to construct the model. Therefore, this study attempts to use the IFOA algorithm to solve the key parameters of ESN, so as to make the model better suitable for the topic of tourism demand forecasting.

ESN algorithm is simple, the convergence speed is fast, and it is not easy to fall into local optimum. It is a recursive neural network that excels at solving nonlinear issues. An input layer, a reserve layer, and an output layer make up the ESN network. To create a dynamic and sophisticated hidden layer, the reserve pool is first randomly produced. The reserve pool transforms the activation information into the output layer information, whereas the input layer is in charge of transforming the input information into the initial activation signal (Tian, 2021). The input layer and the output layer are composed of input weights and output weights respectively, and their weight values do not change during the training process. The overall network relies on changing the size of the output weight of the reserve pool for network training, so its training process is simple and less time-consuming (Mahmoud et al., 2021). Figure 3 depicts the ESN network's overall organisational structure.

Figure 3 Basic structure of ESN network (see online version for colours)



The implementation process of the ESN algorithm is divided into the training stage and the testing stage. The main objective of the training stage is to obtain the state vector of the training process. After the weights are obtained in the training phase, the data matrix in the test set is input into the ESN network, and the predicted value of the output data is obtained after the calculation in the reserve pool and output according to the weights. Specifically, W_{in}, W, and W_{out} are defined as the connection weights of the ESN network's input layer, reserve pool, and output layer, in that order. Among them, the input layer contains a node k, and its value is determined by the dimension of the input information. The reserve pool contains nodes n, which also represent the number of neurons in the reserve pool. The dimension of the output information determines the value of a node $x(t+1) = H\left(W_{in} \cdot u(t+1) + W \cdot x(t) + W_{Back} \cdot y(t)\right)$ in the output layer.

It is only essential to modify the weights between the reserve pool and the output layer W_{out} during the model training procedure. In the ESN network, the feedback information from each neuron's output layer at the previous instant is combined with the information from the current moment's input layer as it enters the reserve pool, and then, based on a certain weight, the input signal of the neuron is created. Finally, the activation function converts the signal into the next state vector, and its formula is expressed as:

$$x(t+1) = H\left(W_{in} \cdot u(t+1) + W \cdot x(t) + W_{Back} \cdot y(t)\right) \tag{8}$$

In formula (8), the input vector at step t is represented by H, the activation function is represented by $u(t)$, and the condition of the reserve pool is represented by $x(t)$ at step $t-1$. $y(t)$ represents the output vector at the step t, and $y(t+1)$ represents the output vector of the next step. The function expressions of $u(t)$, $u(t)=\left[u_1(t),u_2(t),\ldots,u_k(t)\right]^T$ $x(t)=\left[x_1(t),x_2(t),\ldots,x_n(t)\right]^T$ $y(t)=\left[y_1(t),y_2(t),\ldots,y_l(t)\right]^T$, and $y(t+1) = H_{out}\left(W_{out} \cdot \left(u(t+1), x(t+1), y(t)\right)\right)$ are as follows:

$$\begin{aligned} u(t) &= \left[u_1(t), u_2(t), \ldots, u_k(t)\right]^T \\ x(t) &= \left[x_1(t), x_2(t), \ldots, x_n(t)\right]^T \\ y(t) &= \left[y_1(t), y_2(t), \ldots, y_l(t)\right]^T \end{aligned} \tag{9}$$

The output vector of the next step can be deduced from formula (9), and its formula is as follows:

$$y(t+1) = H_{out}\left(W_{out} \cdot \left(u(t+1), x(t+1), y(t)\right)\right) \tag{10}$$

In formula (10), H_{out} represents the activation function of the output layer. From formula (10), it is clear that the input vector for the next step, the state vector for the following step, and the output vector for the current step all work together to determine the output vector for the following step. ESN is mainly composed of a training phase and a testing phase. The training process can be divided into two steps: obtaining the training state and solving the output weight. To prevent a scenario where the scale is too big or too small and influences the weight of the network, the input data must be scaled before getting the training state. The actual input value of the ESN network can be expressed as:

$$u(t) = IS * U(t) \tag{11}$$

In formula (11), IS represents the scaling factor, which is a constant between 0 and 1. During the training process, there is a forgetting point to avoid the influence of the initial state on the overall network. Therefore, after the ESN network is initialised, it gathers the reserve pool's current state data from the forgotten point, and its matrix formula is as follows:

$$\left\{x(q), x(q+1), \ldots, x(Q)\right\} \tag{12}$$

In formula (12), $X=\begin{bmatrix} u(q)\cdots u(Q) \\ x(q)\cdots x(Q) \end{bmatrix}^T$ $Y=\left[H_{out}^{-1}\left(y(q)\right)\cdots H_{out}^{-1}\left(y(Q)\right)\right]^T$ represents the forgotten point of the ESN network and Q represents the total number of input data. The ESN network's state vector and output matrix are represented as:

$$X=\begin{bmatrix} u(q)\cdots u(Q) \\ x(q)\cdots x(Q) \end{bmatrix}^T$$
$$Y=\left[H_{out}^{-1}\left(y(q)\right)\cdots H_{out}^{-1}\left(y(Q)\right)\right]^T \tag{13}$$

In formula (13), $W_{out}=\left(X^{-1}\cdot Y\right)^T=\left(X^T X\right)^{-1} X^T Y$ represents the state vector composed of the state of the reserve pool and the actual input matrix when the forgotten part has been removed. $X'=\dfrac{x-x_{\min}}{x_{\max}-x_{\min}}$ is composed of real output values. The output weight matrix in the ESM network is solved by performing an inverse operation on the matrix, and the following is the formula for the solution:

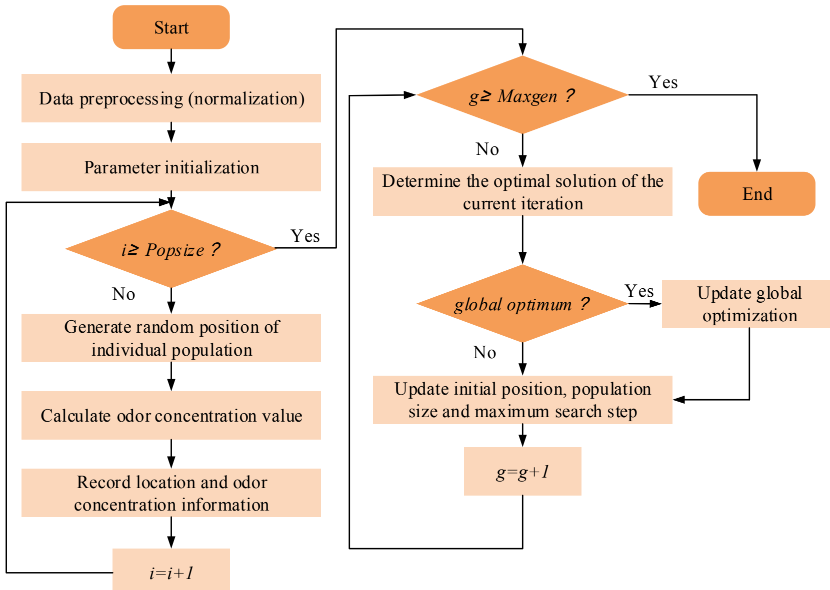
$$W_{out}=\left(X^{-1}\cdot Y\right)^T=\left(X^T X\right)^{-1} X^T Y \tag{14}$$

The data from the test set can be input into the ESN network after the output weight matrix is obtained in the training phase. The calculation is performed through the reserve pool to obtain the predicted value of the output data. Algorithm performance is significantly affected by the size of the ESN network's reserve pool. There are four main parameters in the reserve pool, which are the reserve pool size, sparseness, spectral radius, and secondary input unit scale. These parameters largely affect the calculation results of the reserve pool, so finding the optimal parameters of the reserve pool is crucial to improving the overall prediction effect of the model. In this experiment, the IFOA algorithm and the ESN network are combined, and the IFOA algorithm is used to optimise the ESN network's settings. In the data preprocessing stage. To stop the size of the input data from impacting the network, the data is treated using the data normalization approach. The formula is written as follows:

$$X'=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{15}$$

Figure 4 shows the overall model operation process of IFOA-ESN tourism demand forecasting. The IFOA-ESN model prediction process is mainly composed of data preprocessing, parameter initialisation, ESN parameter optimisation, and ESN prediction. Obviously, the IFOA-ESN model is divided into two stages, that is, the parameter stage of IFOA optimising ESN and the prediction stage of the ESN network. The IFOA-ESN algorithm is more intelligent and accurate than the traditional ESN algorithm. It is shown by the fact that the model may develop a useful prediction model quickly by substituting the conventional way of manually debugging ESN parameters with the global search capabilities of the IFOA algorithm. Furthermore, IFOA has the advantage of strong convergence and can obtain better optimisation results than traditional manual debugging. Building a tourism demand forecasting model that combines the IFOA algorithm and the ESN algorithm will improve the overall operating efficiency of the model in predicting tourism demand.

Figure 4 Operation process of IFOA-ESN tourism demand forecasting model (see online version for colours)



4 Performance verification of tourism demand forecasting model based on IFOA-ESN

In this experiment, two popular tourist cities, Shanghai and Hainan, were selected as representative locations. The IFOA-ESN model was employed to predict the tourism demand in these cities. The monthly data from January 2013 to April 2019 for Shanghai and from April 2013 to December 2019 for Hainan were utilised. The monthly data consisted of the total number of domestic and foreign tourists. To evaluate the performance of the model, mean absolute error (MAE), mean square error (MSE), normalised mean square error root (NRMSE), and mean absolute percentage error (MAPE) were employed as evaluation indicators. Figure 5 illustrates the results of these evaluation metrics, reflecting the prediction accuracy of the model.

The data was initially standardised and preprocessed before the experiment in order to minimise the network's influence from the magnitude of the input data. Figure 6 displays the normalised statistics for the number of visitors in Shanghai and Hainan. As can be observed, this data's fluctuation pattern clearly displayed periodic features.

Initially, the IFOA-ESN model was employed to forecast the number of visitors in Shanghai. The experiment dataset was divided into two segments: the training set and the test set. The training set consists of data from January 2013 to April 2018 while the test set consists of data from May 2018 to April 2019. To better evaluate the IFOA-ESN model's performance, it was compared to other existing models such as ANN, SVM, KELM, and LSSVR. Each model used the 'Baidu + Google' search index to optimise its input structure. Table 1 illustrates the prediction error results of these six models. The results indicate that FOA-ESN had the MAPE and NRMSE of 0.54% and 0.66%, respectively, while IFOA-ESN had the MAPE and NRMSE of 0.40% and 0.61%, respectively. Compared to the other four models, both FOA-ESN and IFOA-ESN performed relatively well, with IFOA-ESN improving the prediction accuracy of FOA-ESN.

Figure 5 Evaluation index system (see online version for colours)

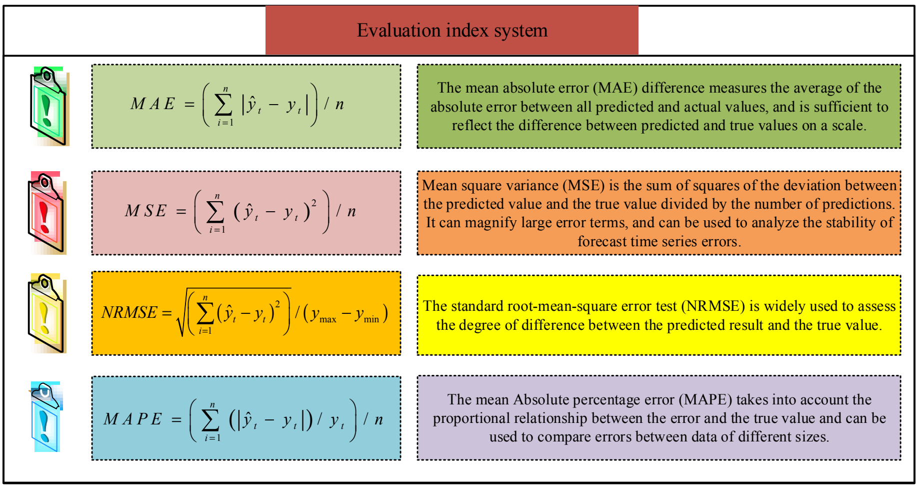


Figure 6 Number of tourists in two places after data preprocessing: (a) trend of monthly Shanghai tourist arrivals and (b) trend of monthly Hainan tourist arrivals (see online version for colours)

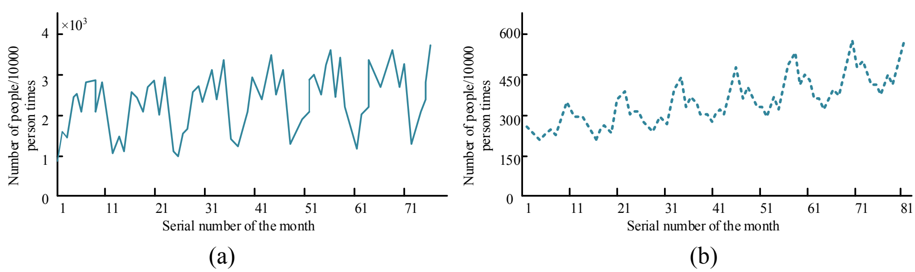


Table 1 Comparison results of prediction errors of six algorithms

Algorithm	*MAPE/%*		*NRMSE/%*	
	No index	*Baidu+Google index*	*No index*	*Baidu+Google index*
ANN	4.03	1.94	4.87	2.23
SVM	3.54	1.92	4.22	2.12
KELM	3.01	0.91	3.98	1.06
LSSVR	3.44	1.81	4.01	1.97
FOA-ESN	0.54		0.66	
IFOA-ESN	0.40		0.61	

Figure 7 shows the error gradient trend graph of FOA-ESN and IFOA-ESN in estimating the number of tourists in Shanghai. The initial iteration of the IFOA-ESN model was located around 0.5%, and the FOA-ESN was located around 0.56%. The main reason was that the adaptive FOA algorithm in IFOA-ESN obtained a better initial position than the traditional FOA algorithm, so it had a faster local search ability and iteration speed and finally obtained better convergence. It can also be seen from the figure that the MAPE value of IFOA-ESN dropped to 0.43% after about 15 iterations. When iterating about 40 times, the MAPE value of IFOA-ESN dropped to 0.41%. During the whole iterative process, the error-index value was always lower than that of the FOA-ESN model, so it can be verified that IFOA had an optimal effect on the overall model.

Figure 7 Error gradient descent chart for predicting the number of tourists in Shanghai: (a) FOA-ESN error gradient trend chart and (b) IFOA-ESN error gradient trend chart (see online version for colours)

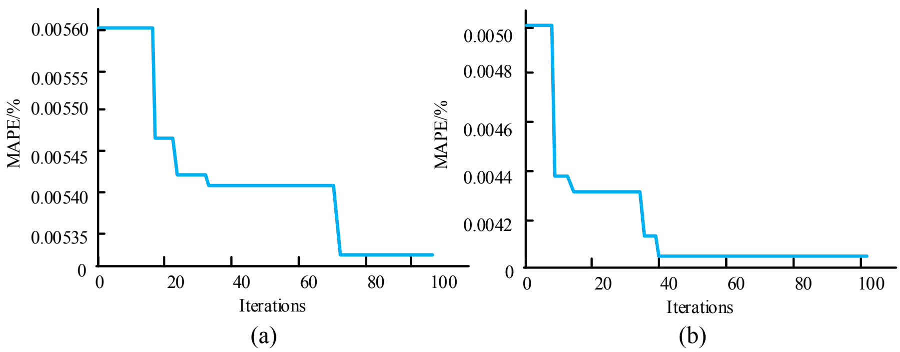


Figure 8 shows the estimation results of FOA-ESN and IFOA-ESN algorithms on the number of tourists in Shanghai. It can be found from the figure that the estimated values of the two algorithms were generally consistent with the real values, indicating that they both had good prediction performance. Compared with IFOA-ESN, the prediction accuracy of FOA-ESN was slightly inferior. It was reflected in the data serial numbers between 0 and 6. Compared to IFOA-ESN, the degree of coincidence between the predicted value of FOA-ESN and the actual value was less pronounced, indicating that its prediction error was greater than that of the IFOA-ESN model. Therefore, the estimation result of the number of tourists in Shanghai also verified that IFOA-ESN had better prediction performance than FOA-ESN.

The experiment continued to anticipate the number of visitors to Haikou, Hainan, in order to further confirm the application impact of the IFOA-ESN model in predicting tourism demand. The experiment first used the data from April 2013 to December 2016 as the optimisation set, the data from January 2017 to April 2019 as the training set, and the remaining data as the test set. The experiment first utilised the optimisation set to generate the fitting's output weight, and then the training set used the optimisation set's parameters to produce the test set's output weight. In addition to comparing the prediction performance of IFOA-ESN and FOA-ESN, the experiment also selected the integrated moving automatic regression model (ARIMA), vector autoregressive model (VAR), principal component analysis optimised vector autoregressive model

(PCA-VAR) and A neural network model optimised by principal component analysis (PCA-BPNN) for performance comparison. Table 2 shows the comparison results of the prediction errors of the above six models. Among them, the MAPE value, MSE value, and MAE value of the FOA-ESN model were 2.40%, 159.51 and 10.59 respectively; the MAPE value, MSE value, and MAE value of the IFOA-ESN model were 1.55%, 71.63 and 6.84 respectively. This showed that the prediction errors of the FOA-ESN and IFOA-ESN models were significantly lower compared with the other four models, and they had relatively better prediction results. Furthermore, the prediction error of the IFOA-ESN model was smaller than that of the FOA-ESN model.

Figure 8 Prediction results of two algorithms on the number of tourists in Shanghai: (a) FOA-ESN predicted number of tourists in Shanghai and (b) IFOA-ESN predicted number of tourists in Shanghai (see online version for colours)

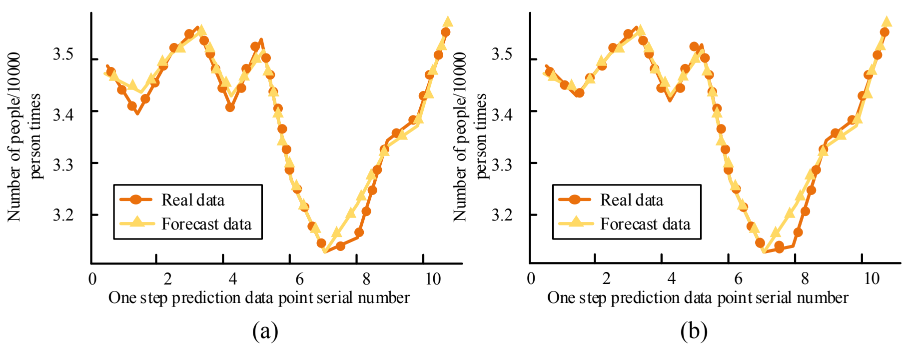


Table 2 Comparison results of prediction errors of six algorithms

Algorithm	*MAPE/%*	*MSE*	*MAE*
ARIMA	14.32	4684.31	63.31
VAR	17.84	8560.01	78.51
PCA-VAR	14.33	5281.01	61.53
PCA-BPNN	6.79	1940.03	32.23
FOA-ESN	2.40	159.51	10.59
IFOA-ESN	1.55	71.63	6.84

Figure 9 shows the error gradient trend graph of FOA-ESN and IFOA-ESN in estimating the number of tourists in Haikou, Hainan. The figure shows that the initial MAPE value of IFOA-ESN in the verification set optimisation process was 1.13%, which was about 0.15% lower than that of FOA-ESN. The MAPE value of the IFOA-ESN model reached about 1.0% in about 6 iterations and dropped to 0.94% in the 15th iteration. However, the FOA-ESN model did not achieve the effect of IFOA-ESN, and its MAPE value in the iterative process was always higher than that of IFOA-ESN. The MAPE value of the IFOA-ESN model on the final test set was about 0.84% points lower than that of the FOA-ESN. This result also verified the effectiveness of IFOA in improving model performance.

Figure 9 Error gradient descent chart for predicting the number of tourists in Hainan: (a) FOA-ESN error gradient trend chart and (b) IFOA-ESN error gradient trend chart (see online version for colours)

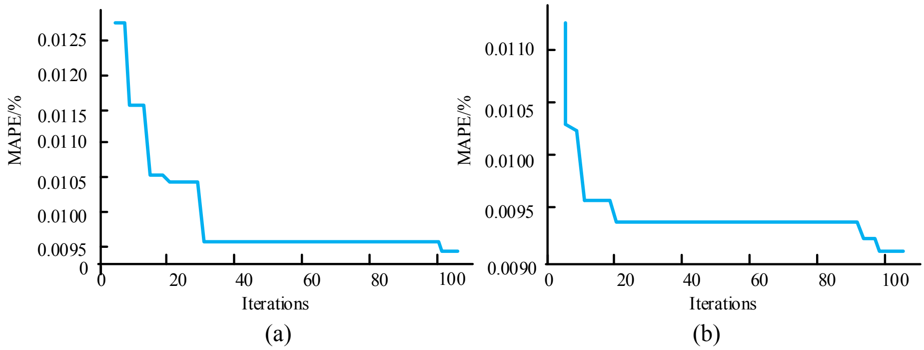
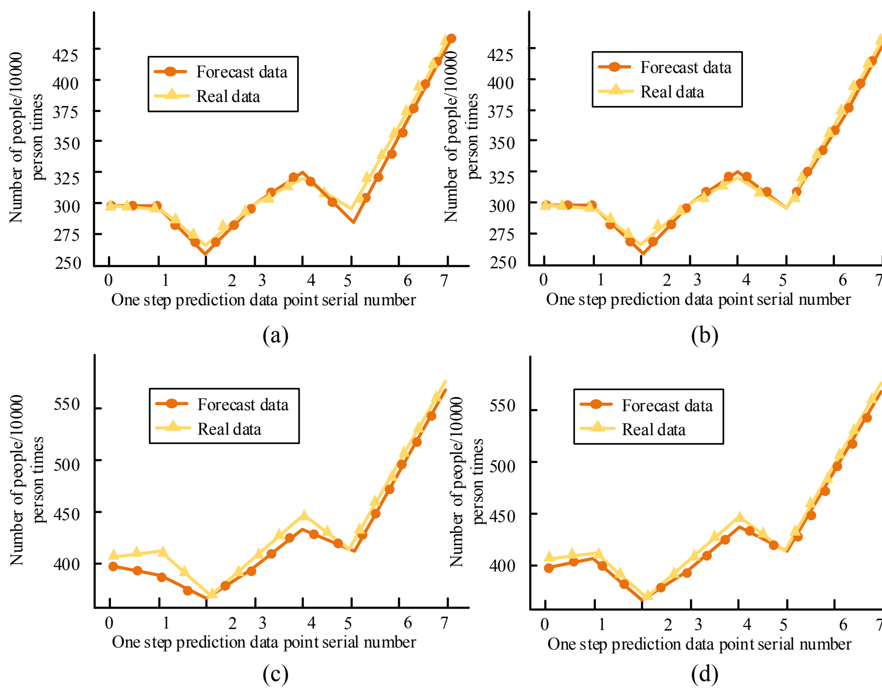


Figure 10 Prediction results of two algorithms on the number of tourists in Hainan: (a) FOA-ESN validation set predictors; (b) IFOA-ESN validation set predictors; (c) FOA-ESN test set predictors and (d) IFOA-ESN test set predictors (see online version for colours)



In the validation set and test set, respectively, the estimated results of the FOA-ESN model and the IFOA-ESN model for the number of visitors in Haikou, Hainan, are shown in Figure 10. The prediction curves of the two models were generally consistent with the true value curves, indicating that both models were suitable for the study of tourism demand estimation. From the data of the test set, the predicted value curve of FOA-ESN deviated far from the true value curve and had few overlapping points. It can also be seen that its estimation error was relatively large. Observing that the predicted value curve of the IFOA-ESN model basically coincided with the true value curve, it can also prove that the estimation error of IFOA-ESN was smaller than that of FOA-ESN. The aforementioned findings further demonstrated that the IFOA-ESN model had a greater optimisation impact in the beginning position, which caused it to have a higher convergence rate and prediction accuracy than the FOA-ESN model.

5 Conclusion

The sustainable development of tourism has an important contribution to the national economy; however, tourism is affected by many unstable factors. An essential issue facing the business is how to estimate tourist demand properly based on unstable elements. Accurate forecasting is also a necessary first step in the allocation of resources for tourism and the implementation of relevant legislation. The experiment constructs a hybrid model of IFOA-ESM, which is composed of adaptive and improved FOA algorithm and ESM algorithm, so as to predict the number of tourists in tourist areas. It primarily uses the adaptive FOA method to adjust the parameters, enhancing the ESM model's predictive capability. Two sets of data are chosen for the experiment to examine the effectiveness of FOA-ESN and IFOA-ESN. The forecast results for the number of tourists in the Shanghai area showed that the forecast performance of IFOA-ESN was better than that of FOA-ESN and the other four models (ANN, SVM, KELM, LSSVR), and its MAPE and NRMSE values were 0.40% and 0.61%, respectively. The MAPE and NRMSE of FOA-ESN were 0.54% and 0.66%, respectively. The prediction results for the number of visitors to Haikou, Hainan, demonstrated that IFOA-forecasting ESN's capabilities were also superior to those of FOA-ESN and the other four models (ARIMA, VAR, PCA-VAR, PCA-BPNN), and its MAPE value, MSE value, and MAE value were 1.55%, 71.63 and 6.84, respectively, while the MAPE, MSE and MAE values of FOA-ESN were 2.40%, 159.51 and 10.59, respectively. The model optimisation of ESN by the proposed IFOA algorithm is reflected in that IFOA can effectively optimise the initial position and improve the entire model's forecast precision and convergence speed. The model has broad application prospects in different types of tourism demand forecasting. The limitation of this study is that it failed to conduct proper external verification, that is, to invite relevant tourism professionals to evaluate the practicability of the proposed model, so it can be used as the next research direction. In addition, in the era of big data, more and more tourism databases have begun to be established. Therefore, the follow-up research will try to use a variety of big data means to enrich the diversity of input information and select the forecasting information suitable for the tourism industry.

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Conflict of interest

None to declare.

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