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ORIGINAL

RESEARCH ON SPORTS ECOTOURISM DEMAND PREDICTION BASED ON IMPROVED FOA ALGORITHM

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ABSTRACT

As the national consumption level rises, the significance of the tourism sector within the national economy becomes more pronounced. Consequently, the share of tourism earnings in the Gross Domestic Product (GDP) continues to escalate. On the basis of the growth of people's economic level, the number of tourists in each scenic spot also increases, and tourist attractions and tourist cities also respond to the need to improve their own management quality and content to seek further development. The occurrence of tourism behavior also changes with the changes of weather, holidays, seasons and special circumstances. How to accurately predict the number of tourists is of great significance for both industry regulators and operators. Many scholars have also tried to use different models to predict tourism demand. AI methods have great advantages over traditional methods in adaptive learning ability and non-linear fitting ability, and have become a key research direction in academic circles in recent years. In this paper, we first improve the standard Drosophila algorithm by adaptively adjusting the fly population number and search step size, while optimizing the initial iteration position and improving the local search ability and search efficiency. Then the improved FOA algorithm is combined with the echo state network to build a two-stage combined prediction model named AFOA-ESN, obtain its key parameters through AFOA optimization ESN, and input the optimized parameters into ESN to form the final combined prediction model. Finally, the monthly data of a local sports ecological passengers was selected to test the prediction effect of AFOA-ESN. The results obtained after the trial show that the use of the AFOA-ESN model is more accurate than the accuracy of the results used by the autoregressive moving mean model, support vector machine model, BP neural network, standard ESN network, and other prediction models, while the convergence speed and prediction accuracy of AFOA-ESN outperformed standard ESN and FOA-ESN, demonstrating the effectiveness of model improvement.

KEYWORDS: Sports; Eco-Tourism; Improved FOA Algorithm

1. INTRODUCTION

Since the 21st century, tourism has ushered in a golden week period of rapid development. In 2017, China's total tourism revenue reached 5.4 trillion yuan, an increase of 15.14% from 4.69 trillion yuan in 2016, much higher than the GDP growth rate. In the past decade, tourism revenue in GDP rose from 4.05% in 2007 to 6.53% in 2017.With the growth of tourism income, the sports ecological tourism industry has also undergone qualitative changes. According to relevant data, China's tourism industry is gradually shifting from the second stage to the third stage, and the future market prospects are very broad. The national policy support and the endogenous growth of tourism supply and demand have jointly created the prosperity and development of tourism for more than ten years. The World Tourism Council's research report predicts that: by 2027, The number of Chinese "new tourist households" (those with new incomes of more than $35,000) will exceed 64 million, Far above second-ranked India (9.4 million households) to 2028, The direct contribution of China's tourism industry to GDP will jump to about US $1.3 trillion (based on 2017 fixed price estimates), Beyond the current top 1 US ($509.4 billion), A 10-year compound growth rate of 6.6%, Global ranking of fifth place; Future l0 years, China's tourism industry will create about 34 million jobs directly, Far higher than second-ranked India (9.38 million), Help to ensure domestic employment. Information on the current and future level of tourism demand and its contribution to the economy is very important due to the business institutions and the decision-making departments of the government. For countries or regions in the Caribbean Sea, the tourism market prosperity is the most critical measure to predict the macro economy of the country or region (Ekkekakis, 2023). Tourism products are perishable, furthermore, precision is of paramount importance when addressing the challenge of forecasting tourism demand. At present, many studies have been conducted on measurement model, decision vector machine model, gray theoretical model and artificial neural network model, but in the face of nonlinear prediction problem, the prediction effect is different. Literature (Sanford, 2017) proposed Echo State Networks (ESN), compared with the traditional algorithm, its model construction mode is more different. The unique structure of this method opens up new research ideas and directions. Echo state neural network reserve pool and traditional neural network algorithm, the connection weight in the network initialization, reserve pool is composed of input weight and output weight, in the process of training, the input weight and reserve pool weight value does not change, just change the size of the reserve pool output weight, so effectively avoid the artificial neural network complex, time-consuming training. Echo state neural network can deal with nonlinear problems well, and the training process is simple and efficient. In nonlinear prediction problems, echo state neural network shows many advantages compared with traditional artificial neural network and other types of algorithms, and has great application prospects. However, in the face of different types of problems and data, the traditional ESN model may have strong random and non-optimal initial parameter setting, and the output results are uncertain. Therefore, this method can further improve the prediction effect of ESN through some optimization methods. The selection of parameters is a major direction. The current research mainly combines some intelligent algorithms to obtain the optimized parameter input, so as to help build suitable prediction models. However, it is difficult to find the appropriate objective function for some parameters such as internal weights, so applying combinatorial optimization is a way to slow down the disadvantages brought by parameter randomization. The Drosophila optimization algorithm (FOA) is a heuristic global search optimization algorithm that is proposed in recent years. It has the advantages of simple computing process, strong global convergence, short execution time, self-organization and adaptability, and strong portability. More and more scholars have applied intelligent algorithm to traditional deterministic optimization problems. In this paper, we will study the combined prediction model of ESN and FOA in order to find a model that can improve the accuracy and reliability of prediction, and apply the combined prediction model FOA-ESN and A FOA-ESN model based on F O A-ESN to the tourism industry demand prediction to provide auxiliary support for policy and operation related decisions in the industry.

2. Review of Research at Home and Abroad

2.1. Research on the Demand Prediction of Sports Ecotourism

Literature (Wei et al., 2024) takes the number of visitors from the top ten source countries to Hong Kong as the data set, According to the four prediction models, ARIMA, ALDM, ECM, and VAR, Several different predictive models were constructed, And to test the prediction effect of the above methods, Found that the combination of prediction can improve the effect of tourism prediction; Literature (Zhang et al., 2023) combines linear and nonlinear statistical models to make predictions for time series with possible nonlinear features, To test the prediction accuracy of the combined model by using time series datasets of the outbound travel demand in Taiwan, Comparing a single prediction model with a combined model combining the two methods, It was found that several combined predictive models had more accuracy than a single prediction model, And can identify the turning point of the change of the tourism environment; Literature (Gao, Pan, & Xu, 2022) studies the prediction effect of four methods: time series model, metrology model, gravitational model and expert decision system, Finding that the simplest and lowest cost time series models are suitable for practitioners, Gravitation model is suitable to solve international tourism problems, Expert decision system is suitable for scenarios where some data is not available; Literature (Andronis et al., 2017) uses seven quantitative prediction methods, Sampling predictions of tourist flow at the 24 starting sites, 1 years and 2 years are selected for prediction, The results show that the l-year forecast period is better than the 2-year period. In the process of data and the research itself, literature (Pang et al., 2019) studies the relationship between prediction accuracy, data characteristics and research characteristics, and literature (Andersen, Ottesen, & Thing, 2019) makes a comprehensive analysis of nearly 2000 published tourism prediction studies, indicating that data characteristics and prediction accuracy vary in different types of prediction methods, so selecting appropriate prediction model according to the data characteristics can effectively reduce the prediction cost. At present, many scholars have studied the driving factors of the change of sports ecotourism demand. Literature (Wang, 2023) uses a measurement model to predict Hong Kong tourism data from 2001 – 2008, The factors that found the biggest impact on the number of tourists in Hong Kong were tourism costs, economic conditions (measured by the income of tourist origin), the price of competing products and the reputation of tourists, These factors can be used as input variables to provide important information for the prediction of Hong Kong tourists; Literature (Niu et al., 2013) conducted a systematic analysis of tourism needs, and studied a relatively general algorithm to explore the influence of qualitative non-economic factors on tourism, including leisure time factors and climate factors. The results showed that leisure time and climate influence more factors to tourists than economic factors, It proves the importance of qualitative non-economic factors in tourism motivation theory and demand analysis; Literature (Rodnick & Planas, 2016) incorporates business sentiment indicators to the model, Experimental results show that business sentiment indicators improve the accuracy of fit and prediction, Expanding business sentiment surveys to tourism will bring huge benefits; Literature (Cao et al., 2024) introduces consumer expectations in time series models, Four models were tested by autoregressive (AR), autoregressive integrated moving average (ARIMA), self-excitation threshold autoregression and Markov transfer matrix. To sum up, sports ecotourism products are perishable, and their accuracy is very critical to tourism demand prediction. The mismatch between tourism resources and demand will cause huge losses to social resources and capital, and affect the social and economic development. Prediction model construction method, data selection and algorithm selection will have a great impact on tourism demand prediction. Therefore, the prediction research of sports ecotourism is of some significance (Pascoe et al., 2021).

2.2. Research on Fruit Fly Optimization Algorithm (FOA)

Literature (Donohue et al., 2023) presents a new population intelligence algorithm with global search capability and fast convergence properties. This algorithm is relatively simple, fast calculation speed, strong solution speed and accuracy, and is currently used in many combinatorial optimization and continuous optimization fields. The most widespread application of FOA in continuous optimization is parameter selection, such as structural parameter (Heijnen et al., 2016) for ANNs, penalty parameter of SVR, and conversion coefficient, etc.(Wu et al., 2020). FOA shows strong search power in the above studies, so this paper considers the selection of the predicted input variables with the FOA algorithm. FOA itself has some shortcomings, such as not suitable for solving the problem of negative independent variables, insufficient stability when solving complex problems, however, the convergence accuracy of this algorithm is not accurate, which is especially prone to local extreme value falling in. so the research of FOA algorithm improvement has high application value, which is a hot direction for the research of FOA algorithm. Literature (Herbert, 2022) proposed the IFFO improvement algorithm, Select the test function to test the improvement effect of the IFFO, The results show that the IFFO is predicted better than the traditional FOA model; Literature (Zhang et al., 2015), by introducing a cloud model to the FOA. The modified Drosophila algorithm, CM-FOA, was constructed, Cloud model can trace the optimization iteration process and random movement process of flies; literature (Tian et al., 2017) proposes a new C FOA algorithm to improve the global optimization capability of original F O A; Literature (Xie et al., 2023) proposed an adaptive variant fruit fly optimization algorithm, Based on the population and the current optimum, Inter with replication by mutation operator at probability, To continue the optimization; Literature (Xie et al., 2023) changes non-linear diminishing characteristics and the relationship between individuals and groups by increasing inertia, An improved IFOA algorithm was constructed; Literature (Dionigi, 2007) proposed a new method for community monitoring using multiple group fly optimization algorithm (CDMFOA), The algorithm requires only a few parameters, The calculation process is simple; Literature (Chuan & Xiong, 2023) for the diversity and stability of balanced populations, A horizontal probabilistic strategy and a new mutation parameter were set, An optimization and refinement algorithm, LP-FOA, The proposed algorithm achieves ideal results on optimizing the continuous function problem and handling the joint supply problem; Literature (García-Romero, Méndez-Giménez, & Cecchini-Estrada, 2022) uses two Drosophila populations, The DDSC-FOA algorithm is proposed, Two subgroups exchange information by updating the overall optimum and recombining the subgroups, Improved the population search dynamics, Slow convergence due to random positions is avoided, It outperforms the conventional FOA algorithms in terms of search accuracy and speed.

3. Research on Sports Eco-Tourism Demand Forecasting Based on Improved FOA Algorithm

3.1. FOA Optimization Algorithm for Drosophila Melanogaster

The Drosophila optimization algorithm was proposed by Pan. The bionic simulation adds the motion mode of fruit flies to the FOA algorithm to find the optimal solution of a certain target, which belongs to a relatively novel heuristic algorithm. FOA algorithm has strong global search ability and fast convergence performance. At the same time, because the algorithm structure is simple and involves fewer variable parameters, so the operation amount is less than most heuristic algorithms. Some experimental results show that FOA has the operability and optimization ability in optimizing the reserve pool parameters of echo-state networks. The FOA algorithm mainly includes five steps: population initialization, random flight, flavor concentration determination value, and flavor concentration, and position labeling. The logical structure of the FOA algorithm is shown in Figure 1:

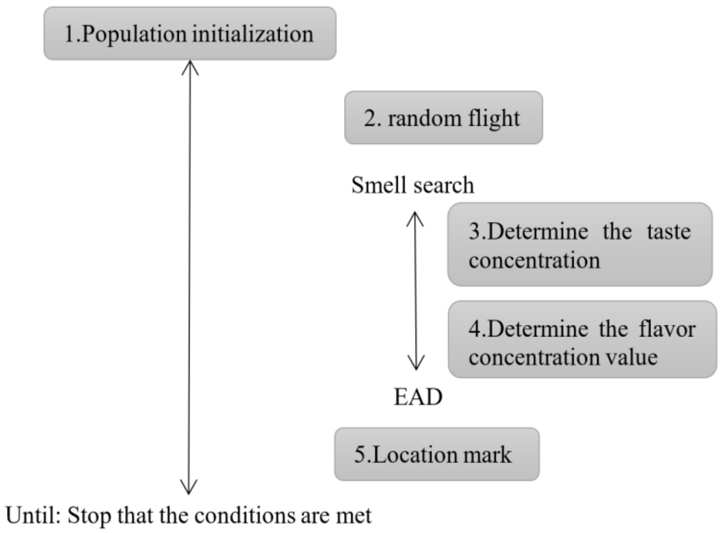

Figure 1: Logical Structure of the FOA Algorithm

Step 1: Population initialization. Population initialization stage needs to define the basic characteristics of flies, first the size of the group (Sizepop) determines the number of random positions at each iteration, the maximum number of iterations (Maxgen), the total number of flies through olfactory foraging, X_{axis} and Y_{axis} represent the initial position (the current position represents the moment during iteration), the search step (S_{length}) represents the maximum distance each fly can fly during each iteration.

Step 2: Random flight. Each fly within the population is given a random flight direction and the location information X_i and Y_i are recorded. The fly population will search for odor within the search step range. The location update formula is as follows:

$$X_i = X_{axis} + S_{length} \quad (3\text{-}1)$$

$$Y_i = Y_{axis} + S_{length} \quad (3\text{-}2)$$

Step 3: Calculate the flavor concentration determination value (S_i).The taste concentration determination value of the Drosophila population was used because the abscissa and ordinate of the Drosophila position in some functions cannot express the Drosophila position, so the reciprocal value of the distance function was used as the obtained concentration determination value S_i.S_i is not the final flavor concentration, and the parameter needs to be substituted into the function to be optimized. It is worth noting that the flavor concentration determination value is not counted in this algorithm.

$$Dist_i = \sqrt{Xi^2 + Yi^2} \quad (3\text{-}3)$$

$$S_i = 1/Dist_i \quad (3\text{-}4)$$

Step 4: Determine the flavor concentration value ($Smell_i$). The flavor concentration values of the Drosophila population behave mathematically as the dependent variable size of the function to be optimized, which represent the prediction error size of the neural network optimization in this study. Based on the measurement of the fruit fly's preference for certain odors, the concentration of food scent can be calculated using the function specified in equations 3 to 5. It is commonly accepted that an increased scent concentration indicates a closer proximity of the fruit fly to the source of food.

$$Smell_i = f(S_i) \quad (3\text{-}5)$$

Step 5: Position tag. Before the Drosophila population flies to the local optimal solution, the corresponding flavor concentration value is calculated for each individual from the location, and the location with the largest flavor concentration value is chosen as the location, the starting position of the next iteration. Meanwhile, if the optimum of the current iteration is better than the previous global optimum, the global optimum is updated with the current iterative optimum.

$$[bestSmell\ bestindex] = \max(Smell_i) \quad (3\text{-}6)$$

$$bestSmell\_global = bestSmell \quad (3\text{-}7)$$

$$X_{axis} = X(bestindex) \quad (3\text{-}8)$$

$$Y_{axis} = Y(bestindex) \qquad (3\text{-}9)$$

The iterative process of the FOA algorithm includes the above steps two to steps five, if the stop condition is implemented (i. e., the number of iterations accumulates to the maximum iteration number), and the current best Smell global is extracted as the optimal solution found in the whole Drosophila search process.

3.2. ESN Echo State Network Prediction Model

The reserve pool of echo state networks varies from traditional neural network algorithms, and the connection weights are randomly generated when the network is initialized. The beginning of an ESN startup generates a reserve pool to serve as a base, and then forms a hidden space with dynamic and complex properties, and the connection weights between neurons within the reserve pool are not adjusted with the training process. Reserve pool is composed of input weight and output weight, in the process of training, keep the status of input weight and reserved pool weight value, change the size of reserved pool output weight, usually according to the ESN actual output value and target value error, through the least squares method to adjust the weight, so effectively avoid the artificial neural network complex, long time training.

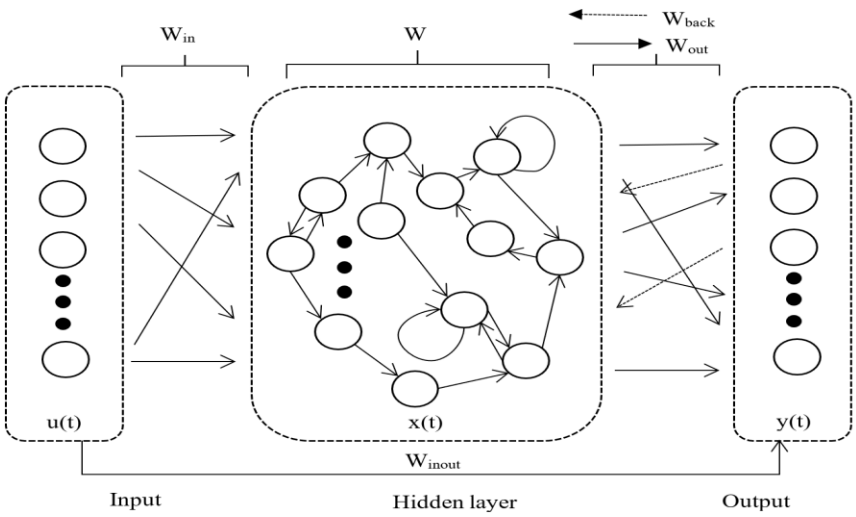

Figure 2: ESN Network Structure Diagram

A typical ESN network contains three levels, where the input layer is used to convert the input information into the initial activation signal, the reserve pool further converts the input layer activation information into the output layer information because of its complex internal connection structure, and the reserve pool has the non-linear dynamics of the recurrent neural network. The network structure is shown in Figure 2, where the solid line is necessary connection and the dotted line is optional connection. The input layer of ESN has K nodes, the value of K depends on the dimension of the input information, the univariate prediction model K is equal to l, and the multivariate prediction model K is greater than l. There are N nodes in the hidden layer (i. e., the reserve pool), representing the number of neurons in the reserve pool. The number of nodes in the output layer is L, depending on the dimension of the output information. The connection weights of the input layer, reserve pool and output layer are represented by W_{in}, W and W_{out}, respectively. If there is no feedback structure, the network weights do not contain Wback. Several weight matrices usually have different scales, depending on the input, output information format and internal connection mode. The weight to be adjusted during training is the weight W_{out} between the reserve pool and the output layer nodes. Recursive neural networks are characterized by short-term memory and function to process nonlinear systems, and the activation function of neurons can be selected according to the actual requirements. The information at the current moment is input from the input layer to the reserve pool. Combined with the feedback information of the state at the last moment and the output layer in the reserve pool, the input signal of the neuron is formed together through a certain weight, and then the input signal is converted into a new round of state vector x (t + l) through the activation function. The update formula is as follows:

$$x(t+1) = f\left(W_{in} \cdot u(t+1) + W \cdot x(t) + W_{back} \cdot y(t)\right) \qquad (3\text{-}10)$$

The f represents the activation function that constitutes the state vector x (t + l). The x (t) represents the state of the reserve pool in the previous step, and the state vector x (0) at time 0 can be randomly generated. The u (t) represents the input vector at step t, the length of which depends on the dimension of the input information. The y (t) represents the output vector in step t, and the y (t + l) represents the next step, as determined by the next input vector u (t + l), the next state vector x (t + l), and the output vector y (t) in the current step. The specific formula is as follows:

$$u(t) = [u_1(t), u_2(t), \ldots u_k(t)]^T \qquad (3\text{-}11)$$

$$x(t) = [x_1(t), x_2(t), \ldots x_k(t)]^T \qquad (3\text{-}12)$$

$$y(t) = [y_1(t), y_2(t), \ldots y_k(t)]^T \qquad (3\text{-}13)$$

$$y(t+1) = f_{out}\{W_{out} \cdot (u(t+1), x(t+1), y(t))\} \qquad (3\text{-}14)$$

3.3. Improved Drosophila Optimization Algorithm to Optimize the Combinatorial Prediction Model of ESN

3.3.1. Improvement Ideas

Due to the key factors and structure setting, the standard FOA algorithm shows four characteristics: the number of individuals in the fly population is determined during the initial stage; the range of activity of each fly (maximum random step) is not fixed; the initial position of the fly population is randomly determined and unique, and the initial position of the next iteration is determined by the location of the current optimal solution. The four features lead to the following problems of the standard FOA algorithm in the implementation process: (I) the individual number of the Drosophila population is fixed. In the process of optimization, the Drosophila population may still consume more computing power despite the poor overall performance of local solutions, thus affecting the operation efficiency of the algorithm. Alternatively, where the local solution performs better, the Drosophila population may miss the optimal solution due to an insufficient number of optimal individuals.(2) The maximum random step size of Drosophila may cause the excessive number of iterations in the locations where the local solution performance is poor, and the local solution cannot be fully mined in the local optima due to the large step size range of the local solution, which affects the efficiency and optimization ability of the algorithm.(3) The starting locations of the Drosophila individuals are randomly assigned and distinct, leading to significant initial solution variability prior to the commencement of the iterative process. This variability can subsequently influence the outcomes of the iterative computations. In order to avoid several problems encountered by the standard FOA algorithm, this paper proposes the adaptive FOA algorithm —— AFOA. The specific improvement ideas are as follows:

（1）Initial positions were optimized to introduce informative flies. Similar to the fruit fly population optimization process, a random position search before the start of the iteration will return the information from the random position solution to the Drosophila population, which selects the optimal location as the initial position for entering the iteration. To expand the initial position search ability of the information flies, the AFOA algorithm gives them a larger random search step size (which can be set to a global search), after which the fruit fly population conducts a local search.

（2）Introducing a variable maximum search step size strategy. The AFOA algorithm introduces the scaling factor, which is the ratio of the current value to the target value of the solution (the scaling factor is the ratio of the map to the target map of the current iteration), and the value of the scaling factor multiplied by the standard search step is the maximum search step of the next iteration. The advantage of random step size is that the current local optimal solution can increase when the solution is poor, and quickly jump out of this range. When the current local optimal solution is good, the step size can be reduced to increase the local search ability at this position.

$$StepLength(t+1) = \frac{mape(t)}{mape\_target} * StepLength\_Standard \qquad (3\text{-}15)$$

（3）Introduction a variable Drosophila population size strategy. This strategy can be simply understood as: when the population of current position is stimulated by higher odor concentration, the number of flies searching for food is increasing, and the number of flies population decreases due to low odor concentration. This strategy can improve the search power of the Drosophila population at the superior local locations of the current solution, while reducing the time-consuming excess at the locations near the non-optimal solution. Similar to the variable search step strategy, the variable population size strategy introduces a scaling factor, which is the ratio of the target value of the solution to the current value (the scaling factor is the ratio of the target map to the current iteration), and the scaling factor multiplied by the standard population size is the size of the Drosophila population in the next iteration.

$$Sizepop(t+1)=\frac{mape\_target}{mape(t)}*Sizepop\_Standard \quad (3\text{-}16)$$

After the above optimization process, the AFOA algorithm can simultaneously improve the operation efficiency and the optimization effect, and the improvement effect of the AFOA algorithm will be detailed in the experimental stage.

3.3.2. The AFOA-ESN Combined Prediction Model

The present study introduces an enhanced Drosophila-based optimization technique integrated with Echo State Network (ESN) to develop an innovative hybrid forecasting framework, designated as AFOA-ESN. This model leverages the FOA's extensive search capabilities for automatic parameter tuning, eliminating the need for manual ESN parameter fine-tuning and facilitating rapid development of a forecasting model tailored to specific issues. In contrast to the standard FOA-ESN, the AFOA-ESN is capable of dynamically regulating the population scale and maximum stochastic step length in response to the ongoing optimization scenario, enhancing the capacity for both local search and escape from local optima, thereby boosting computational efficiency and the overall optimization performance. Additionally, the AFOA-ESN incorporates the concept of 'informed flies' to refine the initial positioning and bolster the algorithm's convergence properties. The AFOA-ESN framework operates as a two-phase hybrid forecasting model. In the initial phase, the Echo State Network's (ESN) parameters are fine-tuned using the AFOA optimization technique, followed by training the ESN on a test dataset to ascertain the pivotal parameter settings. The subsequent phase entails the execution of predictions using the offline ESN, which has been calibrated with the optimized parameters.

（1）Data preprocessing. Data is fed into the integrated forecasting system to ensure that variations in input data size do not impact the network's performance. To achieve this, data preprocessing is typically conducted, and the resultant processed data serves as the input for the model's prediction network. The standard procedures for data normalization are encapsulated in the following formulae:

$$X' = \frac{X - X_{min}}{X_{man} - X_{\min}} \quad (3\text{-}17)$$

(2)Parameter initialization: the parameters of AFOA algorithm and ESN network need to be initialized, and the parameters of AFOA algorithm include standard population size, standard maximum random step size, maximum iteration number, and its data information is determined by the flight; the parameters include spectral radius size, input node, output node, sparsity, etc.

(3) ESN parameter optimization: There are two layers of AFOA cycle structure, the first cycle structure is the random position of the Drosophila population, and then the cycle structure of iterative count. After the fly's position is random, the smell of that direction is strong, and the stronger the taste, the next flight target is that direction. After a series of screening flights, the final parameters and processes;

(4) ESN network prediction: this link needs to refer to the predicted error value, judge the optimization effect of AFOA, and finally find out the best network parameters and predicted values.

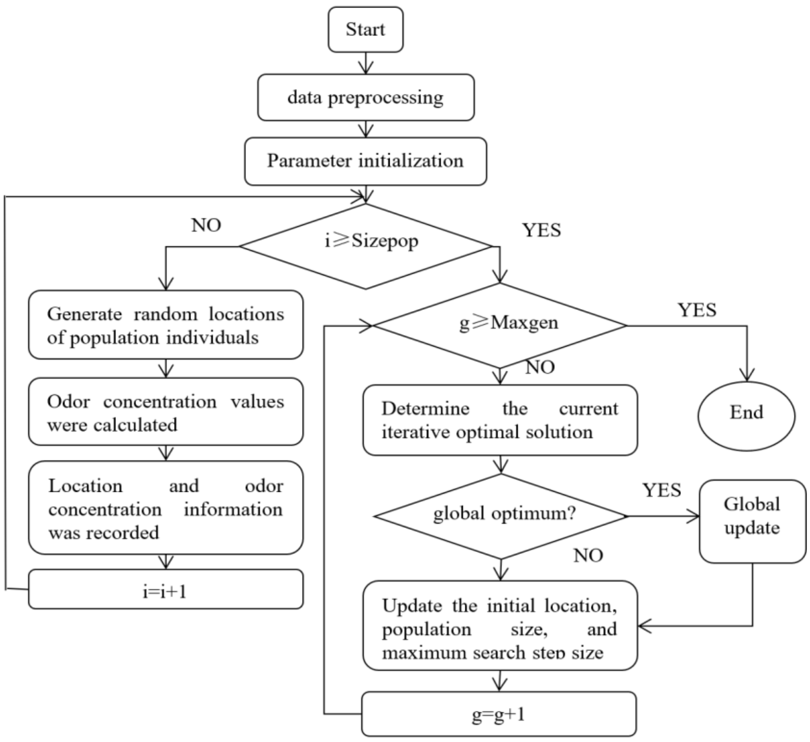

Figure 3: The AFOA-ESN Combined Prediction Model Execution Process

4. Experimental Analysis

4.1. Data Analysis

In this paper, we comb the features and principles of FOA algorithm and ESN neural network respectively, put forward the AFOA-ESN combination prediction model, and observe the prediction effect of FOA-ESN and AFOA-ESN through experiments. The experimental data is the monthly data of the number of tourists in a certain place, which is the sum of the number of domestic tourists and the number of foreign inbound tourists. The data time is from 201l to April 2017, showing a strong cyclical characteristic in form. This data is used to verify the ability of FOA-ESN model to improve ESN network and the prediction efficiency and prediction accuracy of AFOA-ESN model compared with FOA-ESN model, compared with the results of Sun, ANN, SVR, LSSVR, KELM-lin, KELM-poly, KELM-rbf, KELM-wav and various algorithmic models combined with search index.[24] To agree with the original test conditions, all data items were preprocessed using the Logl0 (N) function.

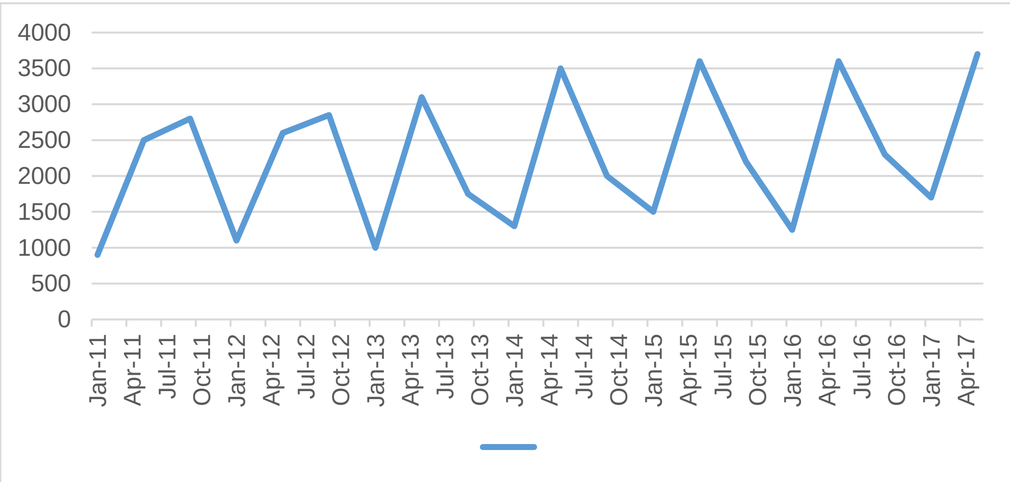

Figure 4: Number of Tourists in a Certain Place (Ten Thousand Person-Times)

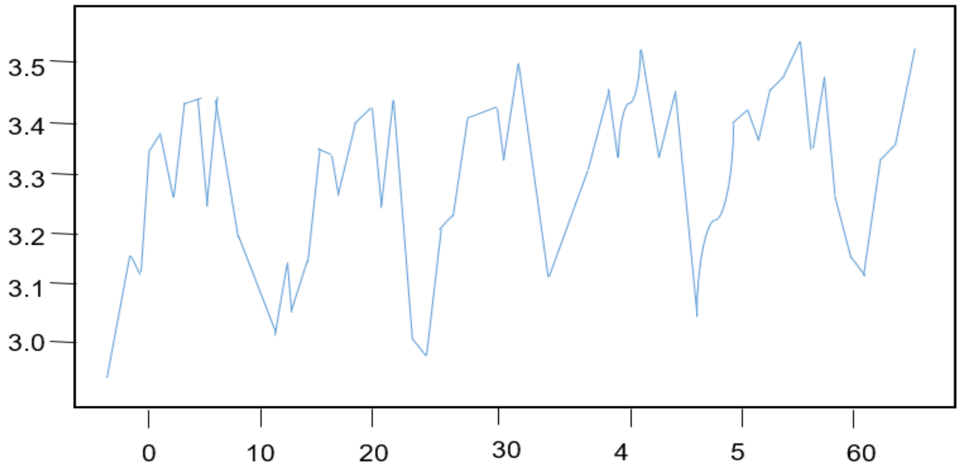

Figure 5: Number of Visitors to a Local Area (Log10 (N))

4.2. Error Evaluation Index

Three sets of experiments test the application effect of ESN, FOA-ESN and AFOA-ESN models in tourism demand prediction from different dimensions. Usually, experiments need to evaluate the prediction results combined with several different error measures, in order to analyze and compare the effects of various prediction methods from multiple perspectives. Comprehensive application of various error evaluation indexes can improve the comprehensiveness and objectivity of the prediction model effect measurement. The average absolute error (MAE) difference measures the average of the absolute error of all predicted values and the actual value, more enough to reflect the difference between the predicted value and the real value.

The average square difference (MSE) is the sum of squares of the deviation between the predicted value and the true value divided by the number of prediction times, which will amplify the large error term, and can be used to analyze the stability of the prediction time series error, with a wide range of applications. Root mean square difference (RMSE) is the square root on the basis of mean square difference (MSE), which is also an error statistics method considering the absolute value scale. The average absolute percentage error (MAPE) takes into account the proportion between errors and true values, and can be used to compare errors between data of different sizes. Usually, MAPE values below I0% indicate excellent results.

$$MAE = \frac{\sum_{t=1}^{n}\left|\hat{y}_t - y_t\right|}{n} \tag{3-18}$$

$$MSE = \frac{\sum_{t=1}^{n}\left(\hat{y}_t - y_t\right)\wedge 2}{n} \tag{3-19}$$

$$RMSE = \left(\frac{\sum_{t=1}^{n}\left(\hat{y}_t - y_t\right)^2}{n}\right)\wedge 0.5 \tag{3-20}$$

$$MAPE = \frac{\sum_{t=1}^{n}\frac{\left|\hat{y}_t - y_t\right|}{y_t}}{n} \tag{3-21}$$

4.3 Predict the Number of Visitors in An Area Based on the AFOA-ESN Model

The hardware and programming environment of this group of experiments are the same as that in Chapter 2. The method is one-step prediction method, predicting the 37th data with 1 to 36 data. Finally, the 12 predicted values in the test set are compared with the real value, and analyzed by two error indicators, MAPE and NMSE. FOA-ESN showed excellent prediction accuracy and optimization, with MAPE of 0.53% and 0.67% NMSE, with both indicators. At the same time, the FOA-ESN model is very robust, and the prediction error of each data is controlled within 1.59% (MAPE). FOA-ESN can reduce the error gradient rapidly, proving that this method can effectively solve the demand prediction problem in the tourism industry. The AFOA-ESN further improved the prediction accuracy compared to the FOA-ESN model, with a MAPE control within 0.41% and an NMSE of 0.66%. At the same time, due to the existence of information flies and adaptive mechanism in AFOA algorithm, the algorithm can obtain better initial positions than FOA algorithm, with faster local search ability and iteration speed, and show faster convergence ability. The MAPE of the initial iteration of AFOA-ESN model is around 0.5%, which is about 0.06% lower than that of FOA-ESN model. In terms of convergence speed, at the tenth iteration of AFOA-ESN model, the MAPE drops below 0.44% and below 0.42% after forty generations, and the error index is lower than the FOA-ESN model. The improvement of AFOA-ESN model shows the rationality and applicability of the optimization algorithm.

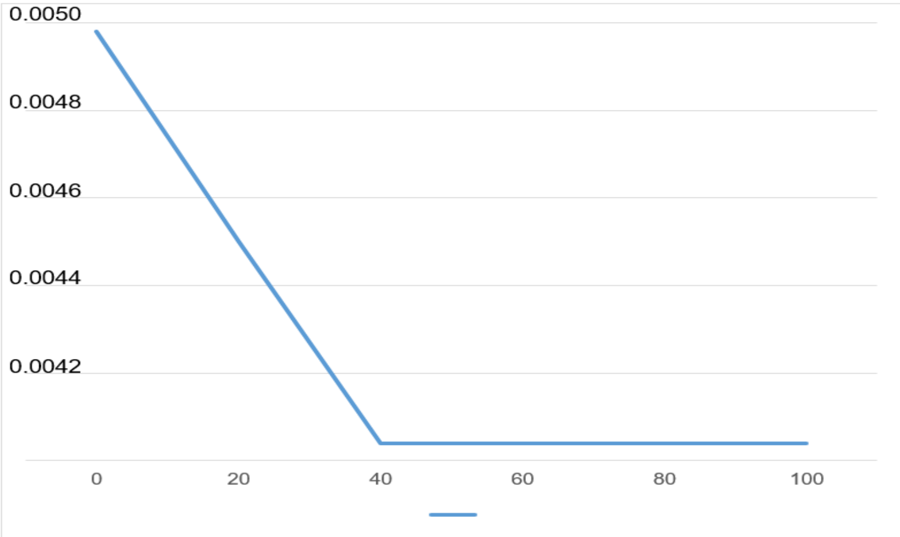

Figure 6: AFOA-ESN error gradient chart

5. Conclusion

With the continuous development of national economy, the tourism industry plays a more and more important role in the economy. Accurate prediction of tourism demand is a key link of policy making and resource allocation. The number of tourists has strong seasonal, cyclical, non-linear and uncertainty, so how to predict the number of tourists with higher accuracy is an urgent problem to be solved in the industry practice. The FOA algorithm is simple and fast. The temporal prediction performance of ESN network has been confirmed by academia, and the key parameters of ESN network can have an important influence on the fitting effect. This paper proposes the AFOA adaptive algorithm, introducing the information fly algorithm mechanism to optimize the initial iteration position, while adjusting the number of flies and random search step size through odor concentration adaptation. After the above optimization process, the AFOA algorithm can simultaneously improve the operation efficiency and optimization effect. Then, the experimental data and the error evaluation index can show that the prediction of the FOA-ESN model can maintain a stable state in different time periods, and it is very robust. Meanwhile, the AFOA-ESN is better than the FOA-ESN model in terms of initial position optimization, convergence speed, and prediction accuracy.

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