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APPLICATION OF ANN IN TOURISM BUSINESS DEVELOPMENT FOR DEMAND FORECASTING AND MANAGEMENT OF TOURISM HEADCOUNT

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Abstract. With the rapid development of tourism, it is imperative to forecast tourism demand to maintain the long-term stable development of the tourism industry and make good planning for future tourism enterprises. The study uses the classical model of artificial neural network-BP neural network for tourism number demand prediction, given the problems of traditional BP neural networks, such as prematurity and poor convergence speed, this paper studies the iterative optimization of the algorithm of particle swarm fusion immune mechanism and finds out the optimal network parameters, to build an IAPSO-BP tourism demand prediction model. Tourist amounts from 2007 to 2017 in certain area-related data samples, the training model of iterative speed and fitting effect, and the rolling forecasting method will be used to predict the 2018-2022 years of travel. It can be seen from the convergence curve that the convergence speed of parameter optimization of the IAPSO algorithm is the fastest; the improved IAPSO-BP network has the best training fitting effect, with a relative average error of 2.03% and an absolute average error of 4.37%, which is better than other forecasting methods. The IAPSO-BP prediction model has higher accuracy and better performance, which can provide an effective basis for the development planning of tourism enterprises and has higher practical application value.

Key words: : tourism enterprises, BP neural network, demand forecasting, immune particle swarm

1. Introduction. Tourism is booming as people's living standards improve and their spiritual and cultural needs grow. Conducting tourism demand forecasting in future management planning work is extremely important [23]. Establishing effective and scientific tourism demand forecasting can provide tourism enterprises and the tourism industry with future directions for tourism development, help managers plan the rational application of tourism facilities and other resources, and provide a strategic basis for tourism companies to develop their development [9]. Due to the many factors affecting tourism demand, traditional forecasting models' demand prediction is ineffective; the prediction error is large, and the search for high-accuracy forecasting methods is an important issue in tourism research. Artificial neural networks are systems that simulate the brain to process information efficiently and have good classification and prediction functions. Among them, feedforward back propagation neural network (BPNN) has high fault tolerance and is widely used in various fields [25]. In traditional BPNN, the training is prone to local optimal and slow learning convergence, the research uses particle swarm algorithm combined with immunity mechanism to improve the BP network, optimize the parameters of the neural network, enhance the global search capabilities, and avoid the phenomenon of "premature". Using the improved BP algorithm to construct the tourism demand prediction model can improve the accuracy of prediction, promote the long-term stable sustainable innovation and development of tourism enterprises, facilitate the improvement of the tourism system, and realise the rational management and utilization of tourism resources.

2. Related Work. Establishing effective tourism demand forecasting models and finding efficient tourism demand forecasting methods are important research topics for many researchers. park E research team proposed a method for forecasting tourism numbers from news data, using seasonal regression averaging to select news topics, and testing the effectiveness of the selected news topics in forecasting demand. the results confirmed that forecasting models using news topics outperformed comparison models and can promote close integration between tourism destinations and news media [16]. Xiao Y research scholars proposed a hybrid model to predict tourism traffic demand to avoid tourism congestion, using an integrated empirical model decomposition to remove noise interference from the sequence and using the search composite index for tourism traffic prediction.

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The model training results showed that compared with the contrast model, the prediction error of the proposed model is lower, instructions to remove noise interference can improve the model prediction accuracy [22]. Chen L researchers developed a multivariate prediction method using data rearrangement technology, grouping tourism demand sequences to represent specific poles of demand each year and then reordering them to predict seasonal demand. The Hong Kong demand forecasting empirical analysis concluded that the model could significantly improve the prediction accuracy compared to the traditional univariate model [5]. Breda E and other scholars used tourism flow data from Italy as a sample to estimate expenditure elasticity concerning income and exchange rate for tourism demand in Italy. They found that the elasticity of tourism expenditure concerning the exchange rate was negative, varying from -0.5 to -0.7 and between -0.5 to -0.7. The factors affecting expenditure are mainly the number of tourists [3]. Ouassou et al forecasted the tourist demand of the Moroccan region, and proposed a hybrid prediction method combining traditional methods with artificial intelligence techniques, from the analysis of the prediction results, the hybrid prediction method can overcome the limitations of both traditional and artificial intelligence techniques and outperformed other contrasting models, with high accuracy of prediction results [15]. Nasirzadeh F et al. proposed a prediction interval method based on artificial neural networks to predict people's labour productivity more effectively. The results indicate that the method constructed by the research institute can effectively predict the value of labour productivity and can be widely applied in different projects with very objective performance [14]. Yang F's team proposed an optimization method based on artificial neural networks to improve the prediction accuracy of diesel engine preheating and recovery systems. In the experiment, a genetic algorithm was introduced to improve the BP neural network, and 7 committed steps improved the system's output power. The results show that the optimized data error is small, and the prediction accuracy of the system is significantly improved [23].

With the good achievements of artificial neural networks in the field of prediction, more and more researchers carry out in-depth research. Jahani A. et al researchers added multiple layers of perceptrons to an artificial neural network model to analyze the impact of human activities on biodiversity, through the analysis of vegetation, soil and other variables, found that human activities can affect soil moisture and reduce the diversity of vegetation, the results of the study can help managers develop plans to reduce some human activities [8]. Al R scholars conducted a study on the prediction of tourism visits. They proposed using artificial neural networks as a computational tool to predict tourism visitation data using multiple regression. The results showed that the method showed the correlation of the predictor variables and improved the accuracy of the prediction, which can help tourism sector managers understand the visitation [1]. Soh A N et al. researchers. Used the tourism composite index to predict the fluctuation of the tourism market, and the results showed that using the seasonal adjustment method could highlight the signal of tourism demand, predict the prospective development of the tourism market, and provide an information basis for macro regulation of tourism development [19]. Mandal A research scholars used artificial neural network models to estimate engine emissions from new fuels as well as to check performance attributes, using different algorithms and functions for training, and experimental results showed that artificial neural networks helped to predict data from the early stages of the experiment and that pollution from new fuels was reduced under different engine load conditions. That detection using artificial neural networks was better than other methods [12]. Cachim P researcher proposed the use of artificial neural networks for modelling to deal with complex problems in the face problems such as wood design specifications, training multilayer feedforward neural networks for predicting the temperature of wood cross sections under fire; the investigation results showed that artificial neural networks can effectively predict the temperature of wood cross sections and the results obtained can help to calculate the strength of members [4]. Hota S and other researchers proposed combining elephant swarm optimization methods with ANN models to apply to the mutual fund NAV data prediction. The performance of the obtained model was compared with ANN, ANN-GA, and ANN-DE models during the experiment. The results indicate that the comprehensive performance of the proposed model has always been optimal [7]. Researchers such as Park A proposed a research method based on improved artificial neural networks and vector autoregression to effectively predict the US dollar exchange rate. The root mean square deviation is used as the index to compare the predictive ability of different models. The data shows that the performance of the model built by the Institute is better, and more than 30% has reduced the Root-mean-square deviation [17, 13].

A brief description of the research results at home and abroad shows that artificial neural networks are

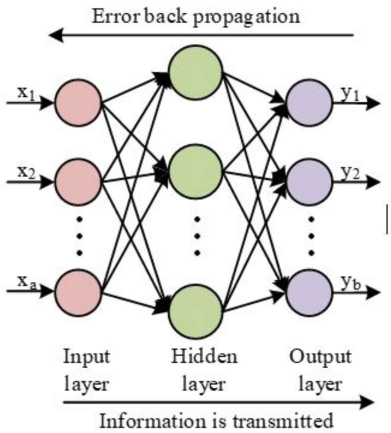

Fig. 3.1: BPNN structure diagram

widely used, and there are more methods to predict tourism demand. Still, the accuracy of the prediction needs to be improved. The study proposes a particle swarm algorithm combined with an immune mechanism to optimize the parameters of artificial neural networks and establish a tourism demand prediction model to improve the model prediction accuracy and promote tourism development.

3. Construction of a tourism demand forecasting model based on IAPSO-BPNN.

3.1. BP neural network algorithm and its optimization. Predicting tourism demand, providing a theoretical framework for business tourism management, and promoting the steady growth of tourism are all extremely important as the number of tourists increases. An information processing system called an artificial neural network (ANN) imitates the neural architecture of the human brain; it uses computers to combine electronic components to accomplish the brain's functions of memory, information processing and judgment, and so on. In practical applications, most use BP neural networks, which are the essence of the forward network in artificial neural networks [18]. In BP neural networks, information is propagated forward while the parameters in the network are corrected using error backward adjustment, gradually reducing the error between the ideal value and the actual value, achieving the effect of fast convergence to reduce the internal error of the system [24]. The three main components of BP neural networks are the input, hidden and output layers; by mutual connection weights between layer and layer, there is no connection between neurons; each layer contains multiple neurons, and a typical three-layer BP network structure is shown in Fig 3.1. When the BP network learning algorithm is run, it first selects a structurally reasonable network, sets all adjustable parameters (weights and thresholds) to uniformly distributed smaller values, and sets the expected error to ε. Secondly, the input sample calculation is performed, and the weights and thresholds of the output layer and hidden layer nodes are corrected. Finally, it sets $n = n+1$ and inputs new samples (or samples from a new cycle) until the network error meets the predetermined requirements. The input order of samples in each training cycle should be randomly reordered. When the BP neural network propagates forward, the data information passes through the input layer to the hidden layer, and the output layer obtains the result information through processing the hidden layer. It assumes that the input data information is $x = (x_1, x_2, \ldots, x_a)^T$, there are neural elements in the input layer, and a_1 neural elements in the hidden layer of the BP neural network, and the output information is $x' = R^{a_1}$. The output expression of the n neural element in the hidden layer is Equation (3.1).

$$x'_n = f\left(\sum_{i=1}^{a} w_{ij} x_i - \theta_n\right), n = 1, 2, \ldots\ a_1 \tag{3.1}$$

In equation (3.1),w_{ij} represents the weight value between the input layer and the hidden layer; x_i is the output of the input layer neuron, and $i\theta_k$ is the threshold between the two layers. The output layer has b neurons, and the output $y \in R^b$, and the output layer expression is shown in equation (3.2).

$$y_k = f\left(\sum_{n=1}^{a_1} w'_{ij}x'_n - \theta'_k\right), k = 1, 2, \ldots, b \tag{3.2}$$

In equation (3.2),$w_{ij}^{'}$ represents the weight between the hidden layer and the output layer; $\theta_k^{'}$ is the threshold between the two layers and $f(x)$ is a continuously derivable Sigmoid function $f(x) = \frac{1}{1+e^{-x}}$, so the derivative of the function is equation (3.3).

$$f'^{(x)} = f(x)(1 - f(x)) \tag{3.3}$$

In practical application requirements, a bipolar Sigmoid function is also used, with an expression as in equation (3.4).

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{3.4}$$

After obtaining the output value and comparing it with the expected value, the error signal is propagated backwards, and the propagation process propagates forward from the output layer by layer, correcting the weights by feeding back the error so that the output value is infinitely close to the expected value. The error formula for calculating the first k sample is equation (3.5).

$$E_k = \frac{1}{2}\sum_{n=1}^{b} (y_{nk} - T_{nk})^2 \tag{3.5}$$

In equation (3.5),T_{jk} is the expected output value of the n neuron element; y_{jk} is the actual output value of the n neuron element. The correction formula for the connection weights of the neurons in each layer is shown in equation (3.6).

$$\Delta\ w(k+1) = \Delta\ w(k) - lr \times\ g(k) \tag{3.6}$$

In equation (3.6),lr stands for learning efficiency,$g(k)$ stands for local gradient vector, the expression is $g(k) = \left.\frac{\partial E(w)}{\partial w}\right|_{w=w(k)}$. and E stands for the error function. The execution flow of the BPNN algorithm is shown in Fig 3.2.

From Figure 3.2, it can be seen that the BP network model is based on the error backpropagation algorithm in artificial neural networks as its learning algorithm. Its learning process consists of four processes: The input mode is a "pattern forward propagation" process from the input layer through the middle layer to the output layer, and the desired output of the network and the actual output error signal of the network are corrected layer by layer through the middle layer to the input layer through the "error backpropagation" process of correcting the connection weight, The process of network "memory training", which involves the repeated alternation of "mode forward propagation" and "error back propagation", is the process of "learning convergence" where the global error of the network tends to the minimum. The nonlinear mapping ability of BPNN is strong, and each layer of the structure can be set with arbitrary parameters to obtain different effects according to the actual application, but the essence of the BP neural algorithm is using the gradient descent method, and the initial conditions can easily affect the performance of the algorithm [21]. The network training process will only go "downhill", which is very easy to appear prematurely and the global search ability is not strong; the BP algorithm has a fixed learning factor in the learning process, and the learning factor has certain values to achieve the minimum final error, which seriously affects the convergence speed of the algorithm. The amount of hidden layers and nodes in the network structure is difficult to determine, and there is no rigorous explicit

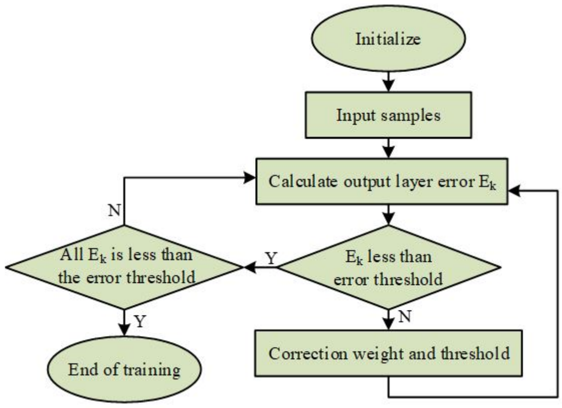

Fig. 3.2: BPNN algorithm execution flow chart

data support, and can only rely on experience, while in practical applications, the laws of the problem vary greatly and the structure is more difficult to determine, these shortcomings make BP neural networks much less effective for wide application [11]. In order to avoid the premature phenomenon of the BP algorithm and enhance the global search ability, the study uses the algorithm of particle swarm combined with an immune mechanism to train the network structure, and the results obtained are used as the parameters of the BP algorithm, which is trained to search for the global optimal parameters.

In Particle Swarm Optimization (PSO), particles determine the distance and direction of flight based on the velocity of the current optimal particle and the fitness value, search around the current optimal particle, and update their position information as the number of iterations increases until the global optimum is found [2]. In the P dimensional search space, there exists a population of M particles, and the ith particle' position in space is represented by $X_i = (x_{i1}, x_{i2}, \ldots, x_{iP}), i = 1, 2, \ldots, M$, the velocity variable of the ith particle is represented by $V = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The particle fitness is generated according to the objective function, the optimal particle information obtained from the current search is represented by $P_i = (p_{i1}, p_{i2}, \ldots, p_{iP})$, and the location information of the optimal individual in the population is represented by $P_g, g \in \{1, 2, \ldots, M\}$. During the iteration, the particle is updated with the operation formula shown in equation (3.7).

$$\begin{cases} V_i^{t+1} = \chi\left(wV_i^t + c_1 * r_1 * (P_i^t - X_i^t) + c_2 * r_2 * \left(P_g^t - X_i^t\right)\right) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \\ w = w_{\max} - \frac{w_{\max} - w_{\min}}{num_{\max}} \times num \end{cases} \tag{3.7}$$

In equation (3.7), t is the amount of iterations,c_1, c_2 is the learning factor, which is generally positive,r_1, r_2 is usually a random amount distributed at$[0, 1]$; w represents the inertia weighting factor,$wmin_{max}$ stands for maximum and minimum of w; χ is the compression factor, the expression of which is given in equation (3.8).

$$\chi = \frac{2}{\left|2 - \varphi - (\varphi^2 - 4\varphi)^{\frac{1}{2}}\right|} \tag{3.8}$$

In equation (3.8),$\varphi = c1 + c2, \varphi > 4$. The PSO algorithm is a global optimization algorithm, simple operation, and very easy to implement, but PSO converges faster and tends to fall into a local optimum. The immune system's antigen recognition and memory learning capabilities can increase the abundance of the population, improve the global search ability and avoid "premature maturity". In this study, the immune mechanism is introduced into the particle swarm algorithm, and the particles are regarded as antibodies to ensure that the particles can maintain high fitness values; in each iteration, the global optimal individual obtained by the PSO algorithm is regarded as the immune factor, and the particles are "vaccinated" to update the particle swarm by immune selection [6]. The particle swarm algorithm improved with the immune information processing mechanism is called Particle Swarm Optimization with Immune Algorithm (IAPSO). In the IAPSO algorithm, the excellent particles generated in each iteration are regarded as memory cells, and when the newly generated particles are less adapted, they are replaced by the memory cell particles; the particles are reselected based on the affinity between antigen and antibody for the randomly generated N particles, and the expression of affinity is shown in equation (3.9).

$$Q_i = \frac{1}{F_i} \tag{3.9}$$

In equation (3.9), F_i is the particle's fitness calculation formula function. The selection of new particles is based on the affinity value, and the selection probability determined by the affinity is given by equation (3.10).

$$P_{i1} = \frac{Q_i}{\sum_{u=1}^{M+N} Q_u} \tag{3.10}$$

The particle concentration can also determine the probability of selecting a new particle, and the particle concentration formula can be inferred from the fitness function, whose expression is given by equation (3.11).

$$D_i = \frac{1}{\sum_{u=1}^{M+N} |F_i - F_u|} \tag{3.11}$$

The probability of selection determined by the particle concentration is shown in equation (3.12).

$$P_{i2} = \frac{D_i^{-1}}{\sum_{u=1}^{M+N} D_u^{-1}} \tag{3.12}$$

The probability of particle selection is determined by both the affinity and the probability of particle concentration selection and is expressed in equation (3.13).

$$P_i = aP_{i1} + (1-a)\,P_{i2}, i = 1, 2, \ldots, M+N \tag{3.13}$$

In equation (3.13), a is the weighting factor, which takes a value between 0 and 1. The size of P_i is used to rank the $M+N$ particles, and the first N with the larger value is selected. In the vaccination mechanism of the immune system, one vaccination is completed by randomly selecting a particle at the new particle and swapping the position of the randomly selected particle at P_g; The immune selection of the vaccinated particles is done by comparison of fitness and probabilistic selection values for discarding.

The IAPSO algorithm is strong in global search and weak in local search, while the BP neural network algorithm is the opposite; Combining the two and training the network can improve the generalization ability as well as the prediction accuracy of the neural network [10]. The flow of the IAPSO-BP algorithm to train the network and obtain the optimization parameters is shown in Figure 3.3.

In Figure 3.3, setting the initial parameters and GenerateN particles, the individual fitness of particles is calculated, and the best ones are retained as memory particles. According to Equation (3.7), new N particles are generated, detect the fitness and replace them. A total of M particles were randomly generated, and N particles were selected from M+N particles according to the affinity concentration and particle concentration; It regenerates N particles by immunization and vaccination operations and repeats iterations until the optimal particles are obtained; It converts the optimal particles into the initial parameters of the BPNN, and the parameters are modified by BPNN algorithm.

3.2. Construction of IAPSO-BP neural network-based tourism headcount demand forecasting model. The factors that affect the demand for tourism numbers are mainly the attractiveness of the destination to tourists, the income of individual tourists, travel preferences, etc., which need to be taken into account when predicting the demand for tourism numbers to provide a basis for the development of its tourism enterprises. Designing a network prediction structure is a comprehensive problem that needs to be considered to meet a

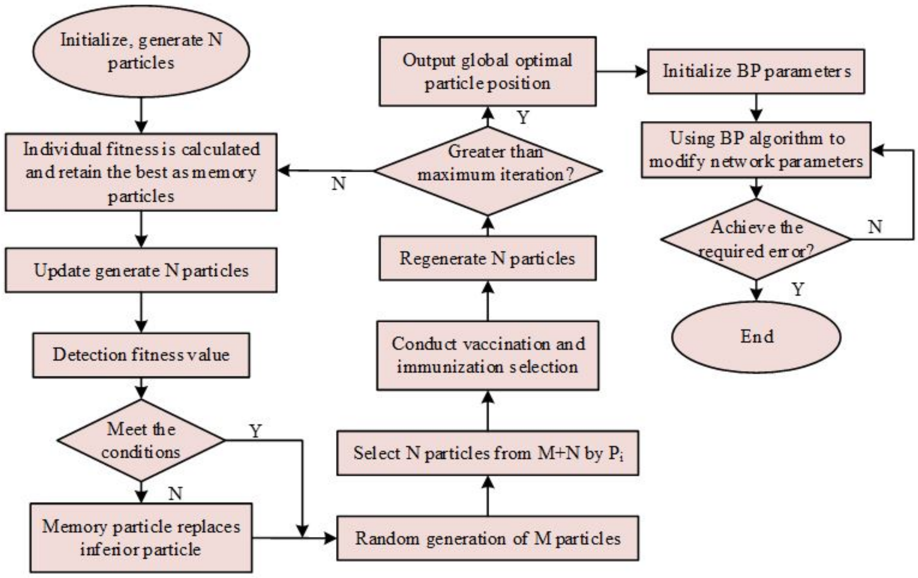

Fig. 3.3: IAPSO-BP algorithm training network flow chart

variety of different needs, and in constructing a model for predicting tourism headcount demand, it can simply be reduced to a problem of choosing a network size with a certain number of samples [20]. In a BP neural network structure, an implicit layer can solve the mapping relationship of any continuous function, and a simple three-layer BP neural network structure can accomplish the mapping of any space. With the increase of samples, can increase the amount of hidden layer neurons to improve the accuracy of network training, determining the amount of hidden layer neurons n_1 as shown in equation (3.14).

$$n_1 = \sqrt{n+m} + a \tag{3.14}$$

In equation (3.14), m and n represent the number of neurons in the output and input layers, $a \in [1, 10]$. The BP network model is a nonlinear system; if the initial value is too large, it will make the weighted output, and in the saturation zone of the function, the adjustment process of the weights cannot be stalled; the design process chooses a smaller initial value. The network is in the process of learning, the learning rate determines the amount of change in the resulting weights. A large learning rate indicates that the network is unstable, and when designing, a smaller learning rate is considered for training and adjusted at any time. In order to ensure that the data for sample training are of the same order of magnitude, the data must be normalized and pre-processed, and the processing formula is equation (3.15).

$$h_n = \frac{2\,(h - minh)}{maxh - minh} - 1 \tag{3.15}$$

In equation (3.15), h denotes the raw input data, and h_n denotes the pre-processed data. When training the network, sometimes overfitting occurs, and the sum of network weights and bias can be introduced on the basis of the mean squared difference MSE of the network as a performance function, which can be reduced to a certain extent; the network training method is studied using batch variation, and only one training function needs to be set for use in the network, which is relatively easy to operate. The tourism demand forecasting model using IAPSO-BP is shown in Fig 3.4. The indexes for forecasting are selected and the network parameters are initialized, the sample data and pre-processed data are input, the IAPSO algorithm is used for parameter search, the BP network model is constructed with the obtained optimal network parameter, the network learns itself, the threshold and weights are corrected, and the forecasting results are finally obtained.

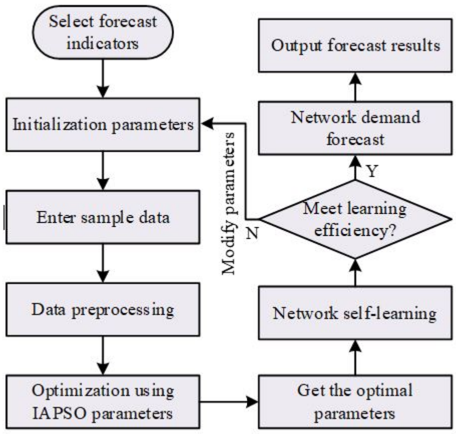

Fig. 3.4: IAPSO-BP prediction model flow chart

Table 4.1: Basic experimental hardware environment

Parameter variables	Parameter selection
Operating environment	MATLAB
CPU dominant frequency	2.62Hz
GPU	RTX-2070
Operating system	Windows10
System processor	Intel Core i7-8700K CPU 3.70GHz
System running memory	32.0GB
Programming program	Python
Data analysis platform	SPSS24.0
Data storage system	MySQL

The IAPSO-BP tourism demand forecasting model uses the logical relationship of neural networks to predict the value of the future moment by analyzing the value of the past moment. Reliable raw data can improve the accuracy of the model's prediction results, and to ensure the reliability of the data, the data collected should reflect the local tourism trend, i.e. collecting tourism data information over a continuous period of time; the sample information is complete in terms of elements and variables The data should reflect the actual local situation. Forecasting methods include single-step forecasting, multi-step forecasting and rolling forecasting. The study uses a rolling forecast method to forecast tourism demand, starting with a single-step forecast, inputting historical data $X_i, X_{i+1}, \ldots, X_{i+n}$ and outputting the forecast X_{i+n+1} and repeating the iterations until inputting $X_{i+m-1}, X_{i+m}, \ldots, X_{i+m+n-1}$ and outputting the forecast X_{i+m+n} at m.

4. . Analysis of tourism demand forecasting model based on IAPSO-BP. To verify the effectiveness of the IAPSO algorithm in solving the BP network parameters, four standard functions were selected for simulation experiments. Before the formal start of the experiment, the basic hardware environment of the experiment should be set up, as shown in Table 1. To ensure the experiment, the number of iterations of all algorithms was set to 1000, the population size was 100, and it repeated many times for the different basic functions obtained. Figure 4.1 shows the convergence curves of PSO, IA and IAPSO under four standard functions.

From Figure 4.1, it can be seen that under the four standard functions, when the number of system iterations is 100, the convergence accuracy of the research method begins to enter a stationary period and approaches zero infinitely in the subsequent stages. At the same time, when the number of system iterations is about 400 times, the convergence accuracy of the GA algorithm and the IA algorithm begins to approach a plateau and

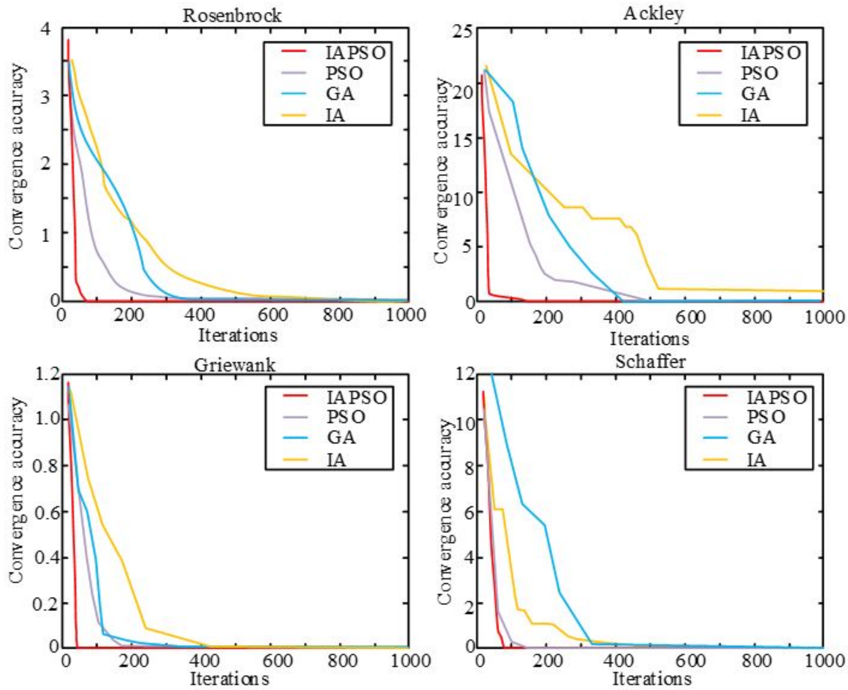

Fig. 4.1: Iterative curves of four algorithms

infinitely approaches zero. However, the rate of convergence has been slow, and there are obvious differences in the rate of convergence under the four functions. In addition, as the number of system iterations increases, the convergence accuracy of the PSO algorithm also decreases, and it performs a stable convergence accuracy state faster than the GA algorithm and IA algorithm. To sum up, the IAPSO algorithm has the fastest rate of convergence and the best performance, indicating that the IAPSO algorithm has the highest efficiency in BPNN parameter search. The number of tourists in a city from 2007-2017 was used as the network training sample, the number of tourists from 2007-2016 was used as the network input and the number of tourists from 2008-2017 was used as the output. The error threshold between the actual output value and the ideal output value is set as 0.01, and the neural structure of the network for predicting the number of people was determined to be 2-7-2. In order to test the performance of the proposed IAPSO-BP model, the training is compared with the basic BPNN model, the GA-BPNN model is improved using the genetic algorithm and the PSO-BPNN model is improved by particle swarm algorithm, and the minimum error plot of the network obtained from the training is shown in Fig 4.2.

From the analysis in Fig. 4.2, it can be concluded that the minimum error curves of the four neural networks have the same trend, all with the increase of training, the minimum error of the network slowly decreases, BP neural network in the training 7500 times, reached the set error, stopped training; GA-BP neural network in the training 6400 times, reached the set error to stop training; When the number of training reached 6000 times, PSO-BPNN The PSO-BPNN model reached the set error and stopped training when the number of training times reached 6000; the IAPSO-BP neural network reached the set error and stopped training when the number of training times reached 5000, indicating that the IAPSO-BPNN proposed in the study completed the training faster and performed better than other network models. The fitting effect of the prediction results obtained from the training is shown in Fig. 4.3.

From the analysis of the fitting effect in Figure 4.3, it can be seen that the predicted results of the four prediction models are consistent with the actual trend, but there are certain differences in the fitting effect. With the passage of time, the difference between the predicted results of the research methods and the actual

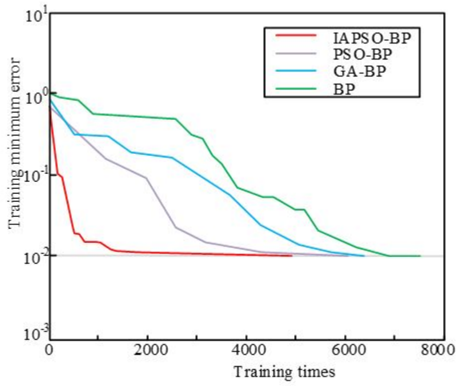

Fig. 4.2: Training minimum error result chart

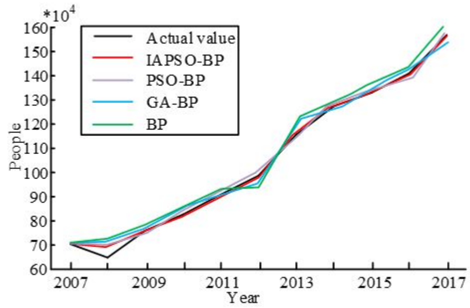

Fig. 4.3: Training fitting effect diagram

values becomes smaller and smaller, and it has always been in the state of the best fit. The fitting values of research methods, PSO-BP, GA-BP, and BP neural networks were 0.951, 0.932, 0.911, and 0.879, respectively. When the time was 2008, the number of tourists significantly decreased due to the impact of geological disasters, which resulted in inaccurate predictions from all four algorithms. The difference between the predicted curve of the BP neural network model and the actual value is significant, while the fitting effect of the GA-BP neural network model and the PSO-BP neural network has increased. Based on the above results, it can be concluded that the IAPSO-BPNN model constructed by the research institute has the highest prediction accuracy and high performance. To further illustrate the superiority of the IAPSO-BPNN prediction model, the errors of the predicted and true values were compared and the results of the relative mean error and absolute mean error obtained are shown in Table 4.2.

From Table 4.2, the relative mean error of the IAPSO-BPNN model is 0.83% smaller than PSO-BPNN, 1.64% smaller than GA-BP network, and 2.48% smaller than the BPNN; the absolute average error of the IAPSO-BPNN model is 0.75% smaller than the PSO-BPNN model, 3.42% smaller than the GA-BP network, and 3.86% smaller than the BPNN model 3.86% smaller, all indicating that the IAPSO-BPNN model prediction outcome have smaller errors and higher precision. Taking the number of tourists from 2007-2016 as the network input, the network calculated the number of tourists from 2008-2017 to get the prediction value of 2017, then the whole output was reused as a new input to calculate the number of tourists from 2009-2018 to get the predicted value of 2018, and the prediction number of tourists for each year from 2018 to 2022 was rolled out, and the prediction results are shown in Fig 4.4 is shown.

From Figure 4.4, it can be seen that over time, the predicted values of the four algorithms for the number of tourists' tourism demand gradually increase over time and are constantly changing. The prediction results of the IAPSO-BP neural network match the real situation best, with a prediction accuracy of up to 0.974. The

Table 4.2: Comparison of prediction precision

Prediction model	Relative mean error (%)	Absolute mean error (%)
BP	4.51	8.23
GA-BP	3.67	7.79
PSO-BP	2.86	5.12
IAPSO-BP	2.03	4.37

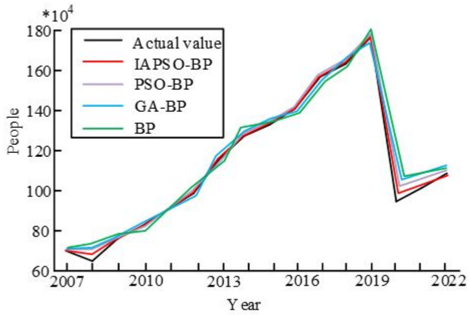

Fig. 4.4: Tourist demand forecast results

result curve of the PSO-BPNN model is in good agreement with the actual value, with a small error and a prediction accuracy of up to 0.928; The difference between the predicted results of the GA-BPNN model and the actual values is small, with a prediction accuracy of 0.913; The prediction accuracy between the number of tourism demand predicted by the BP model and the actual value is relatively high, and has always been at the lowest, with a prediction accuracy of only 0.901. The above results indicate that the degree of fit between the predicted curve of the number of people under the research method and the actual value is the highest, indicating that IAPSO-BPNN has the best prediction effect and superior algorithm performance. At the same time, it can be found that in 2008, the number of tourists suddenly decreased, which was caused by the earthquake disaster that year. However, from 2019 to 2020, the number of tourists dropped suddenly and significantly, which was because the outbreak of COVID-19 made forecasting more difficult. The box line plot in Fig 4.5 shows the dispersion of the absolute errors of the four forecasting network models. From Figure 4.5, the upper and lower quartiles, median and outliers of the absolute error box line plot of the BPNN model prediction are more than the other three neural networks, and the upper quartiles of the GA-BPNN model and the median of the PSO-BP are smaller than the upper quartiles and median of the IAPSO-BP network respectively, but both have more outliers than the IAPSO-BPNN model and overall, the IAPSO-BPNN outperformed the other three predictive neural networks in terms of prediction performance.

5. Conclusion. The tourism industry has opened up more and more development opportunities under the growing spiritual and cultural needs of people. Establishing tourism demand forecasting and doing a good job of tourism operation planning can develop the sunrise industry of tourism in a long-term and stable manner. The study uses the IAPSO algorithm to carry out parameter optimization of the BPNN, and the optimized parameters obtained establish the neural network predictive model, and the algorithm is tested and analyzed to predict the demand for the number of people conducting tourism in a certain area. The results show that the IAPSO algorithm parameters proposed in the study converge fastest and most efficiently in the search for optimization; among the four network models trained, the IAPSO-BP network reaches the set error the fastest, stopping training after reaching 5000 times; the rolling prediction fitting effect obtained, the IAPSO-BP network has the best fitting prediction curve, with a relative average error of 2.03% with the true value which was 0.83% smaller than the PSO-BPNN model, 1.64% smaller than the GA-BPNN model and 2.48% smaller than the BPNN model; the MAE was 4.37%, which was 0.75%, 3.42% and 3.86% smaller than other prediction models respectively; the prediction results of IAPSO-BPNN had smaller error with the true value, and the

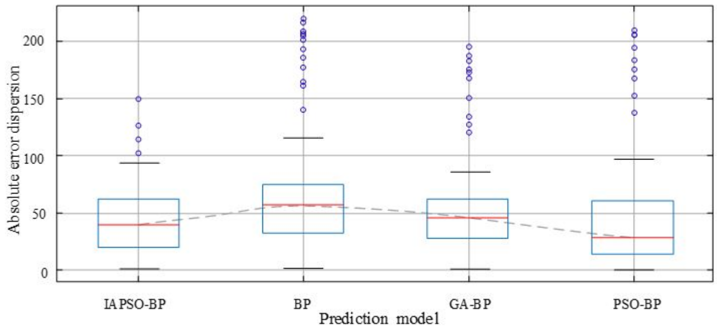

Fig. 4.5: Absolute error box diagram of four prediction models

prediction performance was better than other comparison models. The prediction results are more accurate and can provide a practical and effective basis for tourism enterprises and tourism economic management departments to formulate development plans and reasonably plan the allocation of resources in the tourism market. Although the research has achieved certain results, the training of the prediction model requires lots of historical data as samples, and the actual tourism statistics have obvious seasonal differences, the sample data is insufficient, which affects the precision of the predictive model, and the research on the application of the predictive model to more complex problems is not sufficiently studied. Due to the limitations of tourism demand, the experiment only applied the research method to predict tourism demand in southern regions such as Sichuan in China and did not apply the research method to other countries or regions for experimental data validation. Therefore, future experiments will focus on predicting more factors affecting tourism demand in other regions.

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