Railway Freight Volume Prediction Based on SSA-BP

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Abstract: In order to accurately predict the railway freight volume, this paper proposes a railway freight volume prediction method based on Sparrow search algorithm (SSA) optimized Back Propagation (BP) neural network. This method utilizes the characteristics of fast convergence speed and strong optimization ability of SSA to optimize the initial threshold and weight of BP neural network, and effectively overcomes the problem that BP neural network is easy to fall into local optimization. Taking the railway freight volume data of China from 2001 to 2020 as the research object, the grey correlation analysis method is used to select the relevant influencing factors, and then the SSA-BP model is established to fit and predict the railway freight volume, and the prediction is compared with the traditional BP neural network and PSO-BP model. The example analysis shows that the MAPE value of SSA-BP model is 2.03%, which is the minimum of the models used. The prediction accuracy of SSA-BP model is better than that of BP neural network and PSO-BP network model, and SSA has faster convergence speed and better optimization effect than PSO.

Key words: railway transportation; sparrow search algorithm; SSA-BP; freight volume forecasting

1. INTRODUCTION

The national " Fourteenth Five-Year Plan" railway development plan points out that China's railway development is in an important stage of improving the network and improving efficiency, and will comprehensively promote the high-quality development of railways, making the facility network more perfect. It is expected that China's railway operation mileage will reach 165,000 kilometers in 2025. With railway transportation playing an increasingly important role in the logistics system, it is urgent to improve the competitiveness of railway transportation and comprehensively promote the high-quality development of railways. As a key link in railway transportation, railway freight volume prediction has extremely important strategic significance and has gradually become one of the hot issues of academic concern.

With the in-depth exploration of researchers, many forecasting methods have emerged in the field of railway capacity forecasting. Traditional forecasting methods include time series analysis[1][2], gray forecasting method[3][4], etc. The time series analysis method has the advantages of easy to understand the modeling process and simpler operation, but it has high requirements on the integrity of historical data and ignores the effect of influencing factors in the system; although the grey prediction method does not have high requirements for data

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integrity, it is also limited by data and only applies to short and medium term prediction[5]. The railway transportation system is a complex dynamic system with many influencing factors acting together, and the degree of influence of these factors varies, so the railway freight forecasting problem presents a high degree of nonlinearity and fuzziness. Artificial neural networks have powerful learning ability and good fitting effect on nonlinear features, so they are widely used in freight volume prediction, such as Long Short-Term Memory (LSTM) neural networks[6] and Generalized Neural Network (GNN)[7], etc. However, some neural network forecasting has the problems of easily falling into local optimum and slow convergence. scholars have made a lot of researches to overcome these drawbacks when applying neural networks for railway freight volume forecasting. Wang et al[8] applied gray correlation analysis to determine the influencing factors related to railway freight volume, and then applied BP neural network to forecast railway freight volume. Zhou et al[9] established a new combined prediction model and proposed an improved PSO-BP neural network to determine the combined weights. Zhang et al[10] proposed an ES-GA-BP railway freight volume forecasting model, and the example verified that the combined input ES-GA-BP method can effectively predict the fluctuating freight volume forecasting problem with relatively high prediction accuracy. Most of the above methods use traditional optimization algorithms to optimize the initial threshold and weight of the neural network. However, due to the limitations of the algorithm itself, there are still some shortcomings, such as easy to fall into local extremum and weak optimization ability. SSA, first proposed by Xue[11] in 2020, is a new swarm intelligent optimization algorithm based on the foraging and anti-predation behavior of sparrow population. Compared with traditional optimization algorithms, SSA has a simple structure, is easy to implement, has fewer control parameters, and has strong local search ability. It effectively overcomes the problem that traditional algorithms such as particle swarm optimization (PSO) and ant colony algorithm (ACO) are prone to fall into local optimization when solving problems. It has been applied in the fields of short-term traffic flow prediction[12], precipitation prediction[13], pollution source identification[14] and target's threat prediction[15]. The above research provides a good reference for our research.

Based on the above understanding, this paper proposes a railway freight volume forecasting method based on SSA-BP neural network model. Compared with the existing studies, the following work has been done: 1) Initially, multiple influencing factors related to railway freight volume are selected, and then multiple influencing factors are further preferred based on the correlation degree using gray correlation analysis; 2) In order to improve the problems that BP neural network is prone to fall into local optimal, slow convergence and inaccurate prediction, the sparrow search algorithm is used to optimize the initial weights and thresholds of BP neural network model, and a railway freight volume prediction model based on sparrow search algorithm (SSA) is established to optimize BP neural network; 3) A BP neural network model and a PSO-BP model are established to compare the forecasting with the SSA-BP model. The experimental results show that the SSA-BP model has the highest accuracy among the used forecasting models, effectively overcomes the problem that the BP neural network model easily falls into local optimum, and the SSA converges faster and has a better effect on finding the initial threshold and weights of the BP neural network compared with the PSO optimization algorithm.

The subsequent contents of the thesis are arranged as follows: Chapter 2 is the construction of SSA-BP neural network model, which includes relevant theories and model prediction steps;

Chapter 3 is the example analysis, which mainly includes data processing, selection of experimental evaluation indexes, setting of relevant parameters and analysis of prediction results; the last part is the conclusion.

2. MODEL CONSTRUCTION

2.1 Sparrow Search Algorithm (SSA)

In SSA, we classify the individuals into three categories: producers, joiners and watchers. Among them, the producers are responsible for providing the foraging direction for the whole population, the scroungers follow the producers for foraging, and the watchers monitor the foraging area to watch out for possible predators. The algorithm sets that the watchers in the population is 10%-20%, and the proportion of the total number of producers and scroungers in the whole population is constant, but they are dynamically changing, that is, when a sparrow becomes a producer, there must be another sparrow becoming a scrounger. In the process of foraging, the acquisition of resources is completed by updating the positions of the three.

The population composed of n sparrows can take the following forms:

$$X = \begin{bmatrix} x_{1,1}, x_{1,2}, \cdots, x_{1,d} \\ x_{2,1}, x_{2,2}, \cdots, x_{2,d} \\ \vdots \\ x_{n,1}, x_{n,2}, \cdots, x_{n,d} \end{bmatrix} \tag{1}$$

Where, n is the number of sparrows, and d is the dimension of the variables to be optimized. The fitness value of sparrow is expressed in the following form:

$$F_X = \begin{bmatrix} f([x_{1,1}, x_{1,2}, \cdots, x_{1,d}]) \\ f([x_{2,1}, x_{2,2}, \cdots, x_{2,d}]) \\ \vdots \\ f([x_{n,1}, x_{n,2}, \cdots, x_{n,d}]) \end{bmatrix} \tag{2}$$

Where f is the fitness value.

The location update description of the producer is as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \bullet \exp\left(-\dfrac{i}{\alpha \bullet iter_{\max}}\right) & if \quad R_2 < ST \\ X_{i,j}^{t} + Q \bullet L & if \quad R_2 \geq ST \end{cases} \tag{3}$$

Where, j =1, 2, 3, … , d, t represents the current iteration, $iter_{max}$ is a constant, represents the maximum number of iterations, $X_{i,j}$ represents the position information of the i th sparrow in the j th dimension, and $\alpha \in (0,1]$ is a random number. $R_2 (R_2 \in [0,1])$ and $ST (ST \in [0.5,1])$ represent the warning value and safety value respectively. Q is a random number subject to normal distribution. L represents a matrix of $1 \times d$, in which each element is 1.

When $R_2 < ST$, this means that the foraging environment around the producer is free of predators at this time and that search operations can be conducted in a wider area. When $R_2 \geq ST$, this means that some sparrows in the population have found the predator and have warned them to other sparrows. At this point, all sparrows in the population must quickly find other safe places to forage.

The updated description of the scrounger's location is as follows：

$$X_{i,j}^{t+1} = \begin{cases} Q \bullet \exp(\frac{X_{worst} - X_{i,j}^{t}}{i^2}) & if \quad i > n/2 \\ X_p^{t+1} + \left| X_{i,j}^{t} - X_p^{t+1} \right| \bullet A^{+} \bullet L & otherwise \end{cases} \tag{4}$$

Where X_{worst} is the worst position in the global at the current moment, and X_p is the best position among the positions currently occupied by the producer. A denotes a matrix of $1 \times d$ where each element is randomly assigned a value of 1 or -1 and $A^{+} = A^{T} \left(AA^{T} \right)^{-1}$. When $i > n/2$, this indicates that the i th scrounger with a lower fitness value is not getting food and is in a very hungry state, and they need to fly elsewhere to forage for more energy to meet their needs; when $i \leq n/2$, it indicates that the scroungers is foraging at the optimal position X_p.

The location of the watchers is updated in the following manner：

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \bullet \left| X_{i,j}^{t} - X_{best}^{t} \right| & if \quad f_i > f_g \\ X_{i,j}^{t} + K \bullet \left(\frac{\left| X_{i,j}^{t} - X_{worst}^{t} \right|}{\left(f_i - f_w \right) + \varepsilon} \right) & if \quad f_i = f_g \end{cases} \tag{5}$$

where X_{best} is the global optimal position at the current moment and β is the step control parameter, which follows a normal distribution with variance 1 and mean 0. $K \in \left[-1,1\right]$ is a random number indicating the direction of sparrow movement and also the step control parameter. f_i is the current fitness value of the individual sparrow, f_g and f_w are the current global best and worst fitness values, respectively. ε is set as a constant to avoid the case that the denominator is zero. When $f_i > f_g$, it means that the sparrow is at the edge of the population and is highly vulnerable to predators; when $f_i = f_g$, it means that the sparrow in the population is aware of the danger and will keep approaching other companions to stay away from the danger.

2.2 BP neural network optimized by SSA

BP (Back Propagation) neural network is one of the most widely used and successful neural networks in the world, as the name suggests, the core idea of BP neural network is backpropagation. The output value is compared with the actual value to get the output error, and then the output error is back propagated to all neurons in each layer from back to front, and the error signal obtained from each neuron is used as the basis to adjust its weights and thresholds in combination with the gradient descent method to achieve the purpose of reducing the error. When the global error is less than the expected error, or the learning times reach the maximum number of learning times, then the learning can be stopped. the composition of BP neural network is mainly divided into three parts: input layer, hidden layer and output layer, where the hidden layer can have single layer and multi-layer, but the most widely used is a single layer hidden layer, that is, three-layer BP neural network.

Since the initial weights and thresholds of BP neural networks are generally obtained by random initialization, this makes the training time longer, the convergence speed slower, and the prediction results easily fall into local optimum. Therefore, SSA is introduced to optimize the initial weights and thresholds of the BP neural network to solve the above problems. The implementation steps of SSA-BP neural network model are as follows:

1) Data normalization. In the original data, different feature dimensions often have different dimensions and dimensional units, which will cause the problem that the algorithm cannot converge or converges slowly. Therefore, in order to eliminate the impact of dimensions between different feature dimensions, it is necessary to normalize the original data.

2) Determine the structure of the BP neural network. The number of layers in the hidden layer is determined as needed, the number of neurons in the input layer is m, the number of neurons in the output layer is q, and the number of neurons in the hidden layer p is determined according to the empirical formula.

$$p = \sqrt{m+q} + a \tag{6}$$

where a takes on a constant value between 0 and 10.

3) Determine the SSA parameters. Determine the maximum number of SSA iterations and the population size, then initialize the location of the sparrow population.

4) Define the fitness function and determine the individual fitness values. The individual positions in the population represent the initial weights and thresholds of the BP neural network, and the initial weights and thresholds are used to train the network, and the global error obtained

is used as the fitness function. Find the optimal fitness value of the current population and the optimal individual position.

5) Update the sparrow position. According to formula (3), (4) and (5), the positions of producers, scroungers and vigilantes are updated.

6) Verify that the maximum number of iterations is reached. Verify that the algorithm meets the termination condition, i.e., the maximum number of iterations is reached. When the maximum number of iterations is reached, the optimal individual position is output, i.e., the optimal weight and threshold; otherwise, the iteration is continued.

7) Substitute the optimal weights and thresholds for training. The optimal weights and thresholds output by SSA are substituted into the BP neural network as the initial weights and thresholds for network training.

3. CASE ANALYSIS

3.1 Data preprocessing

The experimental data in this paper are all taken from the official website of the National Bureau of Statistics. The experiment takes the annual data of the national railway freight volume from 2001 to 2020 as the prediction sample, as shown in Figure 1. Taking the railway freight volume from 2001 to 2016 as the training data, and the railway freight volume from 2017 to 2020 as the test data, BP, PSO-BP, SSA-BP and other three network models are respectively established to predict under the Matlab R2020a environment.

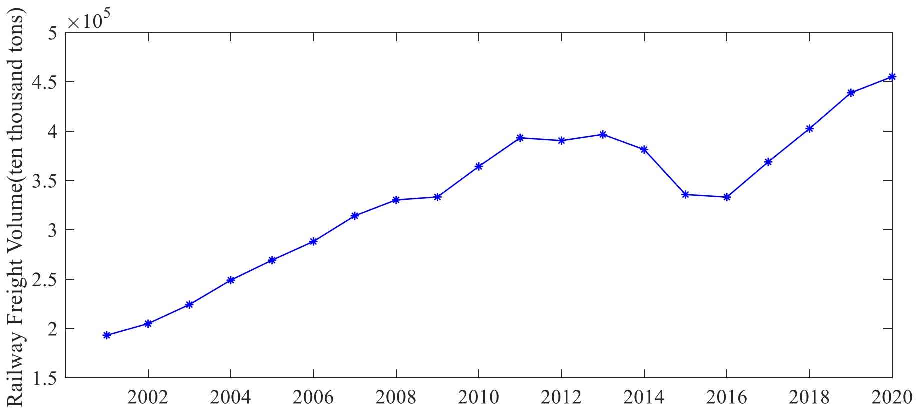

Figure 1. Railway freight volume from 2001 to 2020

Railway freight volume is usually affected by various factors. Through literature research and summary, the following factors are selected in this paper: GDP (X_1), national railway freight turnover (X_2), highway freight volume (X_3), waterway freight volume (X_4), added value of the secondary industry (X_5), railway operating mileage (X_6), raw coal output (X_7), steel output (X_8), and added value of the primary industry (X_9).

Through the grey correlation analysis method, the correlation degree between the above factors and the railway freight volume is as follows: γ_1=0.5202, γ_2=0.9190, γ_3=6744, γ_4=0.5563, γ_5=0.5603, γ_6=0.7457, γ_7=0.8443, γ_8=0.6124, γ_9=0.6065. Because the correlation degree below 0.6 is generally considered as a weak correlation degree factor and is not considered as a key factor, the final selected influencing factors are: national railway freight turnover (X_2), highway freight volume (X_3), railway operating mileage (X_6), raw coal output (X_7), steel output (X_8), and added value of the primary industry (X_9). Some of the final influencing factors are shown in Table 1.

Table 1. Values of some influencing factors

Year	X_2 / hundred million ton kilometers	X_3 / ten thousand tons	X_6 /ten thousand kilometers	X_7 / hundred millions tons	X_8 / ten thousand tons	X_9 / hundred million yuan
2001	14694.10	1056312	7.01	14.72	16067.61	15502.5
2002	15658.40	1116324	7.19	15.50	19251.59	16190.2
2003	17246.70	1159957	7.30	18.35	24108.01	16970.2
2004	19288.80	1244990	7.44	21.23	31975.72	20904.3
…	…	…	…	…	…	…
2017	26962.20	3686858	12.70	35.24	104642.05	62099.5
2018	28820.99	3956871	13.17	36.98	113287.33	64745.2
2019	30181.95	3435480	13.99	38.46	120456.94	70473.60
2020	30514.46	3426413	14.63	39.02	132489.18	78030.90

3.2 Experimental evaluation

To evaluate the model prediction performance, the relative error (RE) and the mean absolute percentage error (MAPE) are selected as the evaluation indicators in this paper:

$$RE = \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$
$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{7}$$

Where, y_i is the original freight volume, $\hat{y}_i$ is the predicted freight volume, and N is the sample size.

3.3 Parameter setting

After many tests to achieve the best results, this paper sets the population size of SSA species sparrows as 30, the maximum iteration number as 30, the upper and lower limits of population individuals as +5 and -5 respectively, the proportion of producers and watchers is 20%, the vigilance value is set as 0.8, the BP neural network structure is 6-7-1, that is, the number of neurons in the hidden layer is 7, and the learning rate is 0.1. The maximum number of iterations is 1000, and the learning objective is 1×10^{-5}.

3.4 Analysis of prediction results

The data were input into the SSA-BP network model for fitting and prediction, and the number of SSA iterations was shown in Figure 2. It can be seen that the best fitness value of the SSA algorithm was obtained after 7 iterations. The comparison between the predicted value and the real value is shown in Figure 3, and its MAPE value is 2.03%. We can see that the SSA-BP model can perform a good fit to the railway freight volume data.

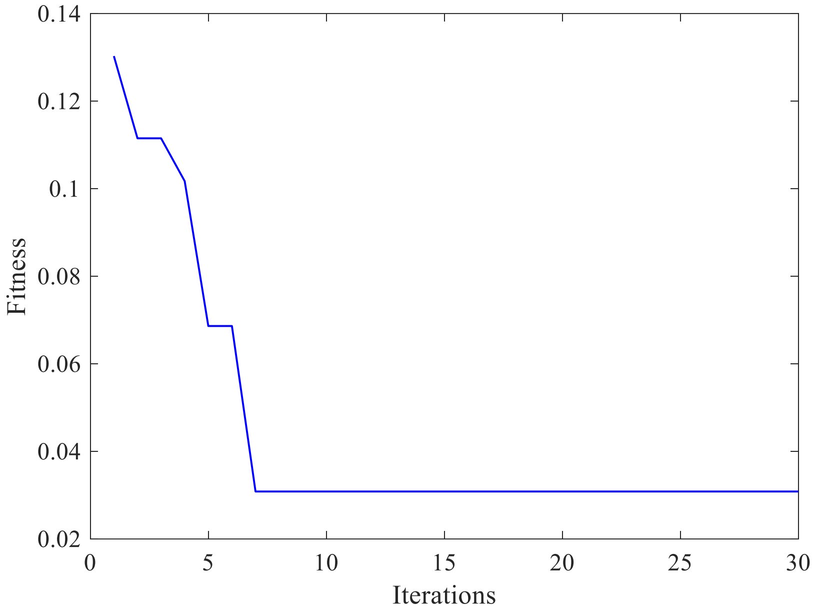

Figure 2. Iterative process of SSA algorithm

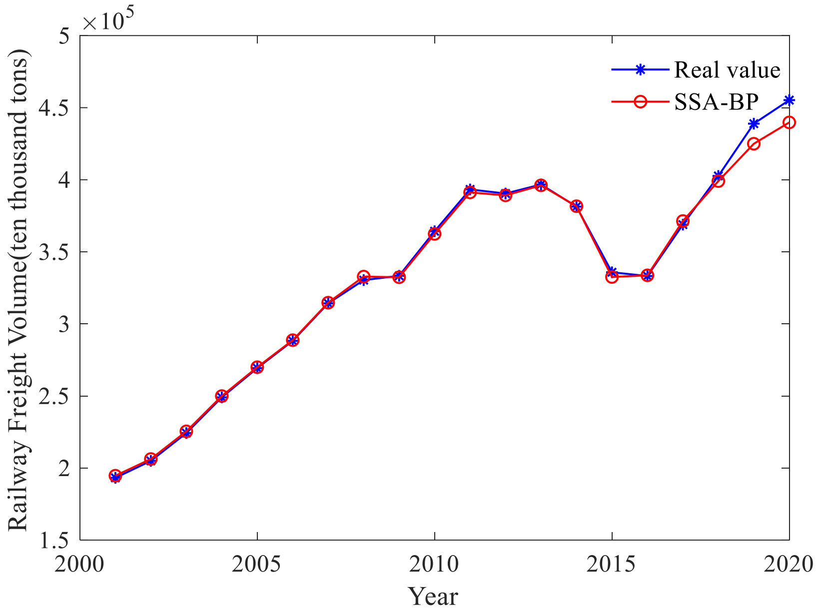

Figure 3. Comparison between the predicted value and the real value of SSA-BP model

In order to prove the effectiveness of the SSA-BP model, this paper uses the traditional BP neural network model and PSO-BP network model to compare the predictions, and the predicted values, real values and prediction error statistics of each model for the railway freight volume from 2017 to 2020 are shown in Table 2.

Table 2. Railway freight volume forecast results and error statistics

Year	Real value (Ten thousand tons)	BP		PSO-BP		SSA-BP	
		Predicted value (Ten thousand tons)	RE(%)	Predicted value (Ten thousand tons)	RE(%)	Predicted value (Ten thousand tons)	RE(%)
2017	368865	363370	1.49	372600	1.01	371400	0.69
2018	402631	395040	1.89	394700	1.97	399100	0.88
2019	438904	391290	10.85	424800	3.21	425000	3.17
2020	455236	406290	10.75	423300	7.02	439800	3.39
MAPE(%)		6.24		3.30		2.03	

In order to more intuitively show the comparison of the prediction effects of each model, we put the fitting prediction curves of the three models into the same figure, as shown in Figure 4. It is easy to see that the prediction effect of SSA-BP and PSO-BP network model is significantly better than that of simple BP neural network, indicating that the two optimization algorithms can optimize the threshold and weight of BP neural network, and effectively overcome the defect that BP neural network is easy to fall into local minima. In addition, the forecasting effect of the SSA-BP model is significantly better than that of the PSO-BP network model, which proves the superiority of SSA.

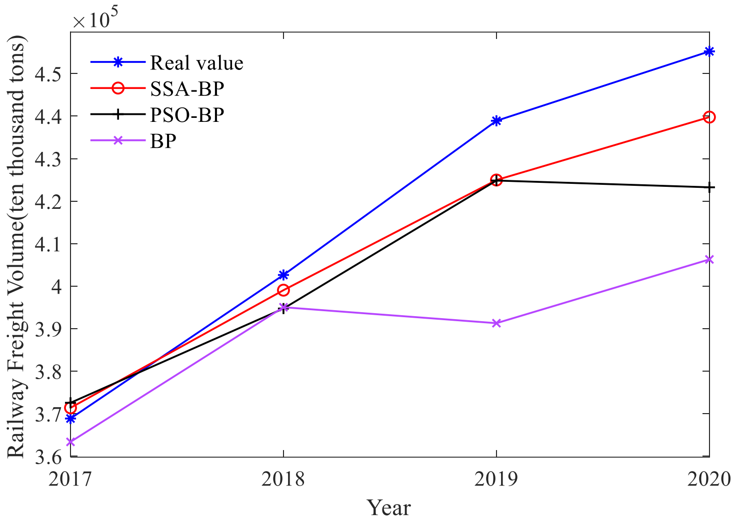

Figure 4. Comparison of the prediction effect of each model

The comparison of the iteration process of SSA and PSO is shown in Figure 5. SSA obtains the best fitness value after 7 iterations, while PSO requires 19 iterations, and the best fitness value of SSA is better than that of PSO. It can be seen that compared with PSO, SSA has stronger optimization ability and faster convergence speed. Therefore, the prediction effect of SSA-BP network model is better.

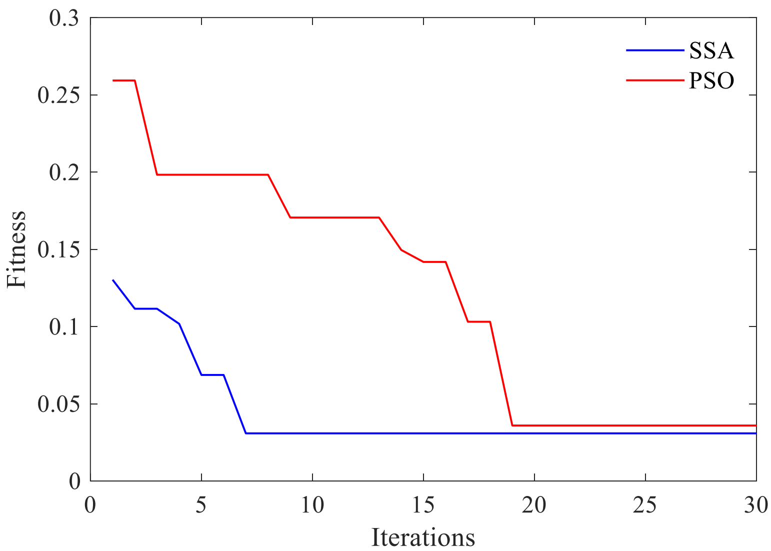

Figure 5. Comparison of SSA and PSO convergence speed

4. CONCLUSION

To improve the existing railway freight volume forecasting method, this paper proposes a forecasting method based on the Sparrow Search Algorithm (SSA) optimized BP neural network, uses the gray correlation analysis to determine the relevant influencing factors, fits the Chinese railway freight volume data from 2001 to 2020 for forecasting, and conducts comparison experiments with BP neural network and PSO-BP network model forecasting. The experimental results show that the evaluation indexes of the SSA-BP neural network model are all the best in the used model, indicating that its prediction accuracy is the highest. Compared with the BP neural network prediction, the SSA-BP network model greatly overcomes the shortcomings of the BP neural network, which is too dependent on the initial value and easily falls into local optimum, by virtue of the strong optimization-seeking ability and fast convergence of the SSA, and has better prediction effect; compared with the PSO-BP network model, the prediction accuracy of the SSA-BP network model is higher. Although PSO has certain optimization effect on BP neural network, SSA has better optimization effect on initial weights and thresholds of BP neural network and faster convergence speed.

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