Port Logistics Demand Forecast Based on Grey Neural Network with Improved Particle Swarm Optimization

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Abstract In order to improve the accuracy of port logistics demand prediction, the improved Particle Swarm Optimization algorithm, Grey Model and Neural Network are combined to construct an Improved Particle Swarm Optimization Grey Neural Network(IPSO-GNN) prediction model, in which the improved Particle Swarm Optimization algorithm is used to find the weight and threshold of the Grey Neural Network to improve the accuracy of the prediction. Using the logistics demand data of Dalian Port, the prediction effect of the proposed IPSO-GNN model is compared with that of the BP Neural Network model, the Grey model, the Grey Neural Network model and the standard Particle Swarm Optimization Grey Neural Network model. The empirical results show that the IPSO-GNN model has high precision and strong stability, which can predict port logistics demand effectively.

Keywords Improved particle swarm optimization grey neural network · Grey relational analysis · Port logistics demand prediction

1 Introduction

With the rise of northeast Asia economic circle, Dalian port logistics will meet greater development prospects and challenges. Port logistics demand is an important indicator in the port logistics system. Accurate prediction of port logistics demand will provide an important basis for the development of port logistics and logistics infrastructure planning. However, port logistics is a complex nonlinear system, which is

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influenced by social, economic, natural and other factors, and the mapping relationship between these factors cannot be described in an accurate mathematical language, which leads to the prediction difficulty.

At present, the methods used in logistics demand forecasting can be divided into two categories: qualitative forecasting and quantitative forecasting. Qualitative prediction methods mainly include expert investigation method, Delphi method, subjective probability method and so on. Qualitative forecasting method is more flexible and simpler, but it is difficult to accurately describe the logistics demand due to the influence of subjective factors. Quantitative prediction methods mainly include moving average method, regression analysis method, exponential smoothing method, grey theory model, neural network prediction model and so on. Using the GM (1, 1) model to predict the port logistics demand of Guangxi Beibu gulf, providing decision-making basis for relevant government departments [1]. Establishing the BP neural network model to predict the port logistics demand of Cao Feidian port and put forward policy Suggestions for the future development of modern logistics [2]. Considering the characteristic of logistics demand with nonlinear changes, proposing a combined forecasting model based on BP and RBF neural network, the empirical results show that the combination forecast model than single prediction model has higher prediction accuracy, reducing the probability of error effectively in larger, making the forecast results closer to reality, and propose the port logistics development planning for the future [3]. Neural network can be used to solve nonlinear and complicated prediction problems, but it has some disadvantages such as large amount of data required for training, high cost of data collection, and easy occurrence of local optima. Although the grey model requires only a small amount of data, the prediction accuracy is not high. The Grey Neural Network (GNN) model makes up for the above defects to some extent, combining the advantages of strong nonlinear fitting ability of Neural Network and high accuracy of Grey Model under the condition of small amount of calculation and few samples. The Grey BP Neural Network model has higher prediction accuracy than the single grey prediction model [4, 5]. The grey neural network model could help enterprises predict the market demand better after transportation interruption, and then empirical research tested its possibility [6]. However, due to the randomness of the determination of initial weight and threshold of GNN, the network is prone to fall into the local optimal, the results of each prediction are different and the deviation is large. Particle Swarm Optimization (PSO) is an optimization algorithm based on swarm intelligence theory, which has good robustness and global search ability. Optimization of GNN weights and thresholds by PSO can make up for the above shortcomings. Particle swarm optimization grey neural network model to predict proton exchange membrane fuel cell (PEMFC) degradation, and the results showed that the prediction accuracy of this method was high [7].

Because the port logistics demand data is relatively small and has strong non-linear relationship, it is very important to establish a suitable model to predict the future port logistics demand, according to the port logistics demand data. GNN has the advantages of strong non-linear fitting ability, small calculation amount and high calculation accuracy for small sample data. PSO has good robustness and global

search ability, which is fully suitable for port logistics demand prediction. However, the standard PSO is easy to fall into local minimum point and the problem such as premature convergence, so this article on the basis of the above study, the improved PSO algorithm (IPSO) optimizes geri weis-corbley weights and thresholds by the weights of the nonlinear regressive strategy and strategy of dynamic accelerated learning factor, adjusting and balancing between global and local search capabilities, building the improved particle swarm optimization of grey neural network forecast model, and applied to port logistics demand forecasting in order to improve the prediction accuracy.

2 Prediction Model Based on IPSO-GNN

2.1 Gray Neural Network

The principle of GNN is to map the whitening equation of Grey Model (GM) into a BP neural network. When the network is trained and converges, the corresponding connection weight coefficient $a, b_1, b_2, \ldots, b_{n-1}$ is extracted from the trained network to obtain a whitening differential equation, and then the data fitting and prediction are performed according to this differential equation [8, 9]. The topology of the gray neural network is shown in Fig. 1.

In the figure, t is the serial number of the input parameter, $y_2(t), y_3(t), \ldots, y_n(t)$ are the network input parameter, $\omega_{21}, \ldots, \omega_{3n}$ are the network weight, $\omega_{11} = a, \omega_{21} = -y_1(0), \omega_{22} = \frac{2b_1}{a}, \ldots, \omega_{2n} = \frac{2b_{n-1}}{a}, \omega_{31} = \omega_{32} = \cdots = \omega_{3n} = 1 + e^{-at}$, y_1 is the network prediction value, and $\theta = \left(1 + e^{-at}\right)(d - y_1(0))$ is the output node threshold of LD layer. The error criterion of the algorithm adjusts the weight
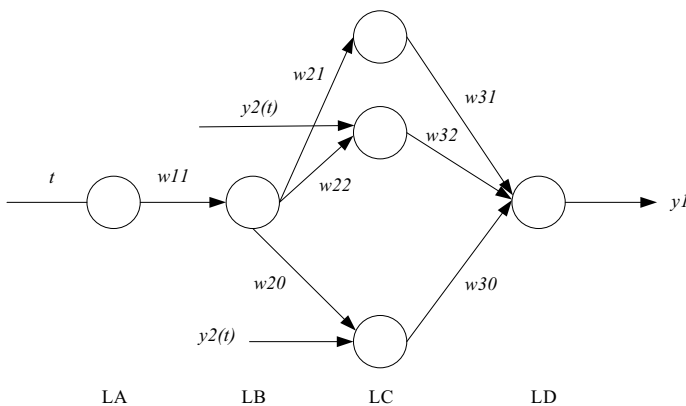

Fig. 1 The topology of the grey neural network

to minimize the deviations. Therefore, it is crucial to obtain the initial value of $a, b_1, b_2, \ldots, b_{n-1}$ of GNN.

2.2 Improved Particle Swarm Optimization Algorithm

The basic idea of PSO [10, 11] is to use the information contained in each particle to express the optimal solution of the optimization problem. The important parameters affect the performance of PSO including flight speed, inertia weight and learning factor. Therefore, optimizing the inertia weight ω and learning factor can improve the performance of the algorithm. Inertia weight ω is used to control the exploration and convergence ability of the algorithm. When the ω is larger, it has stronger global search ability, it is more conducive to local search when ω is smaller. Learning factor is used to guide the algorithm to search for the optimal solution. In the early stage of optimization, particles should be encouraged to search in a larger space to keep the diversity of particles. Therefore, c_1 is larger and c_2 is smaller to speed up the search speed of particle swarm. In the later stage of optimization, the center of gravity of particle swarm is in the global optimal solution, so c_1 is smaller and c_2 is larger to keep particle swarm accurate search. Based on the algorithms proposed in literature [12–14], this paper firstly adopts an improved weight nonlinear descending strategy for setting the inertial weight ω, so that the PSO algorithm can better balance the global and local search capabilities. Secondly, adopting the learning factor strategy of dynamic acceleration, c_1 and c_2 change linearly with the number of iterations. The improved particle swarm optimization algorithm is shown as follows:

- In this paper, inertial weight ω can better balance and adjust the local and global search capability of PSO algorithm by introducing tangent function. The calculation formula is as follows:

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) * \tan\left(\frac{\pi}{4} * \left(1 - \frac{t}{T_{\max}}\right)^\theta\right) \tag{1}$$

- The learning factor c_1 and c_2 of dynamic acceleration in this paper are between the minimum value and the maximum value all the time, so it is easy to avoid c_1 and c_2 falling into the local optimum if the learning factor is too large or too small. The calculation formula is as follows:

$$c_1(t) = c_{1\max} - (c_{1\max} - c_{1\min}) * \frac{t}{T_{\max}} \tag{2}$$

$$c_2(t) = c_{2\min} + (c_{2\max} - c_{2\min}) * \frac{t}{T_{\max}} \tag{3}$$

Among them, t is the current iteration number, T_{max} is the maximum iteration number, θ is the curve adjustment factor, and θ is 2 in this algorithm after several experiments. In general, $\omega_{max} = 1$, $\omega_{min} = 0.5$, the values of c_{1min} and c_{2min} are 1, and the values of c_{1max} and c_{2max} are 2.

The updated formula of particle velocity and position of the improved particle swarm optimization algorithm are as follows:

$$v_{id}(t+1) = v_{id}(t) + c_1(t)r_1(p_{id} - x_{id}(t)) + c_2(t)r_2(p_{gd} - x_{id}(t)) \qquad (4)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (5)$$

Among them, r_1 and r_2 is the random number [0, 1], x_{id} is the current position of the particle, p_{id} is the optimal solution of the particle history, and p_{gd} is the global optimal solution.

2.3 Improved Particle Swarm Optimization Algorithm to Optimize Grey Neural Network

GNN has a fast convergence speed, but its initial weights and thresholds are determined randomly, so that the network is prone to local optimization [14]. Therefore, Improved Particle Swarm Optimization algorithm can obtain the optimal GNN parameters. IPSO-GNN algorithm uses IPSO algorithm to optimize the $a, b_1, b_2, \ldots, b_{n-1}$ parameters of GNN, and takes the mean square error of training samples as the function of individual adaptive value. The global optimal solution as the initial weight and threshold of GNN to train the network, so that achieve the training goal of the network. The specific algorithm steps are as follows:

(1) Divide the original data into training samples and test samples;
(2) *Initialization parameters:* initialize the maximum and minimum value of the learning factor of the particle, the maximum and minimum value of the inertial weight, the position and speed of the particle, and assign a set of parameters corresponding to each position the initial particle passes through. Since the initial weight and threshold of GNN are determined by equal n parameters, the dimension of the particle swarm is $D = n$.
(3) Set the fitness function of particle swarm, prediction mean square error (MSE) of the training sample as the function of individual adaptive value. Because there is only one output neuron of GNN, formula can be simplified as: $MSE = \frac{1}{n}\sum_{i=1}^{n}(o_i - y_i)^2$, among them, n as the number of training samples, o_i is the actual output of the i th sample, y_i is the expected output of i th sample;
(4) Compare and analyse the fitness value of each particle and its corresponding optimal value, and then judge whether satisfying the condition of iteration. If so, these are the optimal parameter combination. Go to step (6); otherwise, go to step (5);

(5) According to formula (4) and (5), the particle speed and position are repeatedly update, and judge if meet the optimal solution conditions. When meeting the conditions that the minimum precision value of fitness or the maximum number of iterations, go to step (6); otherwise, go to step (5);

(6) Obtain the optimal parameters;

(7) Substitute the optimal parameters as the initial weight and threshold of GNN into the network for training until the training error (or iteration times) of the network reaches the predetermined value. The IPSO-GNN algorithm flow shows in Fig. 2.
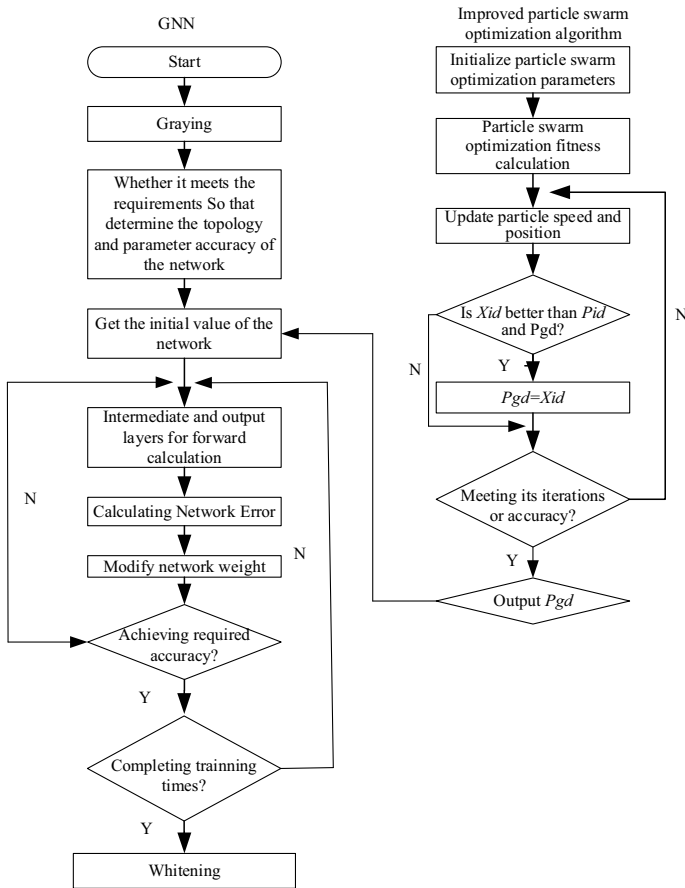

Fig. 2 The IPSO-GNN algorithm flow

3 Selection of Logistics Demand Forecast Index of Dalian Port

3.1 Influencing Factors Analysis of Dalian Port Logistics Demand Forecast

Zhu et al. Select four indicators that are the added value of the primary industry, the added value of the secondary industry, the total amount of import and export, and the investment in fixed assets of the whole society as the indicators to predict the port cargo logistics demand [1]. Gao et al. select the port city GDP, industrial GDP, tertiary industry GDP, total foreign trade, total retail sales, per capita income, and per capita consumption level as the indicators affecting the port logistics demand of Feidian [2]. Cai and Huang Select the three industrial values, total imports and exports, total retail sales of consumer goods and fixed asset investment in the direct economic hinterland as the influencing factors of the logistics demand of Shantou port [3]. Basing on relevant literature, because the port logistics demand amount is closely related to the hinterland economic aggregate, which can predict port logistics demand rely on the correlation between the two. combined with the actual situation of Dalian port logistics development, this paper selects the total regional GDP (a_1), added value of primary industry (a_2), added value of secondary industry (a_3), added value of tertiary industry (a_4), fixed asset investment of the whole society(a_5), total retail sales of consumer goods (a_6), total imports and exports (a_7), annual disposable income (a_8), and annual per capita consumption expenditure (a_9) nine indicators to predict the cargo logistics demand in Dalian Port. The statistical data of logistics demand impact indicators of Dalian port in 2001–2018 is shown in Table 1. Among them, the unit of a_1, a_3, a_4 and a_6 are RMB 100 million, the unit of a_5 and a_7 are dollars 100 million, the unit of a_8 and a_9 are RMB, the unit of a_0 is 100 million tons.

3.2 Analysis and Selection of Logistics Demand Index of Dalian Port

Grey relation analysis is based on the grey system theory proposed by Professor Julong Deng. Processing the various factors through data in incomplete information to find the correlation degree among them [15–17]. Introducing grey correlation analysis method is to further determine the correlation among the logistics demand of Dalian port and various impact indicators. The statistical data of the logistics demand impact indicators of Dalian port is shown in Table 1. It is necessary to select the indicators that have a significant impact on the logistics demand of Dalian port, namely the key indicators (the correlation degree is greater than 0.6). The correlation degree among each indicator and the logistics demand of Dalian port is determined by Calculated by DPS software, the specific results are as follows:

Table 1 Statistics of logistics demand impact indicators of Dalian port in 2001–2018

Year	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_0
2001	1235.6	111.4	574.2	550	305.1	534.2	112.4	7418	6512	1.05
2002	1406	118.4	661.1	626.5	367.9	591.9	129.86	8200	7118	1.12
2003	1632.6	145.6	782.1	704.9	506.9	568.45	155.4	9101	7760	1.26
2004	1961.8	153.1	983.3	825.4	716.2	645.2	194.3	10,378	8672	1.45
2005	2150	185.2	994	970.8	1110.5	732	235.23	11,994	9996	1.71
2006	2569.7	208.6	1229	1132	1469.5	839.3	293.24	13,350	10,534	2
2007	3131	247.6	1536.5	1346.9	1930.8	983.3	363.03	15,109	12,135	2.2
2008	3858.2	289.1	1993.9	1575.2	2513.4	1182.6	449.09	17,500	14,101	2.46
2009	4417.7	313.4	2314.8	1789.5	3273.5	1396.7	403.47	19,014	15,330	2.73
2010	5158.1	345.1	2645.5	2167.5	5084.3	1639.8	501.95	21,293	16,580	3.14
2011	6150.1	395.7	3204.2	2550.2	4580.1	1924.8	585.25	24,276	18,846	3.4
2012	7002.8	451.4	3634.8	2916.7	5654.1	2224	625.63	27,539	20,417	3.7
2013	7650.8	477.6	3892	3281.2	6478.1	2526.5	676.55	30,238	22,516	4.1
2014	7655.6	441.8	3696.5	3517.2	6773.6	2828.4	645.78	33,591	27,482	4.2
2015	7731.6	453.3	3580.8	3697.5	4559.3	3084.3	550.91	35,889	25,824	4.15
2016	6810.2	462.8	2849.9	3497.6	1436.4	3410.1	547.6	38,050	27,119	4.4
2017	7363.9	477.1	3052.6	3834.3	1652.8	3722.5	666.43	40,587	27,191	4.6
2018	7668.5	442.7	3241.6	3984.2	1819.7	3880.1	759.06	43,550	29,928	4.7

Note The data are from the website of Dalian Statistics Bureau

$$\rho_{a1} = 0.6597 \rho_{a2} = 0.7207 \rho_{a3} = 0.5616$$
$$\rho_{a4} = 0.6578 \rho_{a5} = 0.3838$$

$$\rho_{a6} = 0.5823 \rho_{a7} = 0.6475 \rho_{a8} = 0.6406$$
$$\rho_{a9} = 0.6793$$

The larger the correlation value, the greater the impact of this index on the logistics demand of Dalian port is. By sorting the above correlation values, we can get: the values of a_2, a_4, a_9, a_1, a_7 and a_8 six variables are relatively large, that is to say, the added value of the primary industry, the added value of the tertiary industry, the annual per capita consumption expenditure, the GDP of the whole region, the total amount of import and export, and the annual disposable income six indicators are selected as the key indicators. The logistics demand forecast index set of Dalian port is shown in Table 2.

Table 2 Dalian port logistics demand forecast index set

Dalian port logistics demand forecast index	Economic scale index	GDP of the whole region
	Index of industrial organization	Added value of primary industry and tertiary industry
	Domestic and foreign trade indicators	Total imports and exports
	Consumption index of residents	Annual disposable income and annual per capita consumption expenditure

4 Logistics Demand Prediction Dalian Port Based on IPSO-GNN

4.1 Establish a Prediction Model Based on IPSO-GNN

Take the data in Table 1 from 2001 to 2015 as the network training data, and the data in 2016–2018 as the network test data. In order to prevent the net input absolute value too large cause the saturation of neuron output, so that reduce the convergence of training network, it is necessary to make Dalian port logistics demand indicators statistics normalization. IPSO-GNN model sets six input variables and one output variable, and network hidden layer adopts multi-layer deep learning mode.

4.2 Model Prediction Results and Analysis

Empirical research adopts the gradual model analysis method, including BP neural network model, GM (1, 1) model, GNN model, standard particle swarm optimization grey neural network (PSO-GNN) model and IPSO-GNN model to predict the logistics demand of Dalian port. Using matlabr2012b programming software realize the above algorithm. The calculation results of prediction error and mean square error of each prediction model are shown in Table 3, in which the unit of actual values and prediction values are 100 million yuan.

From the Table 3, the following conclusions can be drawn:

- From the comparison of real and predicted values in 2016–2018, the mean error of prediction value under BP neural network model, grey GM (1,1) model, GNN model, PSO-GNN model and IPSO-GNN model are 11.12%, 24.9%, 5%, 2.96% and 1.71% respectively, the mean square errors are 0.2622, 1.4138, 0.0582, 0.0184 and 0.0076. The IPSO-GNN prediction model proposed in this paper has the smallest deviation and the highest accuracy from the original data, which is suitable for the prediction of port logistics demand.

Table 3 Comparison of simulation results

Year	Actual value	BP		GM (1, 1)		GNN		PSO-GNN		IPSO-GNN	
		Prediction value	Relative error (%)	Prediction value	Relative error (%)	Prediction value	Relative error (%)	Prediction value	Relative error (%)	Prediction value	Relative error (%)
2016	4.4	3.969	9.8	5.19	17.7	4.188	4.83	4.239	3.66	4.534	3.04
2017	4.6	4.05	11.96	5.694	23.79	4.279	6.99	4.485	2.51	4.659	1.29
2018	4.7	4.154	11.61	6.261	33.22	4.551	3.17	4.573	2.7	4.737	0.79
Mean error (%)		11.12		24.9		5		2.96		1.71	
MSE		0.2622		1.4138		0.0582		0.0184		0.0076	

- Although there are random fluctuations in the original port logistics demand, the mean error and mean square error of the model in this paper are the smallest. With the increase of the forecast year, the relative error of the forecast results than other forecast models have volatility, while the relative error of the forecast results of the algorithm in this paper decreases year by year, with high stability. The IPSO-GNN model prediction results are in good agreement with the original port logistics demand data, which proves the stability of the algorithm.

5   Conclusions

Based on the study of particle swarm optimization and grey neural network, combined with the characteristics of port logistics demand forecasting, this paper applies innovatively the improved particle swarm optimization grey neural network model to port logistics demand forecasting. The improved particle swarm algorithm optimizes the weight and threshold value of the grey neural network to improve the prediction accuracy, which effectively solves the problems that randomness given by the initial parameters of the grey neural network and easy to fall into local optimum. This present paper compares with BP neural network model, GM (1, 1) model, GNN model, PSO-GNN model, IPSO-GNN model in Dalian port logistics demand prediction results, shows that IPSO-GNN prediction model can significantly improve the prediction accuracy of port logistics demand, and the model stability is stronger.

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