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The analysis of commodity demand predication in supply chain network based on particle swarm optimization algorithm

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ABSTRACT

The supply chain network model is constructed in this study based on comparison of traditional supply chain and the modern supply chain so as to solve the poor communication effect, uncirculated information, and unbalanced supply and demand in enterprises. After three algorithms and three commodity predication models are compared, a model combining with the network neural commodity demand predication method and the particle swarm optimization (PSO) algorithm is used to comprehensively evaluate the predication effect and algorithm performance by using the supply chain data of the enterprises, coming up with an optimal model. Results of the study show that: on national warehouses and regional warehouses, the difference between the predicted value and the actual value of autoregressive integrated (AR) mixture density networks (MDN) (AR-MDN) is 15%, the average outlier is between 450 and 150, the score of root mean square error (RMSE) and mean absolute percentage error (MAPE) is 117.342 and 2.334, respectively. It indicates that the fitting trend, prediction accuracy, and stability of the model are better than those of the autoregressive integrated moving average model (ARIMA) and multilayer perceptron-long short term memory (MLP-LSTM) model. Regarding determination of the stochastic requirements, the average optimal solution of the improved PSO (IPSO) is 0.45, indicating that performance of the algorithm is significantly stronger than that of the PSO algorithm and the artificial bee colony (ABC) algorithm; the comprehensive evaluation score of the combination model for the IPSO algorithm and the AR-MDN commodity prediction model is 67.41 with the optimal effect. The supply chain network model constructed in this study can provide enterprises with a good commodity demand predication method and improve their ability to respond to risks in the supply chain.

1. Introduction

With the continuous development of the economic society, more and more enterprises gradually convert from the original business to cooperative pattern, which will greatly change the structure of modern industrial organization [1]. The traditional supply chain is based on the manufacturers, sellers, and consumers, each of which is an independent

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system and builds a relationship of interest through the circulation of products [2,3]. However, more and more cooperation has emerged in this link, such as commodity supply before payment and commodity selling before cost paying off, which is based on mutual trust. In addition, the exchanges and cooperation between various enterprises become more frequent with the continuous improvement of Internet information technology means [4]. In the face of the impact from the Internet industry, disadvantages of the traditional supply chain system become more obvious, such as untimely communication of information and the uncoordinated supply and demand. As a result, the overall efficiency of the enterprise cannot be improved, because each link is restricted by the upper and lower companies, which is the main contradiction for modern enterprises [5]. With development of the deep learning technology based on the neural network and different data mining algorithms, the supply chain network is optimized continuously, more and more enterprises become the links in the supply chain [6]. In short, it is of great practical significance to establish a supply chain network model satisfying the actual situation for enterprises to assume the smallest risks and obtain the greatest benefits in a market-balanced state, and realize the sustainable development.

Most of the researches on supply chain network focus on simplifying practical problems and strengthening the connection between data and financial information among various enterprises. Among them, Quddu et al. (2018) revealed the impact of municipal solid waste utilization on the performance of the biofuel supply chain network using the combined sample average approximation algorithm [7]. Mishra et al. (2018) solved the design problems of the closed-loop supply chain using the genetic algorithm (GA) and optimization algorithms, and verified the feasibility of the model and the applicability of the developed solution method [8]. Fu (2019) constructed the enterprise supply chain model through the Cplex enhancing constraint method and social impact coefficient and verified it in wine companies, and the results proved that this method is effective and feasible [9]. Madani et al. (2020) developed a new supply chain model with the hybrid heuristic algorithm, and proved its application in practical applicability [10]. Therefore, enterprises face how to use efficient algorithms to meet the stochastic needs of consumers for commodities, which will change with the change of commodity price, logistics, quality, and time [11]. Therefore, whether an enterprise can change and make corresponding decisions according to demand is directly related to the sustainable development of the enterprise under market competition. Using various algorithms and technologies to construct a decision model has become a hot research topic in this field.

After the traditional and modern network supply chain models are compared, various predication models of supply chain network are constructed based on the supply chain network model in modern industrial organizations, using ABC (Activity Based Classification), PSO (Particle Swarm Optimization), and the improved forward algorithm and combine with the neural network predication model, time series model, and average auto-regressive model. The combined model is verified with logistics data of the enterprises, and the various models are evaluated comprehensively. It provides a theoretical basis and has a practical significance for solving the problems in the current supply chain network predication.

The innovations of this study can be summarized as follows. The commodity demand prediction method based on the AR-MDN (Autoregressive Integrated Mixture Density Networks) model is to apply the popular deep learning method to the prediction of commodity demand in the supply chain management of e-commerce; it is an important step in replenishment planning and inventory decision-making; and it is a relatively new thinking and method proposed to reduce the prediction error of commodity demand. The PSO algorithm is improved and applied to the supply chain network optimization model. After comparison with GA (Genetic Algorithm), the IPSO (Improved PSO) algorithm can obtain the global optimal solution, with fast convergence speed and good stability. In addition, it has good performance and can effectively avoid premature convergence of the algorithm, so the proposed algorithm can provide a new solution tool for supply chain network optimization.

2. Literature overview

2.1. Current research state of commodity demand prediction

In different industries, there are different levels of demand prediction. Demand prediction is an extremely important part in e-commerce supply chain commodity inventory management. It is of great significance to improve the accuracy of prediction results by studying the factors that affect the demand. Accurate prediction results are crucial to the replenishment strategy of enterprises and the reduction of inventory costs. Wa et al. (2018) studied the supply and demand management strategies of seasonal commodities, and used the Winter model to make predictions [12]. Tran et al. (2019) improved the gray theory model and applied it to the sales forecast of beverages, and obtained good prediction results [13]. Rahmati et al. (2019) applied the exponentially weighted quantile regression to predict, and it was proved that the prediction results are better. When this method is used as a robust point for prediction, it shows an improvement over the traditional method [14]. Sakizadeh et al. (2019) used the three times exponential smoothing method (Holt–Winters) to predict the demand considering the spatial state [15]. Abbasimehr et al. (2020) used exponential smoothing prediction method to predict the future market demand, but the study did not consider the causal relationship among different variables [16]. Jiang et al. (2020) used the ARIMA model to analyze and predict the monthly beverage sales data of a company in the past 6 years, and obtained a more reasonable prediction result [17]. Ren et al. (2020) used the improved gray theory to predict the future demand for clothing, and applied the prediction results to replenish the clothing in physical stores [18]. Zhang and Ci (2020) studied the historical sales data of wood jewelry products for a limited period of time, and adopted the ARIMA model for prediction, so as to achieve high short-term prediction accuracy; it was found that the goodness of fit and white noise parameters of ARIMA predictive model are statistically significant [19]. Moroff et al. (2021) developed a predictive model that considers the factors affecting demand to analyze the daily sales of perishable foods in retail stores; and this model improved the traditional SARIMA model in terms of performance measurement [20]. In the above literature summary based on traditional time series methods for predicting the commodity demand, it is found that there are few documents that use traditional time series methods to predict the demand for e-commerce commodities, and most of them focus on the prediction of the demand for limited types of goods in offline physical stores.

2.2. Current research state of supply chain network optimization

In the early supply chain management, members of the supply chain network usually predict the development trend of the procurement volume, production volume, sales volume, and other indicators of the department based on historical data, and optimize the relevant resources of the supply chain network based on the prediction results. Common prediction methods mainly include horizontal prediction method, moving average method, and linear regression method. Although these methods are more convenient to operate, they are greatly affected by external factors, and there are often obvious differences between the predicted results and the actual results. Later, some scholars introduced the Markov chain [21] and Bayesian method [22] to predict and analyze the demand and supply activities of the closed-loop supply chain based on the characteristics of the supply chain network. Compared with traditional prediction methods, the above two methods reduce the influence of the external environment on the prediction results. However, the closed-loop supply chain network is a complex network involving multiple sub-members, both forward and reverse flows. How to effectively integrate the prediction information of the forward and reverse supply chains and deal with uncertain flows remains to be resolved. For the study of optimization models, Tricoire et al. (2017) took the recycling closed-loop supply chain as the research object, aiming the minimize the sum of investment in logistics facilities, operating costs, and transportation costs, and optimizing the design of the reproduction logistics network and based on the characteristics of the recycling capacity of the reproduction logistics system under different conditions. The optimization results can be used as the basis for handling issues such as the number of facilities in the reproduction logistics network, the distribution of material flow, and the location of the reproduction center [23]. Elçi et al. (2018) built a random constrained opportunity planning model for the location of a logistics distribution center with uncertain customer demand, transportation time, and delivery distance under the condition of uncertainty in the supply chain network [24]. Wei et al. (2018) constructed a two-layer model with the lowest logistics cost as the upper-level goal and the lowest transportation capacity input as the lower-level goal; and they studied the location of logistics centers [25]. Different from others, Nooraie et al. (2020) combined with the material demand characteristics of the supply chain from the perspective of the transportation characteristics of the transportation method to construct a multi-objective model of the supply chain production plan, and the optimal transportation method is selected for material distribution activities [26]. Moghdani et al. (2020) proposed a multi-period non-linear programming model involving multi-manufacturers and multi-products for the supply chain model involving multi-manufacturers and multi-products. The model parameters were set to represent the key attributes in the supply chain, and the model was solved by using the MATLAB, [27]. Majumder et al. (2020) established the single-objective and multi-objective shortest path models in uncertain environments in view of the randomness and ambiguity of logistics networks, which are to find the optimal path logistics distribution [28].

2.3. Summary

There are many research results by domestic and foreign scholars on the prediction of commodity demand, but the exploratory research on the prediction of the demand for e-commerce commodities with a large number of types and features and large noise is started in recent years, most of which focus on the prediction by using the machine learning methods. The method of e-commerce commodity demand based on machine learning is mainly shallow network, which makes most predictions use correlation analysis and principal component analysis for feature selection, and then input the selected feature subset into the prediction model for learning. However, when the feature dimension is large, the method of manual feature selection becomes time-consuming, so it is very important to try to automatically perform the feature learning from the original feature set to obtain effective features. Aiming at the disadvantages of existing algorithms (such as large amount of calculation, difficulty in solving large-scale planning, and easy falling into local optimization) in the design of reproduction closed-loop supply chain networks, the hybrid PSO is applied to optimize the closed-loop supply chain network. The algorithm takes the total cost of the closed-loop supply chain as the fitness function, adopts a simplified coding method, and introduces the mutation and crossover operation of the genetic algorithm to realize the discrete optimization of the closed-loop supply chain network structure of reproduction.

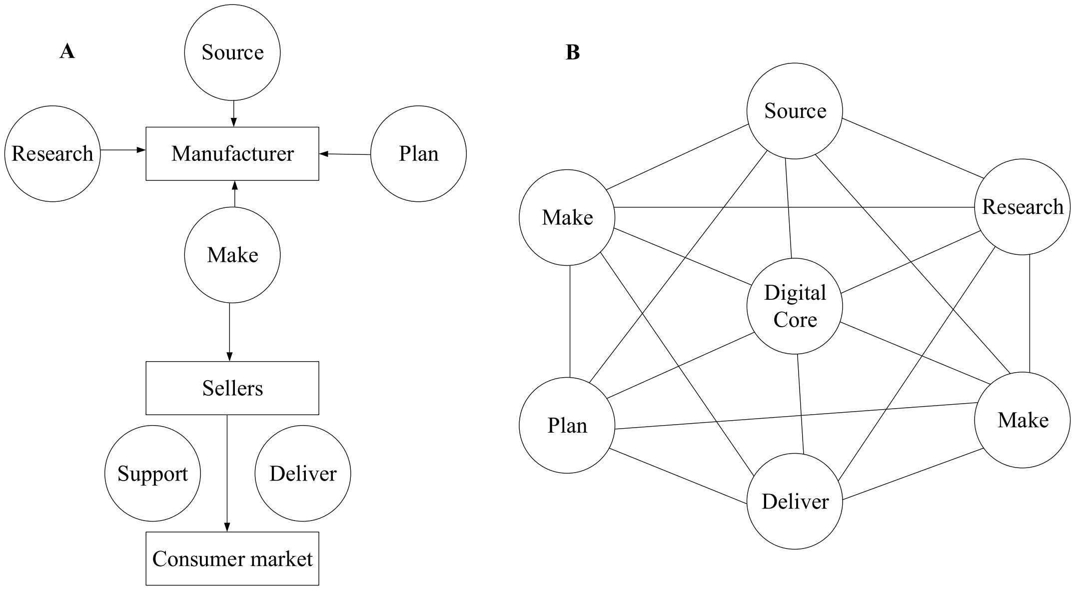

Fig. 1. Conversion of supply chain network of the industrial organization.

3. Methodologies

3.1. The traditional and modern supply chain network

Design of the supply chain network is the process of constructing a supply chain model so that it can utilize the available resources, time, and geographic location better, thus bringing commodities to the market quickly. Based on correct and effective management, the overall function of the supply chain is greater than the sum of the parts of each chain, and the goal of profit maximization of the enterprises can be achieved. Fig. 1 shows the differences and connections between the traditional and the modern supply chain network. It illustrates that the traditional supply chain network is based on the manufacture – retailer – demand market, including all specific links of plans, raw materials procurement, manufacturing, transportation, and sales, so it is a line of service network with the purpose of guaranteeing the balance between supply and demand. The modern supply chain networks make full use of the advantages of network nerves to ensure that all links are interchangeable, interconnected, and affected mutually. Such supply chain logistics has not yet been applied, so it requires more technical and algorithmic supports. The original supply chain management model is improved and optimized based on the modern model in this study, involving three aspects. One is the selection of the supply chain network predication model with the purpose of improving the accuracy of commodity demand predication and reducing related risks. The other is the optimization of supply chain network algorithms with the main purpose optimizing the entire structure to improve operating efficiency. Another is the security of the supply chain network with main purpose of strengthening cooperation between various nodes to improve the efficiency. The models proposed later in this study are based on this, construction of modern supply chain logistics network is achieved through various algorithm and predication methods.

3.2. Construction of a supply chain network model based on commodity demand prediction and optimization algorithms

AR-MDN that can simultaneously simulate correlation factors, time series trends, and demand variance is constructed in this study to simultaneously consider a large number of factors that affect demand, time series trends, and the probability distribution of demand. The AR part of the model is a simulation of correlation factors and time series, while the MDN layer is the output layer of the probability distribution, and the final output of the model is the parameters of the hybrid model. These parameters are the mean, variance, and mixing coefficient of each Gaussian kernel function used by the MDN layer. The ultimate goal of the model is to find the best set of parameter combinations so that the MDN loss function can be minimized, so as to achieve the optimal solution of the model. For supply chain logistics management, the goal of model construction is to minimize the total operating cost of the supply chain network. The standard PSO algorithm is mainly suitable for the optimization problem of continuous space function, while the goal of the reproduction closed-loop supply chain network optimization is to determine the number and location of manufacturing/reproduction factories, distribution/recycling points, and the transportation network of products between various facilities in the reproduction closed-loop supply chain network. This is a typical combination optimization. Therefore, the mutation and crossover

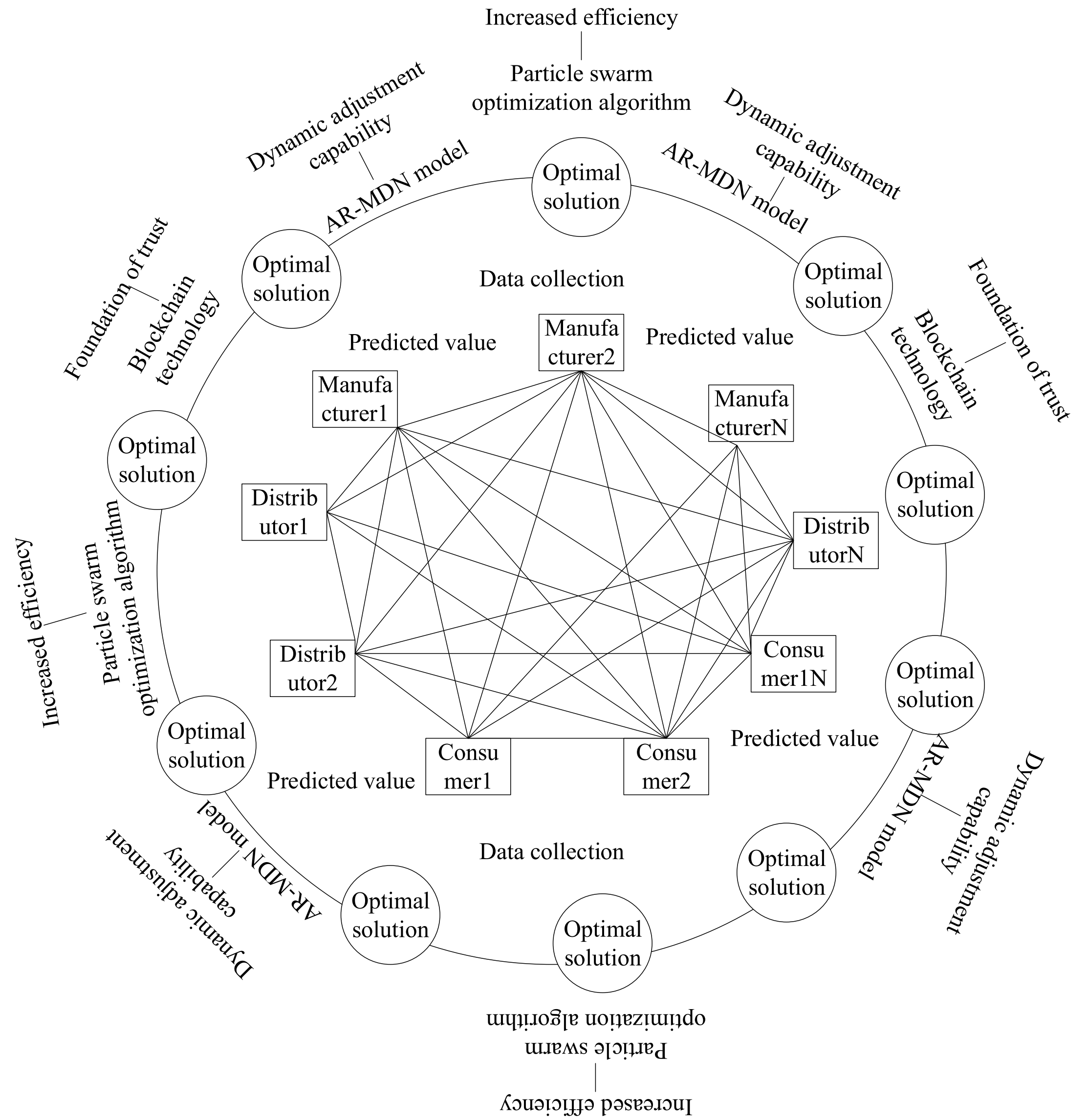

Fig. 2. Supply chain network model based on the commodity demand predication and optimization algorithm.

operations in GA are introduced in the PSO algorithm, and an optimization algorithm for the closed-loop supply chain network structure of reproduction is proposed based on the genetic PSO algorithm. Strengthening cooperation among businesses mainly depends on the implementation of blockchain technology, starting from consumer demand for products, to the improvement of supply chain network efficiency, adding the security guarantee of blockchain, and realizing the supply chain network of industrial organizations optimize. The specific structure is shown in Fig. 2.

3.3. Construction of commodity demand predication model

In the supply chain, the most important point is to master the demand for consumers, so that the merchant can adjust the commodity supply and production rhythm according to the actual demand and reduce the waste of resources. Therefore, a commodity demand predication model has to be constructed firstly in the traditional supply chain network. The common commodity predication models can be divided into three types: ARIMA, AR-MDN, and MLP-LSTM.

Firstly, ARIMA predicts the future by finding the autocorrelation of historical data (it is assumed that the future will repeat the historical trend), requiring that the sequence is stable [29]. It is composed of AR and MA, and its calculation equation is given as follows:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \tag{1}$$

In above equation, X_i is the weighted sum of predicted values, εt represents the white noise sequence, X_t is the historical value, α_t is the weighted coefficient of the past value, and β_t is the moving average of the past white noise.

Secondly, MLP-LSTM is a multi-layer hybrid deep neural network, containing the multi-layer perceptron (MLP) and long short-term memory (LSTM). The structure of MLP-LSTM is composed of input layer, hidden layer, and output layer. The calculation process of the propagation algorithm is given as follows:

$$\alpha^{\mathrm{t}}{}_{\mathrm{h}} = \sum_{\mathrm{i=1}}^{I} \mathrm{w_{ih}} \mathrm{x^t}{}_{\mathrm{h}} + \sum_{\mathrm{i=1}}^{H} \mathrm{w_{h'h}} \mathrm{b^{t-1}}{}_{\mathrm{h'}} \tag{2}$$

Output variable at time t can be calculated with below equation:

$$\mathrm{p^t}{}_{\mathrm{k}} = \sum_{\mathrm{i=1}}^{H} \mathrm{w_{hk}} \mathrm{q^t}{}_{\mathrm{h}} \tag{3}$$

$\alpha^{\mathrm{t}}{}_{\mathrm{h}}$ represents the input variable of node h at time t; $\mathrm{w_{ih}}$ is the weight of the input layer and the hidden layer, $\mathrm{x^t}{}_{\mathrm{h}}$ is the input variable at time t, $\mathrm{w_{h'h}}$ is the weight between the hidden layer at this time and the hidden layer of the previous time, $\mathrm{b^{t-1}}{}_{\mathrm{h'}}$ is the output of hidden layer at *t-1*. $\mathrm{p^t}{}_{\mathrm{k}}$ represents the input variable for the output layer.

Thirdly, AR-MDN is composed of AR model and MND network. AR model is to describe the relationship between current value and historical value. MDN is a mixed density network. It is multi-dimensional and special neural network to simulate a distributed density function with the mixed positive density function. MDN is expressed by a combination of Gaussian kernel functions, and its calculation equation of probability density is given as follows:

$$P(\mathrm{t}\,|\mathrm{x}) = \sum_{\mathrm{m}}^{M} \alpha_{\mathrm{m}}(\mathrm{x})\ \ \varphi_{\mathrm{m}}{}^{(\mathrm{t|x})} \tag{4}$$

$$\varphi_{\mathrm{m}}{}^{(\mathrm{t|x})} = N(\mathrm{t}\,\big|\mu_{\mathrm{m}}(\mathrm{x}), \sigma_{\mathrm{m}}{}^2(\mathrm{x})) \tag{5}$$

In the above equations, m is the number of kernel functions in the mixed model, $\alpha_{\mathrm{m}}(\mathrm{x})$ is the mixing coefficient, and $\varphi_{\mathrm{m}}{}^{(\mathrm{t|x})}$ is the conditional distribution of the target variable t for the mth unit. $N(\mathrm{t}\,\big|\mu_{\mathrm{m}}, \sigma_{\mathrm{m}}{}^2)$ represents the Gaussian distribution of mean μ and variance σ^2. The probability density function can be calculated with below equation:

$$P(\mathrm{t}\,|\mathrm{x}) = \sum_{\mathrm{m}}^{M} \alpha_{\mathrm{m}}(\mathrm{x}) \frac{1}{\sqrt{2\Pi}\sigma_{\mathrm{m}}(x)} \exp\{\frac{(\mathrm{t} - \mathrm{u_m}(\mathrm{x})^2)}{2\sigma^2{}_m(x)}\} \tag{6}$$

3.4. Optimization algorithm of the supply chain network

In the supply chain network, the selection of network algorithms is more important. Different network algorithms affect the adjustment speed of the supply chain network. The entire network can be guaranteed to be in the optimal environment at all times with the optimal algorithm, improving the operation efficiency of the supply chain network significantly. The commonly used network optimization algorithms include ABC and PSO. In addition, it is found in this study that the modification of parameters can improve the efficiency of the algorithm extremely after in-depth analysis of the PSO algorithm, which is the third optimization algorithm namely, the IPSO.

Firstly, the ABC is to carry out different activities based on their respective labor division, and to achieve information sharing and exchange, so as to find the optimal solution to the problem. The essence of ABC algorithm is to consider the process of solving the optimization problem as searching in the dimensional search space. The calculation equation is given as follows:

$$P\,\{X_{\mathrm{n}} + 1 = \mathrm{i_n} = 1, X_1 = \mathrm{i_1} \cdots X_{\mathrm{n}} = \mathrm{i_n}\} = P\,(X_{\mathrm{n}} + 1 = \mathrm{i_n} = 1\,|X_{\mathrm{n}} = \mathrm{i_n}) \tag{7}$$

Secondly, the PSO is an arrangement way to ensure systematization and logicality of complex events [17,18]. According to the definition of the adaptation function, the gradual adaptation value of each substance can be calculated. The optimal position can be changed with the above equation and the gradual adaptation value can be repeatedly calculated during the update at the medium speed. The velocity update equation of particle in q-dimensional space is given as follows:

$$V_{\mathrm{iq}} = \mathrm{V_{iq}} + \mathrm{C_1 rand()(p_{iq-}X_{iq})} + \mathrm{C_2 rand()(p_{gq} - x_{iq})} \tag{8}$$

$$\begin{cases} V_{\mathrm{iq}} = \mathrm{V_{max}}, & \text{if } \mathrm{V_{iq}} > \mathrm{V_{max}} \\ V_{\mathrm{iq}} = -\mathrm{V_{max}}, & \text{if } \mathrm{V_{iq}} < -\mathrm{V_{max}} \end{cases} \tag{9}$$

In above equations, C_1 is the historical optimal weight coefficient for self-search of the particle, C_2 is the global optimal weight coefficient for self-search of the particle, $rand_1()$ and $rand_2()$ are random numbers between 0 and 1, V_{max} is the maximum speed limit, and V_{iq} is the speed of a certain spatial dimension. The equation for position update of particle in

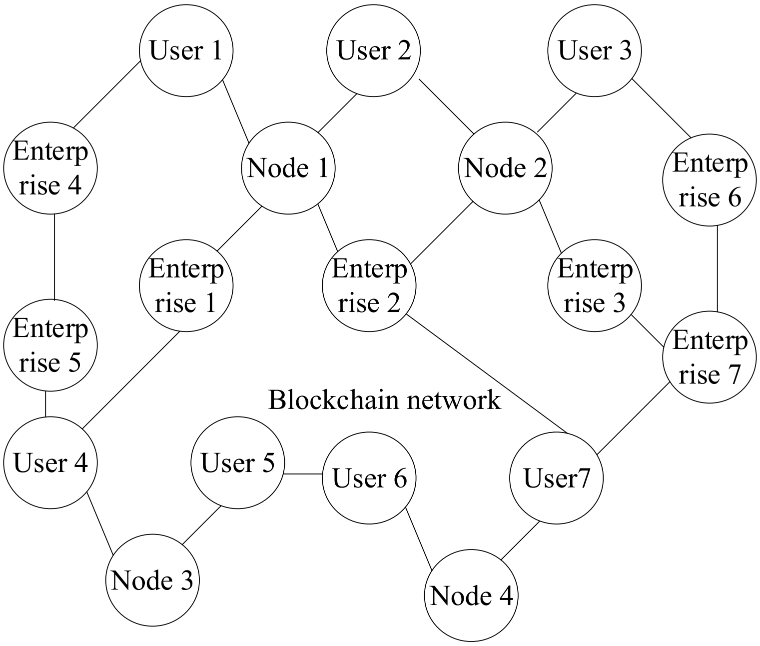

Fig. 3. Optimization of supply chain network by blochchain technology.

q-dimensional space is given as follows:

$$X_{iq} = X_{iq} + rV_{iq} \tag{10}$$

In above equation, r is the elastic coefficient of the speed variable in the updating equation.

Thirdly, the IPSO is the improved version of PSO by adding the GA, cross iteration method, and modifications of corresponding parameters, because the PSO can easily fall into the local minimum value and low search accuracy. The ω linear diminishing method is added for the iterative change, and the specific equation is given as below. This method changes the value of the learning factor at the same rate to improve the results of the algorithm, so that each particle has a global search capability to find a better solution.

$$\omega = \omega_{\min} + \frac{\omega_{\max} - \omega_{\min}}{K_{\max}} \times k \tag{11}$$

In above equation, $\omega_{\min}$ is the minimum inertia weight, which is usually 0.4, $\omega_{\max}$ is the maximum inertia weight, which is usually 0.9, κ is the number of iterations, and $K_{\max}$ is the maximum number of iterations. The linear change method for learning factor to be synchronous with the time is added, and the specific equation is given as follows:

$$c_1 = c_2 = c_{\max} - \frac{c_{\max} - c_{\min}}{K_{\max}} \times k \tag{12}$$

In above equation, $c_{\min}$ and $c_{\max}$ are the uncertain values of $\omega_{\min}$ and $\omega_{\max}$, $c1 = c2 = 2$ is given, and the inertia weight is analogized.

Blockchain technology is a decentralized and distributed network public accounting service platform. Due to its non-tamperable characteristics, it can guarantee the integrity of data. It usually contains multiple nodes, and each node will be accounted by agents (including companies, individuals, and governments) in the corresponding area. The recorded data cannot be modified. If any data has to be modified, it has to be agreed by agents of the entire block network, so this is a better credit platform. The optimization scheme for supply chain network based on the blockchain technology is shown in Fig. 3. It can protect the rights and interests of each node enterprise to the maximum extent. Links of the supply chain influence and trust each other, which is a prerequisite for improving the efficiency of the supply chain network and achieving the cooperation. In this way, it can solve the problems faced by the traditional supply chain network better.

3.5. Performance evaluation indicators of predication results

The existing swarm intelligence algorithms include ABC and PSO algorithms. ABC is proposed by Turkish scholar Karaboga. It is an intelligent algorithm that simulates bee colony to find the best nectar source. Its advantage is that it has a simple iterative equation. The PSO is proposed by Dr. Kennedy of Engineering and Dr. Eberhart of Psychology.

Table 1
Parameter setting of the algorithms.

Algorithm	Scale	Range	Iterations	Limit
ABC	200	[0,400]	500	50
PSO	200	[0,400]	500	–
IPSO	200	[0,400]	500	–
Algorithm	c_1/c_2	Times of experiment	Step size	Value
ABC	–	50	0.05	[0.8,2]
PSO	2/2	50	0.05	[0.8,2]
IPSO	2/2	50	0.05	[0.8,2]

There is no complicated operation such as selection and crossover of genetic algorithm. In the short time after the algorithm is proposed, it uses easy-to-understand procedures to operate. Simplicity has become a hot topic for many scholars. The IPSO is the algorithm proposed in this article. It is improved by adding genetic algorithm and blockchain technology to actual problems based on the standard PSO algorithm. The advantage of IPSO is that the processing speed is effectively improved, especially for data processing. A more detailed classification method is adopted to make its model prediction and optimization more targeted. The advantages of biological heuristic algorithm are that it is gradient-free, highly exploratory, and parallel. Its objective is to study the functions, characteristics, and mechanisms of different levels of biological individuals, groups, communities, and even ecosystems in the natural world, and establish corresponding models and calculation methods, so as to serve the scientific research and engineering applications of human society. It is not only the inheritance and development of artificial intelligence, but also a way to understand and grasp the essence of intelligence from a new perspective. Although deep learning algorithms can effectively process more data sets, they are prone to problems such as poor accuracy and insufficient data training [30]. But for the supply chain network of this article, it is necessary to find the optimal solution through collaboration and information sharing among different individuals in the group. Therefore, the PSO algorithm is adopted for processing.

For MLP-LSTM, the truncated normal distribution is adopted to initialize the weights, and the Adam optimizer is selected to optimize the objective function. For the multi-layer hybrid deep neural network, 24 neurons are used in the fully connected layer; 32 neurons are used in the LSTM layer; and 12 Gaussian kernel functions are finally selected for the probability distribution layer based on the empirical method combined with the trial method. The initial learning rate is set to 0.005. During the training, the model is finally optimized by exponentially decreasing the learning rate with the number of training iterations based on the actual training situation. The gradient decay step size of the exponentially decreasing learning rate is finally set to 50 in this study, and the decay rate is set to 0.95, and the gradient threshold is set to 3. The algorithm parameters for ABC, PSO, and IPSO are shown in Table 1.

Various algorithms and different models are used for evaluation in this study, so as to verify the performance. Verification of the model is evaluated mainly from the following aspects: RMSE, which is a measure of the deviation between the observed value and the actual value; MAPE, which is a statistical indicator that considers the error between the predicted value and the actual value, and can also measure the ratio between the predicted error and the true amount. The specific calculation equations are given as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{\mathrm{i}=1}^{N}(y_i - \widehat{y_i})^2} \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{\mathrm{i}=1}^{N}\left|\frac{y_i - \widehat{y_i}}{\mathrm{y_i}}\right| \times 100\% \tag{14}$$

In above equations, N is the total number of commodity samples, y_i is the actual sales volume of the commodity, $\widehat{y_i}$ is the predicted value of the predication model. For the evaluation indicators of the algorithm, it mainly is to find the optimal solutions for different algorithms, and the results can be calculated according to the corresponding algorithm references.

The data for this algorithm in this study is from the Yuntianchi platform of Alibaba, which is mainly provided by Cainiao Network. It includes the sales data and daily business data of a national logistics warehouse and regional warehouses of the logistics business of Taobao from May 2017 to June 2018, covering more than 1 year of transactions and logistics information of 1200 commodities, involving 15 million pieces of data information. There are 50,210 training samples and 10,203 test samples for the model training data. Determination of corresponding parameters is required for all models during the implementation process.

Construction of the supply chain network is affected by many factors, such as season, commodity update rate, market economy, and consumer demand. Among which, the consumer demand has the greatest impact on the supply chain network. In addition, the consumer demand is divided into deterministic (regular purchase by consumers) and stochastic (the consumption caused by time and economic incentive). Thus, the simulation experiments are designed in this study based on various demands, each part involves different manufacturers, retailers, and demand markets, and the specific

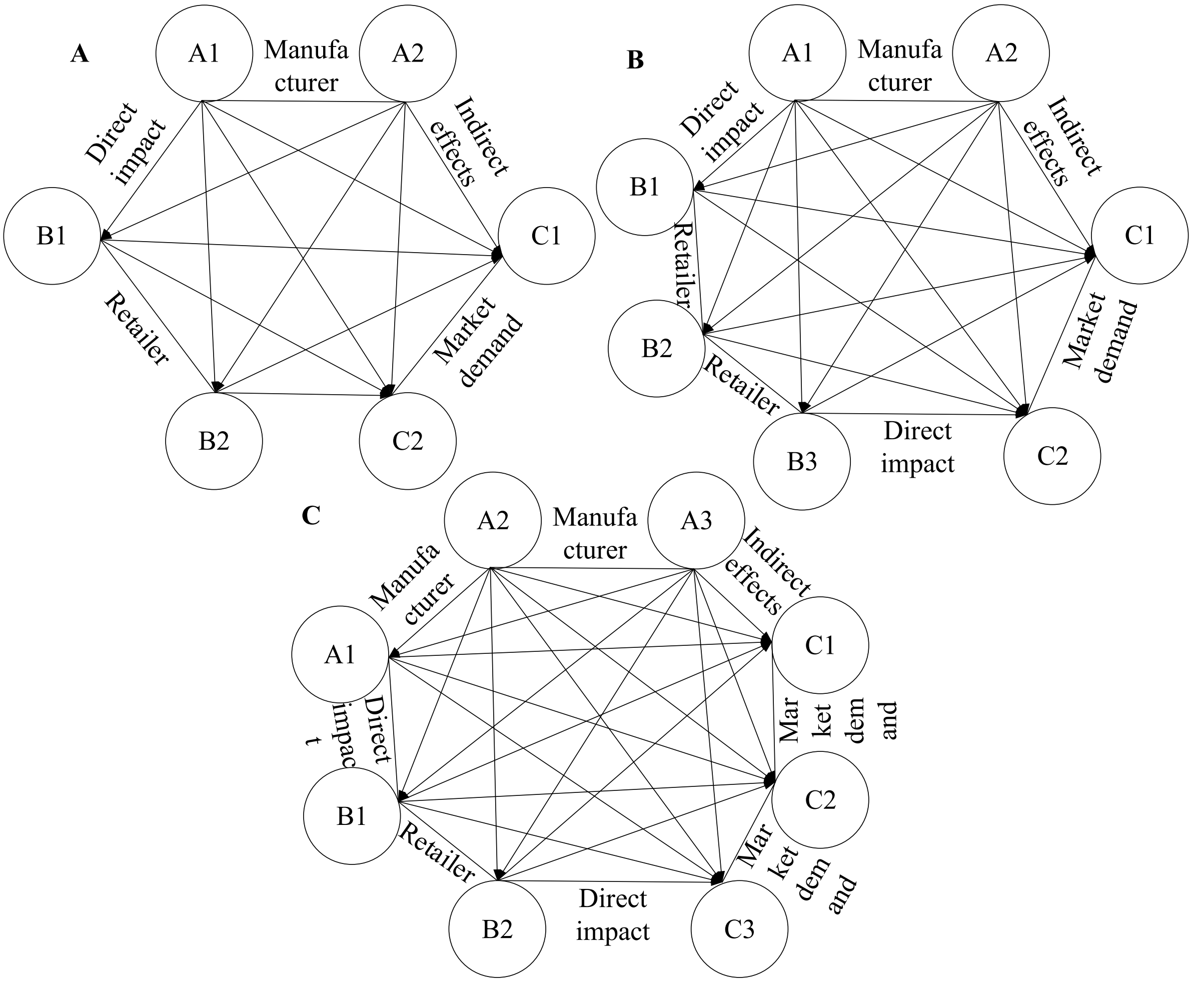

Fig. 4. Design for model verification of simulation experiments of the supply chain network with different demands.

supply chain model is shown in Fig. 4. Fig. 4A covers 2 manufacturers, 2 retailers, and 2 demand markets, Fig. 4B covers 2 manufacturers, 3 retailers, and 2 demand markets, and Fig. 4C gives 3 manufacturers, 2 retailers, and 3 demand markets. Each part is a verification experiment of three models. For convenience, the three verification models under deterministic demand are named as models 1, 2, and 3, and the three verification models under stochastic demand are called as model 4, 5, and 6.

4. Results and discussion

4.1. Performance comparison results of supply chain network models with different commodity demands

Four collections of sales and daily business data of the national warehouse are selected randomly, and the performance comparison results of different commodity demand models of the national warehouse are given in Fig. 5. It reveals that the predicted values of each model under the random test set are quite different compared with the results of REAL training set. The maximum value of MLP-LSTM is 225, 175, 9, and 50, respectively, and its the minimum value is 25, 150, 0.8, and 8 respectively; the maximum value of AR-MDN is 250, 150, 5, and 150, respectively, and its minimum value is 157, 50, 3, and 50, respectively; the maximum value of ARIMA is 150, 125, 6, and 75, respectively, and its minimum value is 100. Under the test set 2, the minimum value is 150, the maximum value of AR-MDN is 150, 100, 3, and 50, respectively, and the minimum value is 50. Above results indicate that the fluctuation degree of each model is MLP-LSTM > AR-MDN > ARIMA, and the predication effect is AR-MDN > ARIMA > MLP-LSTM. The difference between the predicted value and the actual value of AR-MDN is 15%, difference of the MLP-LSTM is 36%, and the difference of the ARIMA is 25%, so the fitting trend and predication effect of AR-MDN are better than those of ARIMA and MLP-LSTM.

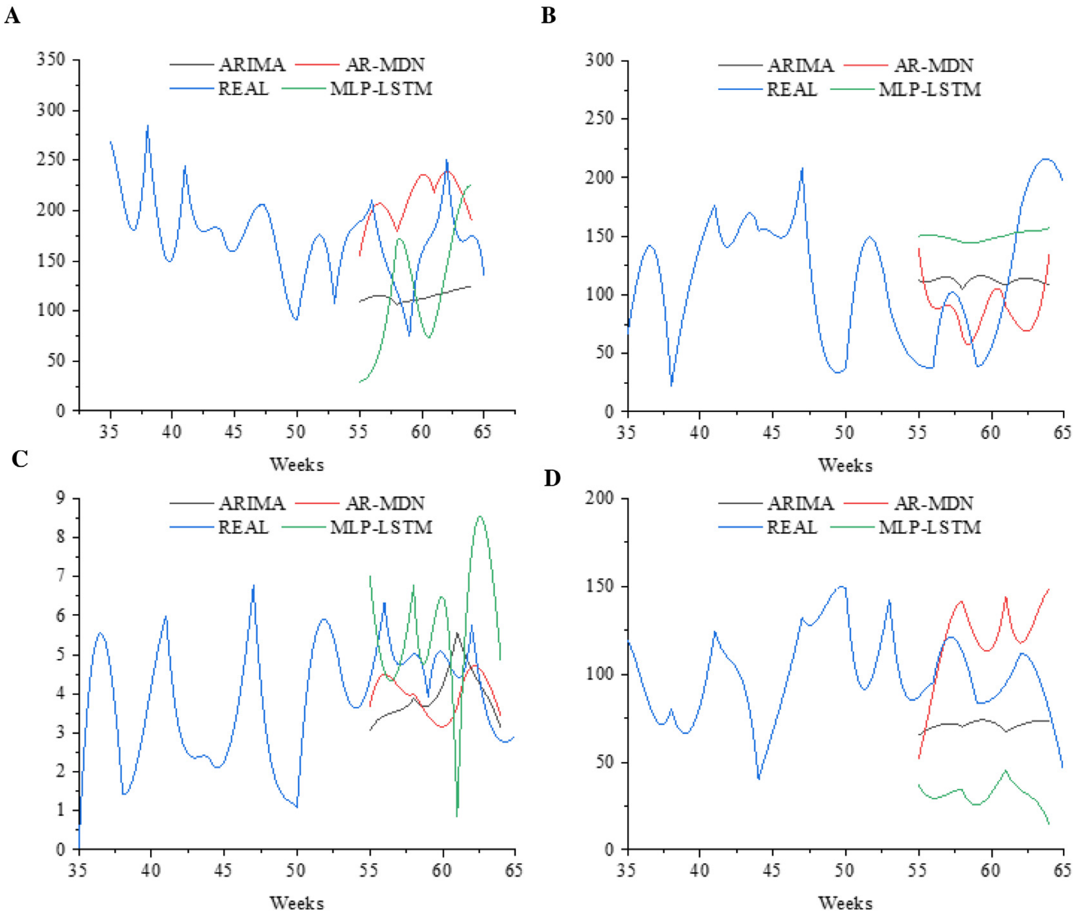

Fig. 5. Performance comparison on models with different commodity demands in the national warehouse. Note: A, B, C, and D represent the difference between the actual values and predicted values of different models under different random training sets, REAL represents the test result of the training set, and the other data in 55–65 week is the results of test set.

The box plot for results on the test set for the performance analysis of different commodity demand models is given in Fig. 6. Under the four sub-warehouses test sets, the maximum value of MLP-LSTM is 600, 520, 300, and 500 respectively, and its minimum value is 150, 125, 135, and 110, respectively; the maximum value of AR-MDN is 500, 350, 490, and 570, respectively, and its minimum value is 125, 150, 130, and 180, respectively; the maximum value of ARIMA is 520, 450, 500, and 500, respectively, and its minimum value is 150, 125, 160, and 150, respectively. The test results of the sub-warehouse suggest that the AR-MDN has fewer outliers than the ARIMA and MLP-LSTM models, indicating that the model has better stability.

On different models, the data of sub-warehouses are used to calculate various indicators of the model. The data are randomly selected from 5 warehouses in sub-regions, and the results are shown in Table 2. It shows that the three models have different performances on different sub-warehouses test sets on RMSR and MAPE. The RMSE of ARMIA, MLP-LSTM, and AR-MDN is 161.78, 150.64, and 117.342, respectively. The MAPE of ARMIA, MLP-LSTM, and AR-MDN is 6.724, 4.844, and 2.334, respectively. On the whole, the prediction error of 5 sub-warehouses for the AR-MDN is smaller than that of ARMIA model and MLP-LSTM model, indicating that the AR-MDN model is more accurate.

4.2. Performance comparison results of different optimization algorithms

Under the deterministic demand, algorithm convergences of different supply chain network models are analyzed and compared, as shown in Fig. 7. It can be found that for model 1, the ABC can reach the optimal solution (0.453) when it iterates for 470 times, the PSO can reach the optimal solution (0.086) when it iterates for 460 times, and the IPSO can reach the optimal solution (0.006) when it iterates for 460 times; for model 2, the ABC can reach the optimal solution (1.124) when it iterates for 470 times, the PSO can reach the optimal solution (0.097) when it iterates for 470 times, and the IPSO can reach the optimal solution (450.123) when it iterates for 480 times; for model 3, the ABC can reach the optimal solution (0.453) when it iterates for 470 times, the PSO can reach the optimal solution (0.568) when it iterates

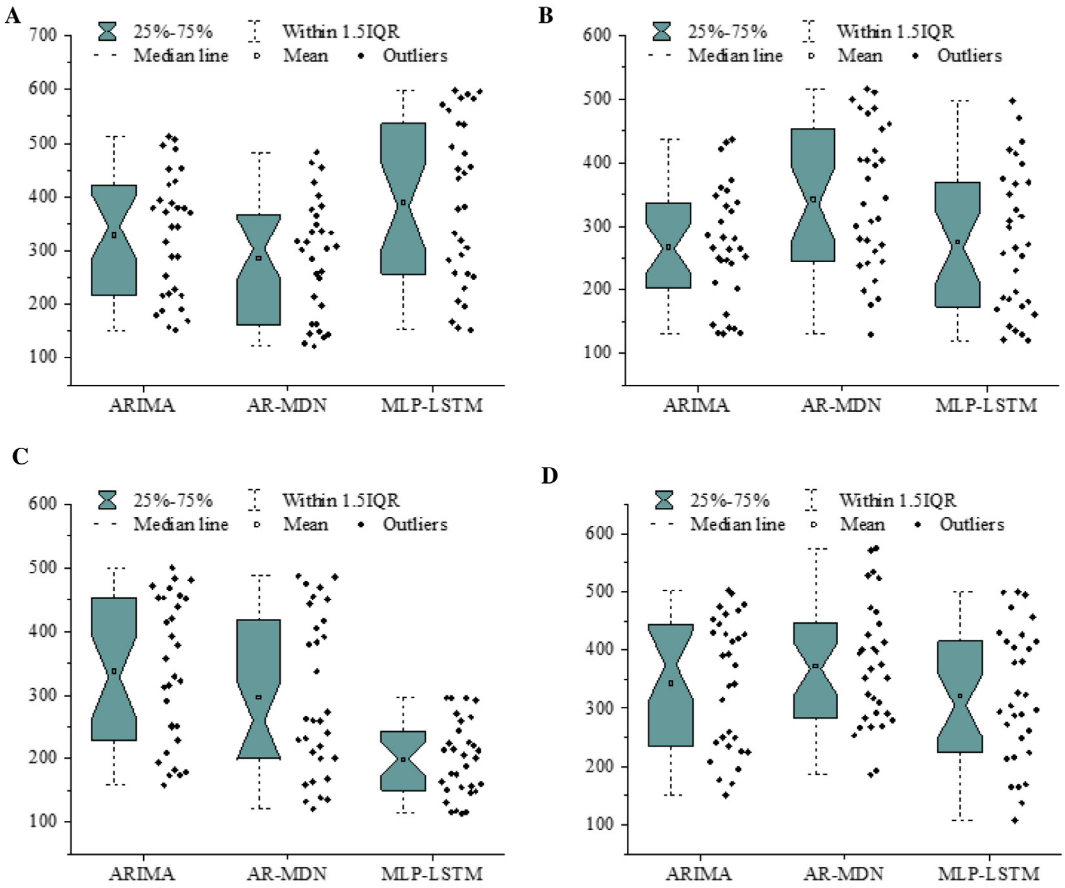

Fig. 6. Box plot for results on test sets for the performances of different commodity demand models. Note: figures A, B, C, and D represent the differences between the actual and predicted values of different models under different random training sets.

Table 2
Indicator results of different models in sub-warehouse test sets.

Indicator	Performance	Sub-warehouse 1	Sub-warehouse 2	Sub-warehouse 3	Sub-warehouse 4	Sub-warehouse 5	Mean
RMSE	ARIMA	185.96	154.71	156.34	179.96	131.93	161.78
	MLP-LSTM	118.92	162.88	212.64	129.09	129.67	150.64
	AR-MDN	120.98	105.16	124.29	112.46	123.82	117.342
MAPE	ARIMA	7.43	6.52	6.65	7.43	5.59	6.724
	MLP-LSTM	2.43	6.59	9.66	2.7	2.84	4.844
	AR-MDN	2.35	2.07	2.49	2.32	2.44	2.334

for 450 times, and the IPSO can reach the optimal solution (0.476) when it iterates for 470 times. In short, performance of the IPSO is significantly stronger than that of the PSO and ABC algorithms of different supply chain network models under the deterministic demand.

Under the stochastic demand, algorithm convergences of different supply chain network models are analyzed and compared, as shown in Fig. 8. It can be found that for model 4, the ABC can reach the optimal solution (1000) when it iterates for 480 times, the PSO can reach the optimal solution (865) when it iterates for 480 times, and the IPSO can reach the optimal solution (165) when it iterates for 480 times; for model 5, the ABC can reach the optimal solution (1059) when it iterates for 480 times, the PSO can reach the optimal solution (100) when it iterates for 300 times, and the IPSO can reach the optimal solution (78) when it iterates for 470 times; for model 6, the ABC can reach the optimal solution (10,256) when it iterates for 480 times, the PSO can reach the optimal solution (4) when it iterates for 480 times, and the IPSO can reach the optimal solution (35) when it iterates for 480 times. In short, performance of the IPSO is significantly superior to the PSO and ABC algorithms of different supply chain network models under the stochastic demand.

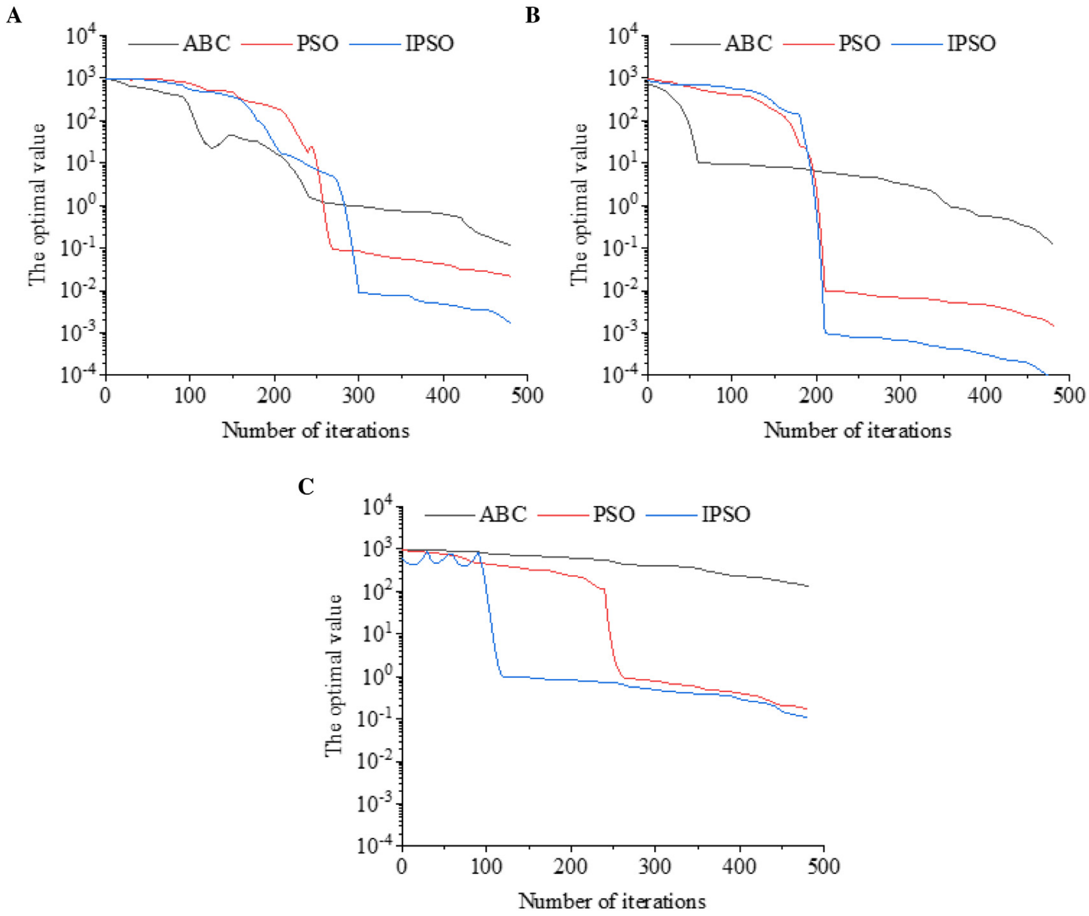

Fig. 7. Convergence analysis on algorithms of different supply chain networks under the deterministic demand.

4.3. Comprehensive comparison results of different supply chain network combinations

Based on the above results, AR-MDN can be used for the commodity predication model, and three optimization algorithms are used for different combinations, and the model is evaluated comprehensively based on the maximum and minimum values. The data are random logistics information data from Alibaba, aiming to evaluate the different combinations. The comprehensive comparison results of different supply chain network model combinations are given in Table 3. Regarding to the prediction of the commodity, it is consistent with above results. The average values of demand prediction for the AR-MDN, ARIMA, and MLP-LSTM are 73.3735, 80.402, and 102.513, respectively, so the predication performance of the AR-MDN is significantly better than that of the ARIMA and MLP-LSTM. The efficacy of supply chains of ABC, PSO, and IPSO is 310.6925, 296.776, and 294.9205, respectively, so the IPSO is superior to the traditional PSO and ABC. Regarding as the combined models and algorithms, the average values of IPSO + AR-MDN, ABC + AR-MDN, and PSO + AR-MDN are 67.41, 86.4675, and 84.42, respectively, so the combined effect of the IPSO and AR-MDN model of the commodity prediction is the best.

5. Discussion

The balance of supply chain network is to maximize the benefits of the entire supply chain network on the basis of ensuring the maximum profit of the decision-making level of manufacturers, retailers, and demand markets in the supply chain. To achieve this goal, it is necessary to coordinate the relationship among various decision makers and consider more factors, such as random market demand and the delivery time deadlines given by various decision makers. In this case, it can make adjustments more effectively without losing competitive advantage in face of the rapidly developing market economy structure. The traditional method of solving the balance of supply chain network is to transform it into a variational inequality and solve it through the modified projection method. The modified projection method relies heavily on the Lipschitz constant, the iteration step size, and the setting of the initial point. Based on the above reasons, an IPSO

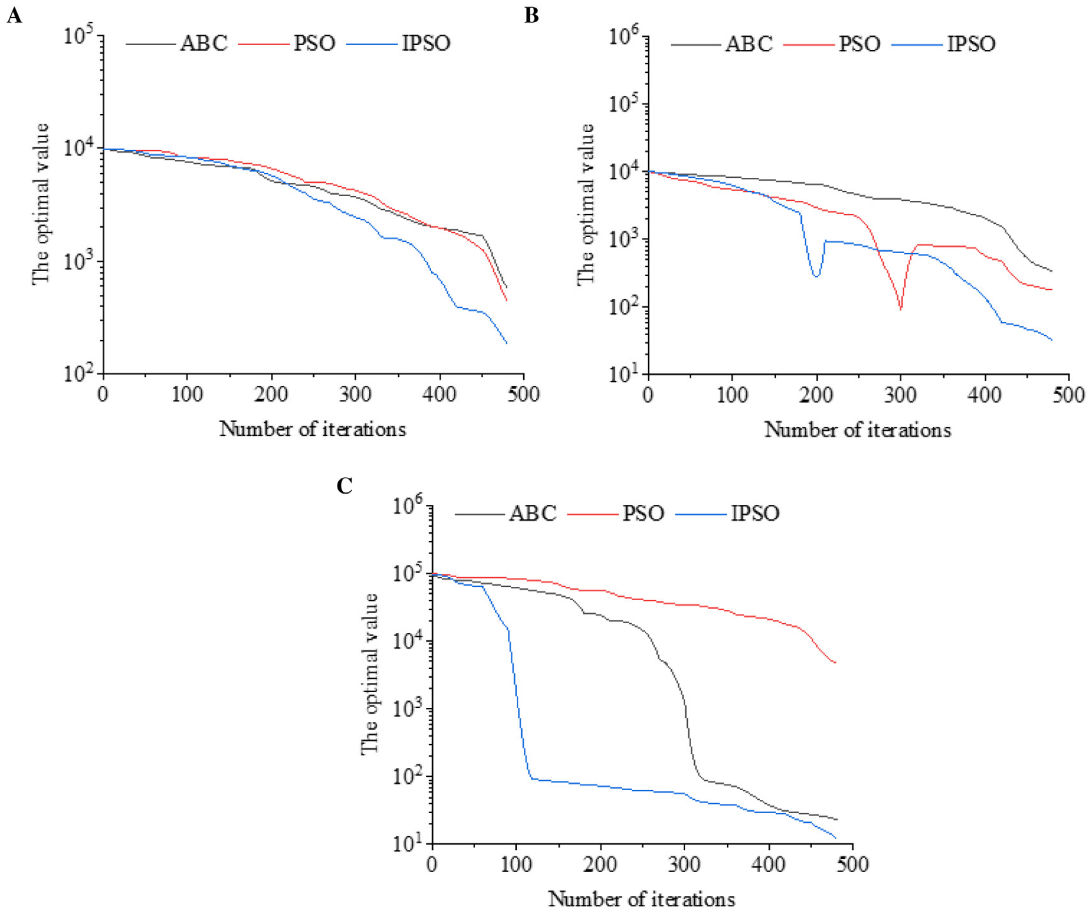

Fig. 8. Convergence analysis on algorithms of different supply chain networks under the stochastic demand.

Table 3
Comprehensive comparison results of different supply chain network combinations.

Indicator	Performance	Maximum	Minimum	Average
Demand prediction	ARIMA	145.667	59.359	102.513
	MLP-LSTM	113.576	47.228	80.402
	AR-MDN	106.289	40.458	73.3735
Efficiency optimization	ABC	520.529	100.856	310.6925
	PSO	500.596	92.956	296.776
	IPSO	500.487	89.354	294.9205
Hybrid model	IPSO + AR-MDN	100.557	34.263	67.41
	ABC + AR-MDN	120.467	52.468	86.4675
	PSO + AR-MDN	124.254	44.586	84.42

algorithm is proposed in this study, which is compared with the ABC algorithm and the standard PSO algorithm. The results provide a new method for solving the balance of supply chain network.

Based on the basic and derived feature clusters, the AR-MDN multi-layer hybrid network model is adopted to predict the short-term demand for e-commerce products under the deep learning methods. The prediction results are compared with the real data. It is found that the fitting trend is good, RMSE and MAPE are small, indicating that the AR-MDN model has good accuracy. Such results are consistent with the findings of previous related studies [31]. In addition, above results indicate that the optimal value curve of the PSO algorithm whose learning factor changes asynchronously shows an approximate linear decline, which is particularly effective in achieving the balance of supply chain network. The ABC algorithm is "premature", so it is easy to fall into the local optimum, which has been reported in the relevant literature [32]. Particles cannot effectively jump out of the local optimal solution; the standard PSO algorithm can search for the optimal solution, but cannot dig deep to find the optimal solution, and can eventually fall into the local optimal [33]; the convergence accuracy of the PSO algorithm with the asynchronous change of the learning factor is much higher than other algorithms. The improved algorithm can search extensively in the solution space in the early stage of the search without falling into the local optimum, and it can explore in-depth near the approximate optimal solution in the latter stage of the iteration. The population always has strong exploration ability, indicating that the IPSO effectively balances the ability of global search and local search. Compared with Nagurney's modified projection method, the results obtained by the two algorithms are basically the same, but the IPSO algorithm requires no consideration on a series of parameters such as Lipschitz constant, initial value conditions, and iteration step size, which may have a greater impact on the results.

6. Conclusion

After the traditional and modern network supply models are compared, three models of commodity prediction are compared for the construction of the supply chain network model, three optimization algorithms are compared for the supply chain network efficiency, and the blockchain technology is used for combination of different models and algorithms for construction of the supply chain credit in this study. Finally, the optimal supply chain network model is proposed and verified. In national warehouse and regional warehouses, the fitting trend, prediction accuracy, and stability of AR-MDN are better than those of ARIMA and MLP-LSTM models overall. Regarding the deterministic and stochastic demand, the performance of IPSO is significantly stronger than that of the PSO and ABC; the combination of IPSO and AR-MDN model of commodity prediction has the best performance. Although the performance of all models has been tried to be analyzed as comprehensively as possible in the study, it needs to be improved in the following aspects due to limitations from some objective conditions such as ability level and research funding: first, the data prediction in this study is homogeneous without consideration of special circumstances such as holidays; second, there is still a lack of verification and improvement in different regions and different time periods for the models. In future, some in-depth researches will be conducted in these two directions.

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