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Research Article

Inventory Management Optimization of Green Supply Chain Using IPSO-BPNN Algorithm under the Artificial Intelligence

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This exploration is aimed at reducing the waste of resources in the supply chain inventory management and provide better services for green supply chain management. It mainly proposes a backpropagation neural network (BPNN) model based on improved particle swarm optimization (IPSO) (IPSO-BPNN) and applies it to inventory management prediction. First, the important technologies of green supply chain and intelligent supply chain are analyzed from the perspective of the ecological environment. Next, the particle swarm optimization (PSO) algorithm is optimized based on the adaptive improvement of the learning factor and the addition of the speed mutation operator. Then, it is applied to the learning and training of BPNN. Finally, the simulation experiment of the combination model is conducted. The application fields of the combination model are analyzed. The results show that a single BPNN model will produce large errors in the training process. The final error of BPNN using the traditional PSO algorithm is 0.0259, while the error of BPNN optimized by IPSO is 0.0163. The optimized combination model has higher accuracy, better performance, and the lowest error rate. The classification error rate of its training set and test set is 1.51 and 2.16, respectively. The mean square error of the training set is 0.0163 and that of the test set is 0.0229. Under 6 ~ 12 different hidden nodes, the daily measurement model error and monthly measurement model error are both low when the number of nodes is 11. Moreover, the training set is always better than the test set. Finally, the network structure of the combination model is determined as the structure of 6-11-1. This prediction module will provide purchase volume suggestions and inventory volume suggestions to provide a feasible direction for the green development of inventory management.

1. Introduction

This exploration will study green supply chain management from the sustainable development perspective. Since the second half of the 20th century, due to the progress of science and technology, mankind's ability to use nature has increased rapidly and the scale of developing nature has expanded unprecedentedly. It creates unprecedented wealth and high-speed economic growth in human history. With the deterioration of the ecological environment and the further aggravation of the natural resource shortage, enterprises begin to think about how to realize the sustainable development of energy [1]. The increasingly serious environmental problems have forced enterprises to reexamine their production mode and increase the capital investment in green production to reduce the damage to the environment [2]. As the final end of the supply chain, consumers need to supervise and report enterprises' products. Paying attention to the green degree of the enterprise's products in real time is responsible for itself and the whole society [3]. Present consumers pay more attention to environmental issues and green production than ever before. As one of the crucial sustainable development strategies, remanufacturing has attracted extensive attention. The most critical product recycling problem in remanufacturing process needs to be solved in combination with a green supply chain [4]. A green supply chain requires all enterprises in the supply chain to pay attention to the impact on the environment [5]. Green supply chain management is a new concept combining supply chain management with environmental protection. Its core idea is to comprehensively consider and

optimize manufacturing resource utilization and environmental protection in the supply chain management's key business circulation process [6].

The rise of the green supply chain is to meet the needs of more and more consumers for green products and sustainable development. "Green" requires producing recyclable products to reduce environmental pollution in use. More importantly, it is essential to focus on effective resource utilization in the production process [7]. Therefore, the green supply chain requires all member enterprises in the supply chain, from the procurement of raw materials to recycling recyclable waste, to focus on the impact on the environment. The research on the coordination of a green supply chain can increase enterprises' economic and social benefits, improve their competitiveness, save resources, and protect the environment [8]. Inventory management in the green supply chain is the third profit source of enterprises. This exploration takes inventory management in the green supply chain as the starting point. The economic value of inventory includes increasing customer satisfaction, preventing various losses caused by the shortage, and increasing the market share of products. However, inventory also brings pressure from huge costs and resource reuse to enterprises [9]. Thereby, a reasonable control strategy and inventory management will bring greater economic and environmental benefits to enterprises. Green supply chain management is proposed as a new concept combining environmental protection with supply chain management. Its core idea is to comprehensively consider environmental protection and optimal utilization of manufacturing resources in the key business circulation process of the supply chain management. It ensures the realization of the added green value of products and plays a positive role in promoting green consumption [10].

With the rapid progress of computer technology, green supply chain management has entered the intelligent stage. In recent ten years, neural network theory and practice have made remarkable progress, which once again expands the connotation of the computing concept [11]. Major companies in technologically developed countries have a special preference for neural network chips and biochips. The neural network has successfully solved some problems that other methods cannot solve because of its characteristics of parallel processing, distributed storage, and adaptation [12]. The neural network was originally applied to pattern recognition. Now, it has been extended to many fields, and the most common is prediction [13]. It can also be used to solve various classification problems, such as pattern recognition, translation, bank credit risk assessment, and signature recognition [14]. The neural network technology has the characteristics of distributed information storage, large-scale parallel processing, good self-organization, and self-learning ability. Hence, it is widely used in the field of supply chain management [15]. The backpropagation neural network (BPNN) is the most widely used. However, the BPNN learning algorithm is based on gradient descent, which has some problems, such as slow convergence speed, easy to fall into a local minimum, and long training time [16]. Particle swarm optimization (PSO), which has the characteristics of fast convergence and simple calculation, is introduced as the learning algorithm of BPNN to optimize its parameters to improve the model's performance. However, the algorithm has the phenomenon of premature and slow speed in the later stage of evolution [17]. This exploration will optimize the algorithm. The optimization idea includes adding mutation operator and adaptive adjustment of learning factor.

Under the background of sustainable development, based on the idea of improving the inventory management level in green supply chain management, this exploration introduces an artificial intelligence (AI) algorithm and PSO algorithm to predict inventory management. First, green supply chain technology and inventory management background are introduced. Next, the PSO algorithm is improved, and two improved methods are proposed: adding mutation operator and adaptive adjustment of learning factor. Finally, the improved PSO (IPSO) algorithm is combined with BPNN and applied to inventory management prediction, and simulation experiments and empirical analysis are carried out. The research innovation is to apply AI technology based on the PSO algorithm to the field of the green supply chain. This exploration provides a reference for the sustainable development of the supply chain.

2. Literature Review

Supply chain management in the ecological environment is proposed in 1996, namely, green supply chain management [18]. The initial research on green supply chain management believes that it includes the whole production process, product composition and product use. It is the combination of the original supply chain thought and environmental protection thought. Finally, the green supply chain must form a long-term and stable strategic relationship within the supply chain [19]. After the 21st century, researchers believe that a green supply chain should include inventory, strategy, and environment. Recently, the definition of green supply chain management is mainly based on the product and production environment [20]. American scholars define it as the setting of supply chain management policies and environmental problems in designing, distributing, and using products and services [21]. Scholars in China define it as the supply chain management that considers the overall environmental benefit optimization [22]. Based on previous studies, a conceptual model of the green supply chain is proposed here. It comprises four subsystems: the consumption system, production system, environmental system, and social system. The model reflects the circular movement of knowledge flow, logistics, capital flow, and information flow in the whole green supply chain [23].

With the progress of AI, the management information system is gradually introduced for intelligent supply chain management. The traditional enterprise management information system is built based on the database and can only provide statistical query functions [24]. At the end of the 20th century, the new enterprise management system closely connected the enterprise's resources with the business process. Moreover, it lays a certain foundation for improving

the enterprise's competitive advantage and efficiency [25]. The enterprise information system in the 21st century can provide decision-makers with auxiliary decision-making information and business data processing capacity. AI brings more convenience to supply chain management [26]. Decision-making technology is the research hotspot of multiple scholars and enterprise management developers. The supporting technologies of decision technology include metaheuristic algorithms and neural network technology [27]. Metaheuristic algorithms have good performance in problem solving and optimization. At present, they mainly include the PSO algorithm, monarch butterfly optimization (MBO), moth swarm algorithm (MSA), Hunger Games Search (HGS), and Runge-Kutta (RUN).

Jha et al. predicted India's GDP based on a multivariable fuzzy time series model and MBO combination algorithm. The results show that the proposed combination algorithm is better than the existing prediction methods [28]. Ramaporselvi and Geetha proposed an adaptive MSA optimization algorithm and applied it to the congestion management for a power system transmission line. Experimental results show that the algorithm's performance is better than the existing technology [29]. Mehta et al. applied HGS to automotive engineering design and optimization. The experimental results show that the algorithm has good robustness in obtaining the best global optimal solution [30]. Yousri et al. proposed an interactive variant of the RUN optimization algorithm to determine the reliable parameters of the single-diode and double-diode model parameters of different photovoltaic cells/modules. The results show that this method provides highly competitive results compared with other well-known parameter extraction methods [31].

AI can solve incomplete, fuzzy, and complex problems by simulating behavior [32]. Artificial neural network technology was born in the middle of the last century and developed rapidly at the end of the 20th century [33]. Because of the large-scale parallel computing ability, neural network technology is widely used in prediction, such as weather prediction, pattern recognition, and statistical calculation [34].

A PSO algorithm is used to solve the problems of the slow convergence speed of BPNN [35]. It was proposed at the end of the 20th century and was originally used to study the foraging behavior of birds [36]. It is widely adopted in pattern classification, neural networks, and function optimization. It is one of the optimization algorithms with superior performance because of its simple operation, easy implementation, and fast convergence speed [37]. It has attracted the attention of multiple scholars, and many researchers have done a lot of research on improving the optimization ability of the PSO algorithm. Thakkar and Chaudhari (2021) discussed existing methods' limitations and potential future research directions to enhance stock market prediction based on the PSO algorithm [38]. At present, the decision-making mechanism based on the PSO algorithm is easy to fall into the premature convergence problem of local optimization. Moreover, there is less research on applying the PSO algorithm in the ecological environment. Hence, this exploration combines it with deep learning and applies it to green supply chain management to fill the research gap in this field.

Based on the definition of green supply chain management in previous studies, this exploration defines it as follows. It is a management mode with sustainable development as the goal. Its activities cover the whole life cycle of products, and its actors include the government, the public, and all supply chain members. The research content here is green supply chain management. There is less research on the combination of the PSO algorithm and neural network and their application in green supply chain management in the previous research. BPNN has good prediction performance, and the PSO algorithm can solve the problems of slow neural network convergence. Therefore, this exploration will combine the two algorithms to study green supply chain management. The scope of supply chain management is wide. Previous studies regard the supply chain as a whole, and there is less research on the details of specific supply chain management. Hence, this exploration takes inventory management in supply chain management as the research object to optimize supply chain inventory management. It focuses on inventory management prediction in supply chain management based on an IPSO algorithm and BPNN. It is aimed at achieving the purpose of green supply chain management finally.

3. Intelligent Inventory Management in the Green Supply Chain

Based on the above research background and the analysis of relevant existing literature, this section mainly constructs the green supply chain management model, analyzes the contents and characteristics of inventory management in the supply chain, and introduces the relevant theories of BPNN and PSO. PSO defects are improved, and the IPSO algorithm is put forward. IPSO is used to optimize the traditional BPNN, and the optimization algorithm is applied to the prediction of green supply chain inventory management to verify the model's performance.

3.1. Construction of Green Supply Chain Management Model. Green supply chain management focuses on the sustainable development of the whole product cycle, including the impact on the environment in procurement, material management, logistics, production, manufacturing, and treatment [39]. It promotes resource reduction, recovery, and reuse in the supply chain's upstream, middle, and downstream activities [40]. It provides a solution to improve the environmental impact caused by supply chain management. Figure 1 presents the overall model of green supply chain management.

Figure 1 displays that the green supply chain management model here includes green procurement, green processing, green marketing, and recycling. After green purchases to suppliers, enterprises will carry out inventory management. Inventory management in green supply chain management is mainly studied. The design of green supply chain management considers the impact of procurement, logistics, material management, production, manufacturing, and processing processes on the environment. In fact, it will
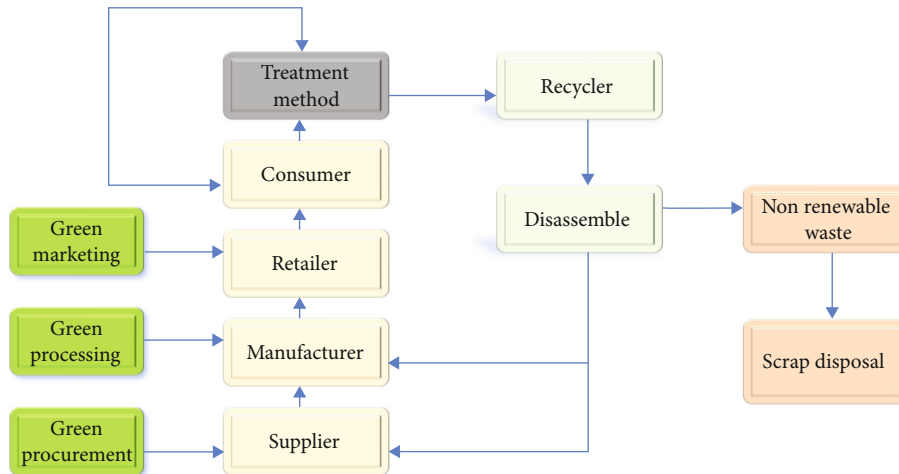
FIGURE 1: Overall model of green supply chain management.

promote the reduction, reuse, and recycling of resources in the upstream, middle, and downstream activities of the supply chain. Environmental supply chain management provides a new perspective, including a two-way supplier of products or services or even a cyclical perspective.

3.2. Contents and Characteristics of Inventory Management.

Inventory in supply chain management includes the materials in the production process, parts or raw materials that have not been used in the enterprise, and the finished products in the production process before they are delivered to customers. Inventory level is crucial for the development and survival of enterprises.

Inventory management functions in enterprise supply chain management mainly include stabilizing the production and operation scale to obtain economies of scale, balancing the time difference between supply and demand, and buffering the impact of uncertain factors. Therefore, inventory plays a vital role in enterprise management and cutting huge costs. Excessive costs make the current costs less and increase storage expenses, taxes, insurance, and the economic burden of enterprises. Due to product aging and other problems, inventory management directly affects the sustainable development of enterprise resources. Besides, excessive inventory will cause great risks to enterprises [41]. Inventory affects the green development of supply chain management and enterprise budget. It should be controlled within a reasonable range to ensure the sustainable development of inventory resources at the lowest cost.

The ultimate goal of inventory control is to reduce inventory costs as much as possible and meet customer needs. There are multiple influencing factors of inventory cost, as shown in Figure 2 [42].

Figure 2 shows that the main influencing factors of inventory cost are storage, ordering, replenishment, and out-of-stock cost. Out-of-stock cost is an opportunity cost. It refers to the expenses incurred by failing to provide services to customers for some reason, or failing to obtain the predetermined profit due to the loss of sales to customers. Besides, it also includes the adverse consequences caused

by the loss of reputation due to some difficult factors [43]. For suppliers, out of stock means losing sales opportunities, reducing profits that could have been obtained, or violating contracts and treaties. If they are punished heavily, they will lose credibility, important customers, and market competitiveness. For manufacturers, out of stock will increase the procurement cost. More seriously, it will stop the work and wait for materials, which will affect the normal production operation [44]. Ordering cost refers to all expenses incurred in the ordering process, including two expenses. One is the fixed cost of ordering expenses, including travel expenses, ordering handling fees, communication expenses, entertainment expenses, and relevant expenses of the person in charge of ordering. The ordering fee is related to the order times, but not to the order quantity. The other is the cost of the ordered goods, which is related to the order quantity. Storage cost refers to the cost invested in maintaining inventory. It mainly includes inventory investment and storage costs. For example, it includes the interest payable on the funds occupied by the goods, the insurance and taxes paid for the goods, and the expenses for using the warehouse, keeping the goods, damage, and deterioration of the goods. Replenishment means that when the customer comes to purchase, there is no stock in the warehouse; however, to avoid losing sales opportunities, the enterprise still persuades the customer to order here, promises to purchase immediately, and then replenishes the goods to the customer. Replenishment has obvious benefits for enterprises. It can occupy fewer funds and less inventory and reduce storage costs, and it is impossible to incur shortage expenses. However, to realize replenishment, replenishment costs often occur [45].

Based on the above, it is found that the problems to be solved for inventory control are divided into three categories in Figure 3.

Figure 3 shows that the inventory control strategy's implementation should meet the demanders' needs, the selection of appropriate control methods, and the supplier's operation mode. The control method is the core of inventory management. The traditional inventory control model
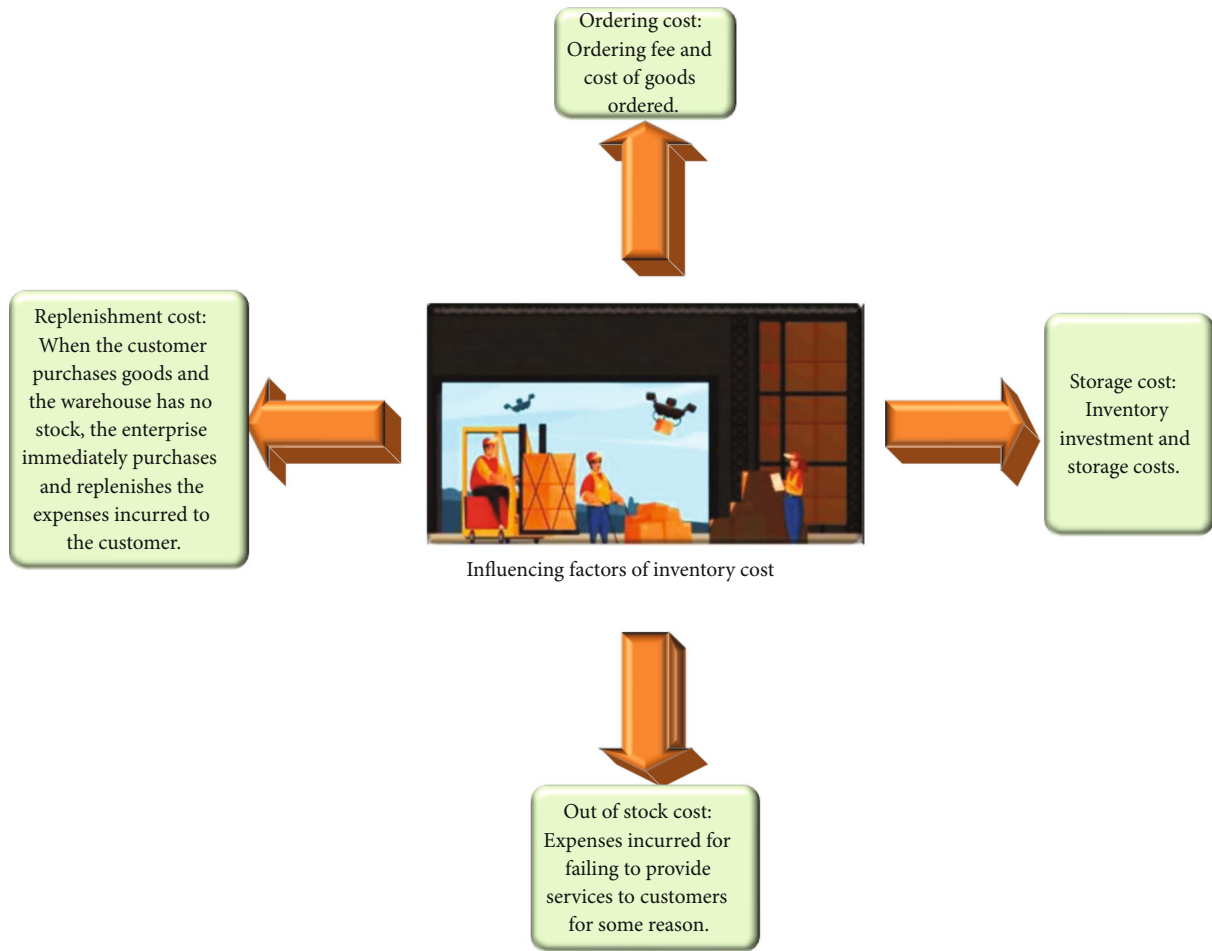
Ordering cost: Ordering fee and cost of goods ordered.

Replenishment cost: When the customer purchases goods and the warehouse has no stock, the enterprise immediately purchases and replenishes the expenses incurred to the customer.

Storage cost: Inventory investment and storage costs.

Influencing factors of inventory cost

Out of stock cost: Expenses incurred for failing to provide services to customers for some reason.

FIGURE 2: Influencing factors of inventory cost.

Judge the demand type, independent demand or related demand, random demand or deterministic demand.

Demand type of demander

Supplier's mode of operation

Allow supplier out of stock or not.

Inventory control strategy

Select appropriate control methods

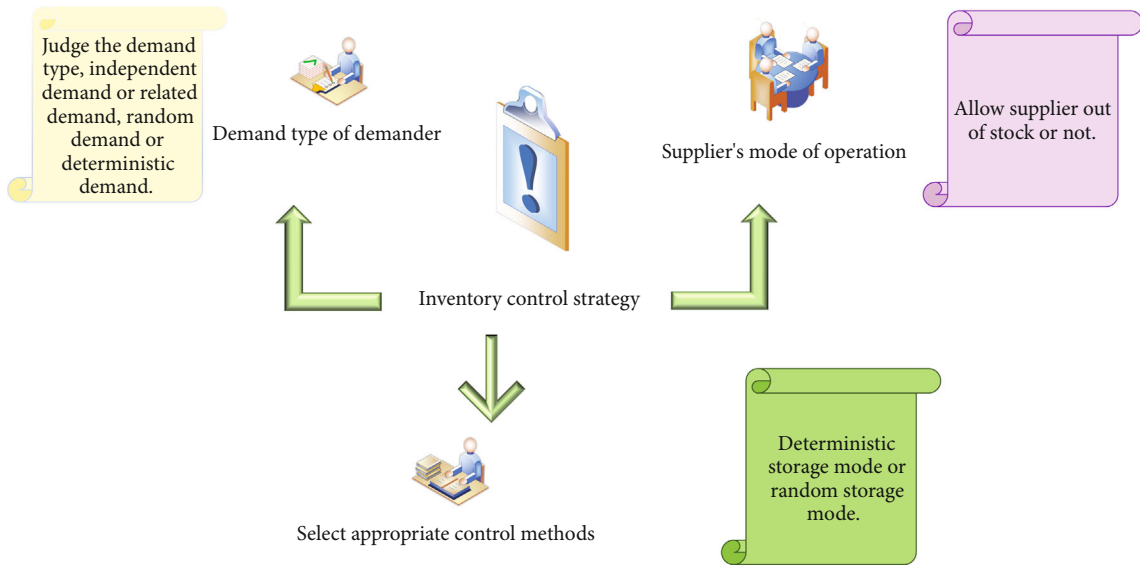Deterministic storage mode or random storage mode.

FIGURE 3: Categories of inventory control.

includes random and deterministic storage models. A new inventory control model suitable for green supply chain management is proposed based on the traditional inventory control model.

The problems to be solved in inventory management under green supply chain management focus more on the communication between enterprises. It includes strengthening the accurate transmission of information among enterprises
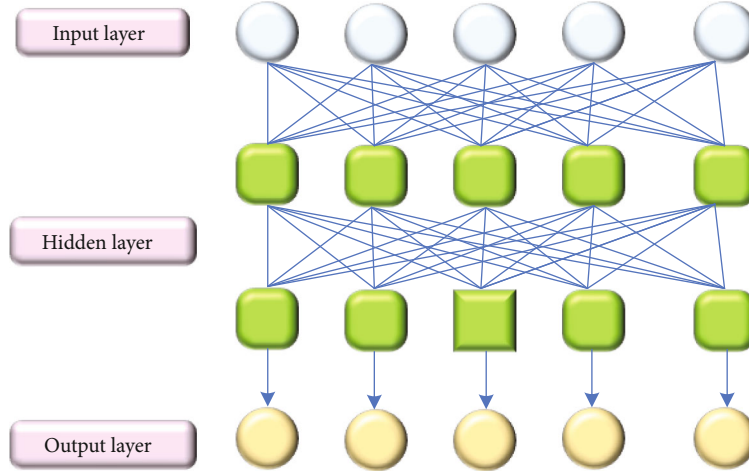
FIGURE 4: BPNN model.

and the smooth transmission of information flow, handling of uncertain problems, and reducing unnecessary waste by strengthening information exchange.

3.3. Basis of BPNN. BPNN is the most widely used neural network at present. Figure 4 is its structural model.

Figure 4 shows that BPNN is a feedforward neural network. Neurons accept the input of the previous layer and output to the next layer. The first layer of the whole model is the input layer, the middle layer is the hidden layer, and the last layer is the output layer. The hidden layer neurons of BPNN use sigmoid differentiable functions like the transfer functions [46].

The parallel processing of BPNN makes it one of the most widely used algorithms. The advantages of BPNN include having strong fault tolerance, dealing with uncertain systems through adaptive and self-learning, and coordinating various input relationships. However, it also has some disadvantages, such as long training time, a large amount of computation, and slow convergence speed. Therefore, a PSO algorithm is introduced because it is easy to operate.

3.4. Introduction to PSO. The mathematical description of PSO is as follows. First, it is to determine the search space and the number of particles in the population. Then, it is to use vectors to represent the particle position and the optimal position in the particle "flight." Next, it is to mark all particles' position and most valuable position. Finally, it is to present the position change rate of particles [47]. The change of particle position is calculated using equations (1) and (2).

$$
\begin{aligned}
v_{id}(t+1) = {} & \omega * v_{id}(t) + m_1 * \text{rand}\,() * (p_{id}(t) - x_{id}(t)) \\
& + m_2 * \text{rand}\,() * \left(p_g(t) - x_{id}(t)\right),
\end{aligned} \tag{1}
$$

$$
x_{id}(t+1) = x_{id}(t) + v_{id}(t+1). \tag{2}
$$

In (1) and (2), m_1 and m_2 are the accelerated factors. ω is the inertia factor, and t is the current iteration times. p_g is

the current global optimal position of the particle swarm. p_{id} is the optimal individual, and v_{id} indicates the position change rate. d is the spatial dimension, and i is the particle serial number.

The initial velocity and position of the particle swarm are generated randomly. Then, they iterate according to the above two equations until the conditions are finally met.

Figure 5 reveals the PSO flow.

Figure 5 shows the flow of PSO. It includes initializing the particle swarm, calculating the fitness value of each particle, comparing the fitness value of each particle with extreme individual value and extreme global value, and determining whether to change the iteration times.

The parameters of PSO include inertia weight, learning factor, maximum, particle dimension, population size, and termination condition. The adaptive adjustment in the inertia weight is determined by

$$
\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{h_{\max}} * h. \tag{3}
$$

In (3), $h_{\max}$ is the maximum number of iterations, h represents the current number of iterations, and ω is the weight.

In the inertia weight setting, the general practice is to set the initial value of ω to 0.9 and make it decrease linearly to 0.3 with the increase of iteration times. It can achieve the desired purpose of optimization. In the PSO algorithm, two acceleration coefficients control the influence of "cognitive" part and "social" part on particle velocity. In the population-based optimization method, it is always hoped that the individual can search in the whole optimization space in the initial stage, so as not to fall into the local value too early. In this way, in the end stage, it can improve the convergence speed and accuracy of the algorithm. Besides, it can effectively find the optimal global solution. According to previous studies, it is better if the acceleration coefficient is less than 4. The selection of the maximum speed should not exceed the particle width range. If the maximum velocity is too high, the particle may fly over the position of the optimal solution. If it is too small, it may reduce the global
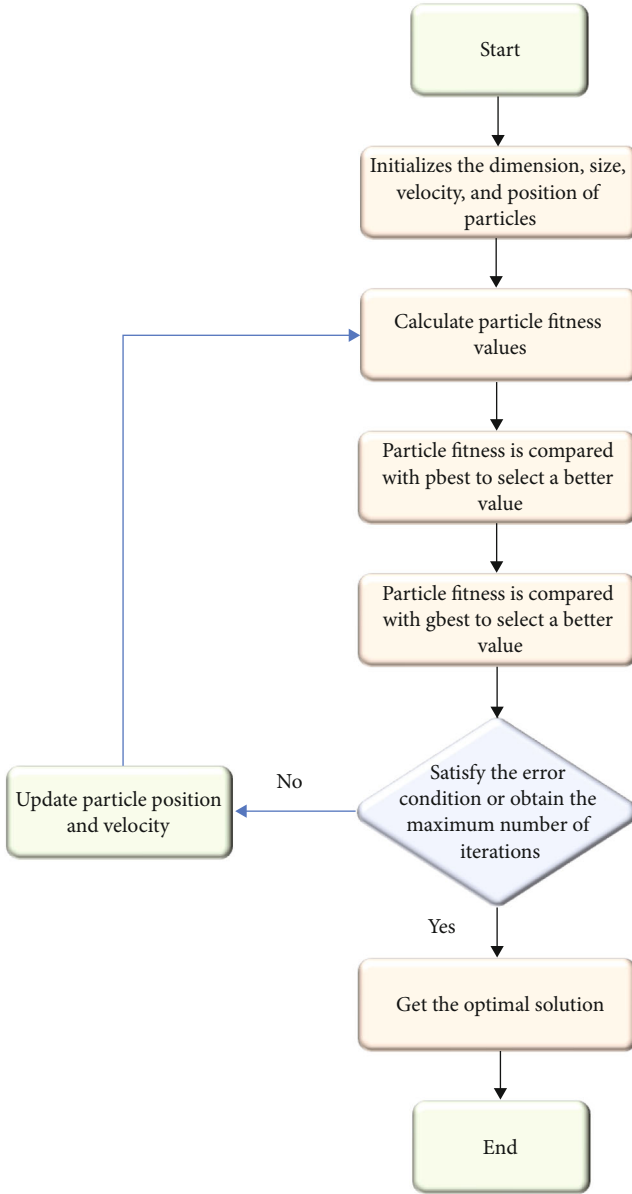
FIGURE 5: Flow of PSO.

TABLE 1: Parameter setting of PSO.

Parameters types	Parameter settings
Inertia weight	The initial value is set to 0.9 and then iterated to 0.3
Learning factor	The sum of acceleration coefficients is less than 4
Maximum speed	Not exceeding the particle width range
Particle dimension population size	The particle dimension is determined by the solution space dimension; the group size ranges from dozens to 200
Termination conditions	Meet the minimum error requirements or reach the maximum iteration times

through the mutation of particle swarm speed when the PSO algorithm has not obtained the optimal solution to avoid falling into the optimal local solution. Learning factors mainly affect the optimization speed and accuracy of the algorithm. Improving its adaptability is of great help to improve the algorithm's overall performance. Therefore, PSO is optimized, including adding mutation operators and improving the adaptive ability to learn factors. A population use variance is adopted to add a mutation operator, as shown in equation (4).

$$\sigma^2 = \sum_{i=1}^{n} \left(\frac{f_i - f'}{f} \right)^2, \tag{4}$$

where n represents the number of particles, f' is the average fitness of particles, and σ^2 is the variance of population fitness. f is the normalized calibration factor.

The convergence degree of population fitness variance can be defined by

$$f = \max \left\{ 1, |f_i - f'| \right\}. \tag{5}$$

Based on the above, mutation operation is performed when PSO does not obtain the fully optimal solution. By mutation of particle swarm velocity, the particles can be further searched. The particle velocity can be calculated by

$$\begin{aligned} v_{\mathrm{id}}(t+1) &= \omega * v_{\mathrm{id}}(t) + m_1(t) * \mathrm{rand}\,() \\ &\quad * (p_{\mathrm{id}}(t) - x_{\mathrm{id}}(t)) + m_2(t) \\ &\quad * \mathrm{rand}\,() \left(p_g(t) - x_{\mathrm{id}}(t) \right) \\ &\quad + \mathrm{flag} * \delta * v_{\max}, \end{aligned} \tag{6}$$

where $\mathrm{flag} * \delta * v_{\max}$ represents the mutation operator and μ is the influence degree of the mutation operator on velocity. The value of δ reads

$$\delta = \min \left\{ \left| \frac{f_g(t) - f_t}{f_t} \right|, 1 \right\}. \tag{7}$$

retraction ability of particles. Generally, the population size does not need to be too large. Dozens of particles are enough. More particles can be selected for some special problems. The number of particles can be up to 100~200. The particle dimension is determined by the solution space dimension of the optimization problem. The suspension conditions are specified according to specific problems after reaching the maximum number of iterations or meeting the minimum error requirements. Therefore, Table 1 is a summary of parameter settings for the PSO algorithm.

The traditional PSO algorithm easily falls into the optimal local solution during its operation, so it is necessary to take some measures to improve it [48]. The improvement strategy of the algorithm is to add a speed mutation operator and improve the adaptability of learning factors. Adding speed mutation operator can further search particles
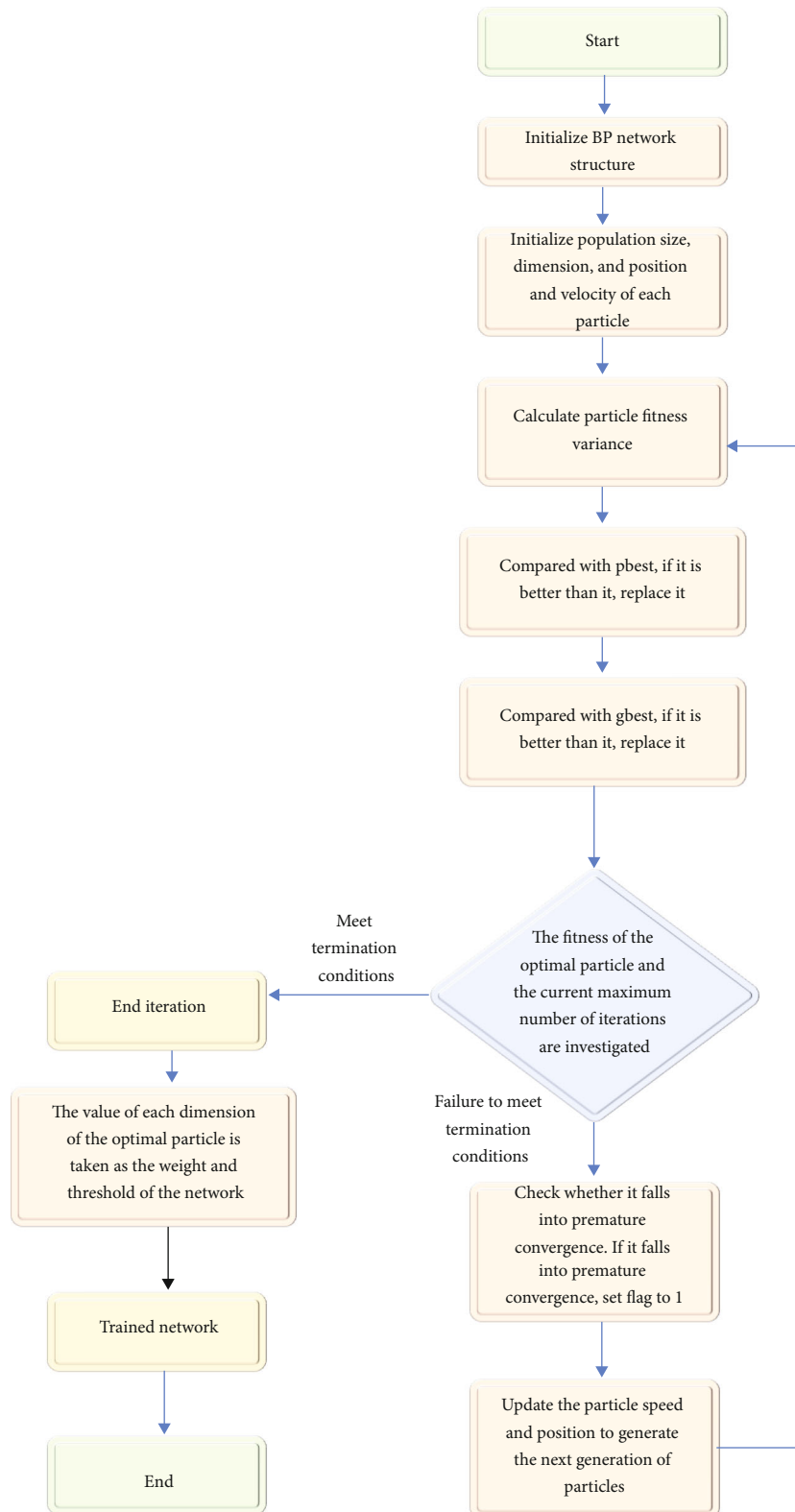
Figure 6: Flow chart of IPSO training BPNN.

In (7), $f_g(t)$ is the fitness value of the globally optimal particle and f_t represents the empirical optimal value.

The acceleration coefficient in learning factors is adjusted in the adaptive adjustment of learning factors. Equations (8) and (9) show the value of the acceleration coefficient.

$$\begin{cases} m_1(t) = 4 * \dfrac{\left| f_a(t) - f_g(t) \right|}{f_a(t)}, \\ m_2(t) = 4 - m_1(t), \end{cases} \tag{8}$$

$$f_a(t) = \frac{1}{N} \sum_{i=1}^{N} f_i(t). \tag{9}$$

In (8) and (9), $f_a(t)$ is average fitness. N indicates the number of fitness.

Equation (1) is improved, as shown in equation (10).

$$\begin{aligned} v_{id}(t+1) = {}& \omega * v_{id}(t) + m_1(t) * \text{rand} \\ & * (p_{id}(t) - x_{id}(t)) + m_2(t) * \text{rand}\ ) \\ & * \left(p_g(t) - x_{id}(t) \right). \end{aligned} \tag{10}$$

3.5. BPNN Based on IPSO.
BPNN is trained with the IPSO and its performance and generalization ability are improved.

Figure 6 displays the flow of BPNN based on IPSO.

Figure 6 shows that when IPSO trains BPNN, the threshold and connection weight of the neural network correspond to the dimension component of each particle in the particle swarm. The fitness function combined with the algorithm is borne by the mean square error of the neural network.

The training sample's output value deviation and particle fitness are calculated by equations (11) and (12), respectively.

$$I_i = \sum_j \left(Q_{ij} - q_{ij} \right)^2, \tag{11}$$

$$R = \frac{1}{n} \sum_{i=1}^{n} R_i. \tag{12}$$

In (11) and (12), Q_{ij} is the expected output value, q_{ij} is the actual output value, I is the output deviation, and R is the particle fitness.

3.6. Model Simulation.
The sample set used in the simulation of BPNN based on IPSO is the Iris dataset. Iris is an Iris tectorum Maxim plant. It is divided into three types: Setosa, Versicolor, and Virginica. Iris database is a widely used pattern classification example system. Pattern classification will distinguish three plants according to four attribute values. The dataset is a commonly used classification experimental dataset, which can be directly downloaded from the website http://archive.ics.uci.edu/ml/datasets/iris. The experimental data are directly selected from the dataset, so there is no data preprocessing.

TABLE 2: Experimental environment.

Category	Specific model
Operating system	Windows XP Professional
Development language	C language
Development platform	MS VS. NET
Grid training	Matlab 6.5
Database	SQL Server 2000
Memory	512 MB DDR
CPU	Pentium (R) 4 2.80 GHz

In the simulation test of BPNN and BPNN based on the traditional PSO algorithm, the network structure is 4-4-3. The PSO scale is 20. The dimension is 35, the maximum number of iterations is 7000, the maximum particle velocity is 0.5, and the minimum error is 0.01. The BPNN structure includes 7 thresholds and 25 weights [49]. The parameter setting of BPNN [50] is $\omega = 0.73$ and $c_1 = c_2 = 1.49$. Equation (13) is the BPNN parameter setting based on the traditional PSO algorithm.

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{\text{iter}_{\max}} * \text{iter}, \tag{13}$$

where $\text{iter}_{\max}$ is the maximum number of iterations and iter is the current number of iterations. $\omega_{\max} = 0.9$ and $\omega_{\min} = 0.3$. c_1 and c_2 adjust themselves. The flag in the mutation operator is initially 0, which is further adjusted in the iterative process. In the mutation condition, $\lambda = 0.0001$.

The network structure of the IPSO algorithm is 6 input nodes and 1 output node, and the hidden nodes are 6, 8, 11, and 12, respectively. The PSO scale is 40, and the network structure determines the particle dimension [51]. Besides, the maximum particle velocity is 0.5, the maximum number of iterations is 7000, and the minimum error is 0.1. The inertia weight is adjusted adaptively: $\omega_{\max} = 0.9$ and $\omega_{\min} = 0.3$, mutation operator flag = 0, $\lambda = 0.0001$.

The network performance evaluation indexes used in the simulation include the classification error rate (E_X) of the training set, the classification error rate (E_C) of the test set, the mean square error (MSE_X) of the training set, and the mean square error (MSE_C) of the test set. Equations (14) and (15) are calculation equations of the mean square error of the training set and the mean square error of the test set.

$$\text{MSE}_X = \frac{1}{2d} \sum_{t=1}^{d} \sum_{k=1}^{n} (a_{kl} - t_{kl})^2, \tag{14}$$

$$\text{MSE}_C = \frac{1}{2q} \sum_{i=1}^{q} \sum_{k=1}^{n} (a_{kl} - t_{kl})^2. \tag{15}$$

In (14) and (15), d is the number of training set samples, t_{kl} represents the desired output of the output neuron, and a_{kl} is the actual output of the output neuron.
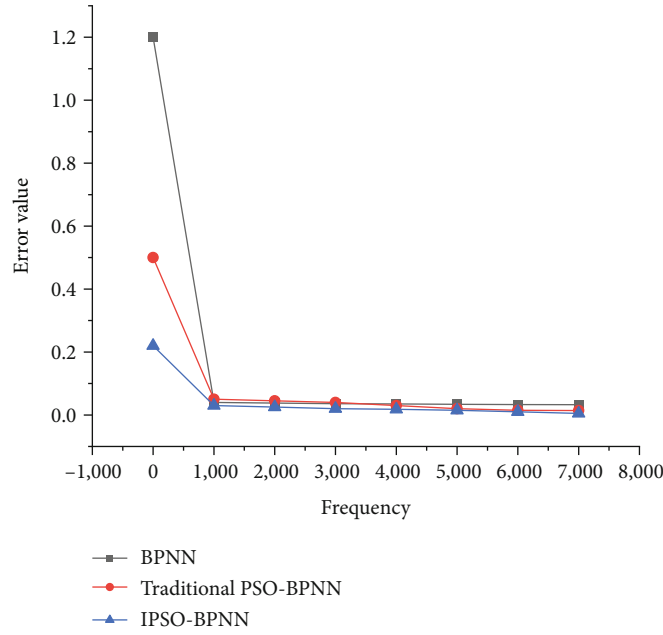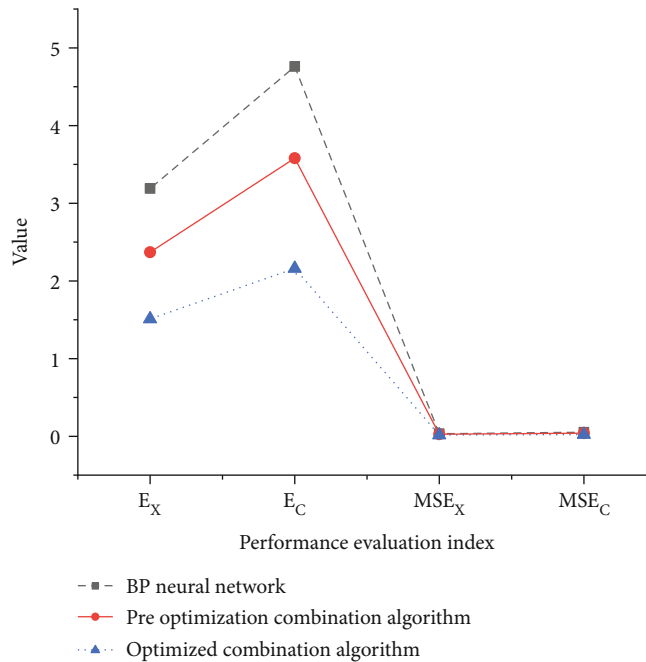
Figure 7: Training errors of BPNN.

Figure 8: Performance comparison of different algorithms.

3.7. Application of the Combined Algorithm in Supply Chain Management. The inventory management in an enterprise's supply chain management system is taken as the research object. The enterprise's supply chain management is divided into three layers: appearance, business, and data. As one of the subsystems of supply chain management, the overall inventory management process includes raw material purchase receipt, picking an issue, movement, and inventory counting.

The combined algorithm proposed in the full text is used to predict the inventory in inventory management to meet the requirements of green supply chain management. The use network is a 3-layer network, and the input nodes are 6. The number of hidden layer nodes adopts 11 nodes with good convergence and generalization. The particle swarm size of the prediction model is 40. The maximum particle velocity is 0.5, the minimum error is 0.01, and the maximum number of iterations is 7000. The mutation operator is 0.0001, the maximum value in the adaptive adjustment of inertia weight is 0.9, and the minimum value is 0.3. The enterprise data are selected from 2018 to 2021 for network training, and the daily test results are compared with the monthly test results in terms of network performance with 6~12 nodes.
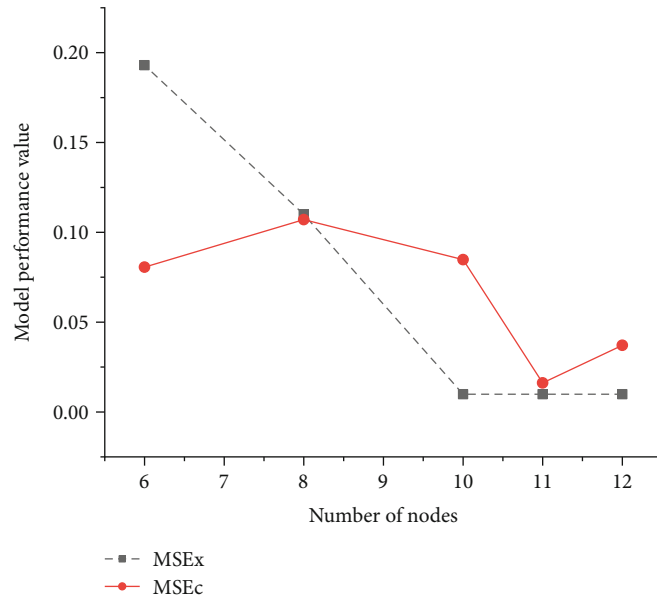
FIGURE 9: Comparison of daily test results of inventory forecast performance of networks with different numbers of nodes.
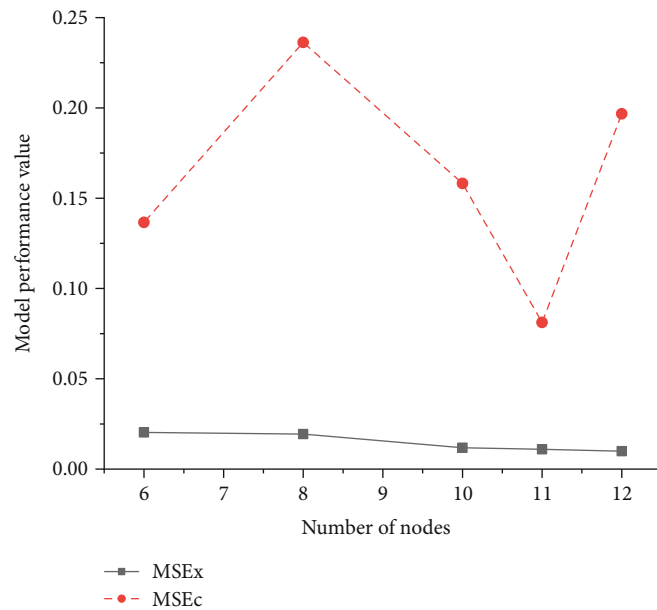

FIGURE 10: Comparison of monthly test results of inventory forecast performance of networks with different numbers of nodes.

Table 2 displays the operating environment of the experiment.

4. Result Analysis of Intelligent Supply Chain Management

4.1. Comparative Analysis of Simulation Results. Figure 7 displays the error results in the training process of BPNN, traditional PSO-BPNN, and IPSO-BPNN.

Figure 7 shows that the training error of a single BPNN reaches the minimum value of 0.033 after 7000 times of training, and the BPNN error using traditional PSO is 0.0259. The BPNN error optimized by IPSO is 0.0163, which

shows that the BPNN model based on the IPSO algorithm has higher accuracy and better performance, and the improvement effect of the PSO algorithm is remarkable. Moreover, the errors of the two combined algorithms are lower than that of a single BPNN, which shows that the PSO algorithm can improve the convergence speed and accuracy of BPNN to a certain extent. After further improving the PSO algorithm, the performance improvement effect of BPNN is more obvious.

Figure 8 displays the performance comparison results of the three algorithms based on the performance indexes.

Figure 8 shows that the generalization error rate and the training error rate of the three algorithms are low and that of

the optimized algorithm is the lowest. The classification error rate of the optimized combination algorithm is 1.51 for the training set, 2.16 for the test set, 0.0163 for the training set, and 0.0229 for the test set. The error rate of BPNN is the highest. It suggests that the performance of the optimized model is better, although the Iris dataset is relatively simple.

4.2. Analysis of the Inventory Forecast Performance of Networks. Figures 9 and 10 are the daily and monthly test results of inventory forecast performance of networks with the different numbers of nodes.

Figures 9 and 10 show that under 6 ~ 12 different hidden nodes, both the daily measurement error rate and monthly measurement error rate show that when the number of nodes is 11, the error rate is low, and the training set is always better than the test set. The minimum value of daily measurement training error appears in the training set when the number of nodes is 11. The minimum value of monthly measurement error is also 0.0099, which appears in the training set when the number of nodes is 11. It shows that when the number of hidden nodes is 11, the model's generalization ability is good and its training error is small. Hence, the network structure of the final combined model is 6-11-1. The inventory control auxiliary module is developed on the VS.NET platform based on the above model. The prediction module can give purchase volume suggestions and inventory volume suggestions, providing a feasible direction for the green development of inventory management.

5. Discussion

The training error of BPNN is large, and the training error of BPNN combined with the PSO algorithm is small. It indicates that the performance of the combined model is better than that of the single model, which is consistent with Li et al.'s research [52]. Using a combined model to study problems has become an important theoretical research method, the IPSO algorithm combined with BPNN has the best performance. It shows that the proposed two optimization methods can improve the adaptive ability of the learning factors, increase the speed mutation operator, and make the particles that have fallen into local optimization jump out of the local solution. In the final comparison of the generalization error rate and training error rate, the BPNN combined with the IPSO algorithm performs best. It proves once again the correctness of the optimization algorithm used. The advantage of this research method is to use the improved algorithm for network learning. Simulation results show that the improved algorithm can effectively shorten the training time of neural networks and enhance the generalization performance of the neural network. The research disadvantage is that only BPNN is selected as a single model in the model comparison, so the results are not comprehensive enough.

6. Conclusion

Nowadays, it is easy to waste resources in supply chain management. Therefore, in response to the green development policy in supply chain management, this exploration uses AI technology to study inventory management in supply chain management. The traditional PSO algorithm is mainly improved by improving the adaptive ability to learn factors and adding the speed mutation operator. The IPSO algorithm is proposed and applied to the learning and training of BPNN, and a combination model with high accuracy is obtained. The research results will provide a reference for the intelligent development of inventory management. They are expected to be applied to major supply chain management to improve supply chain management efficiency. However, there are still some research deficiencies. Due to the limited ability, the performance of the algorithm constructed in inventory management prediction has not been deeply studied. The real-time transmission of supply chain management is not discussed. This exploration only selects two models to compare with the optimal combination algorithm proposed, and only verifies the performance of the improved algorithm after adding two mechanisms. It does not verify the algorithm's performance when adding only one mechanism, nor compare it with other business intelligence tools. Therefore, the follow-up research will focus on applying the combined algorithm constructed in inventory management prediction. It will strengthen the analysis of real-time transmission, select more relevant models for comparative analysis, and provide customers with various optional intelligent decision-making models according to different needs to provide a reference for green supply chain management development.

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