Inventory Forecasting for Medical Environmental Protection Equipment Enterprises Based on BP Neural Network Optimized by Sparrow Search Algorithm

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Abstract: Deficiencies in corporate inventory forecasting are common problems, an inventory forecasting model using a sparrow search algorithm to de-optimize a BP neural network has been developed. Through the actual production of HX medical environmental protection equipment enterprises, the inventory of raw materials is studied, and the five factors that have the greatest impact on the inventory are selected. To establish an inventory forecasting model using the sparrow search algorithm to optimize the weights and thresholds of the BP neural network, and at the same time to compare and analyze the optimized model with the model before optimization. After comparing the results, it can be seen that the BP neural network optimized by the sparrow search algorithm is more stable and the prediction accuracy is more accurate than before, when predicting the inventory of the enterprise due to the optimization of the weights and thresholds.

Keywords: Sparrow Search Algorithm; Inventory Forecasts; BP Neural Network

1. Introduction

The need for disease prevention and control has increased in recent years with the continued emergence of diseases that can be transmitted on a wide scale. China's medical device industry has shown rapid development in recent years, and the size of the medical device market is constantly increasing [1]. Take HX medical environmental protection equipment enterprises as an example, the production mode is order-based production, high degree of customization, its main medical environmental protection disinfection trolley, accessories in more than 2,000 kinds, such a huge variety of accessories, to determine the appropriate amount of inventory of accessories is particularly important. Too much inventory, resulting in increased inventory costs; too little inventory, resulting in the inability to meet orders in a timely manner, affecting the credibility of the enterprise. Therefore, determining a reasonable inventory of accessories and improving the level of inventory forecasting are conducive to reducing the operating costs of enterprises and improving their service level and competitiveness [2].

In the existing market environment, the factors affecting the amount of medical environmental protection equipment enterprise inventory setup are intricate and complex, and there is a very complex non-linear relationship between these factors determining the inventory forecast and the amount of inventory. Traditional mathematical statistical models such as the moving average method for enterprise inventory forecasting can only solve some simple linear problems, and cannot cope with more complex problems. Compared with the research on inventory decision-making based on traditional statistical forecasting methods, there are relatively more studies on inventory decision-making based on machine learning forecasting models, mainly because these machine learning forecasting methods not only have a great improvement in the accuracy and speed of forecasting, but also can take into account the influence of consumer factors on inventory decision-making on the basis of seasonal variations, promotions, and other traditional demand-influencing factors, so that decision makers can make scientific decision-making results [3]. Zhang Yingxin [4] used BP neural network to study the multilevel inventory control problem under stochastic demand, and compared the traditional method with BP neural network, and concluded that the forecasting performance of BP neural network is better. Ma Fayao [5] used BP neural network algorithm and model for inventory forecasting to eliminate the limitations of the traditional model in solving the inventory forecasting problem which is nonlinear and has many influencing factors. Among the many network models, BP neural networks have the distinctive feature of being able to update the network through self-learning, which is widely used in all walks of life, but there are some drawbacks, such as often falling into the local optimal solution, which is an ever-present problem [6]. In order to better solve the enterprise inventory problem, this paper uses the sparrow search algorithm to optimize the BP neural network model to achieve the purpose of better prediction of the enterprise inventory, and illustrates the feasibility of the method by comparing and verifying the results of the enterprise inventory prediction.

2. Sparrow Search Algorithm for Optimizing BP Neural Network Models

2.1 BP Neural Network

BP neural networks are also known as error back propagation neural networks. By learning and storing a large number of input-output model mappings, it is able to learn and memorize a considerable number of input-output model mappings with constant updates, which means that it doesn't require one to look for a mathematical function to describe the relationship between the independent variable and the dependent variable as a first step [7]. Therefore, predictions can be made for new data by adjusting the parameters within the network. BP neural networks are generally multilayer, including basic input and output layers, and also have several hidden layers.

BP neural networks contain two learning processes, forward and back propagation [8]. In a BP neural network, the data is first fed through the input layer and then processed next in the hidden layer, which is a forward propagation process. When training the network weights, then the error signal is propagated forward from the output layer to correct the connection weights of the network along the direction of reduction, which is a process of reverse propagation of error. As learning continues, the final error becomes smaller and smaller. BP neural networks can theoretically have many hidden layers, where a single hidden layer network typically realizes an arbitrary nonlinear mapping by adding the number of neuron nodes.

2.2 Sparrow Search Algorithm

The Sparrow Algorithm (SSA) [9] belongs to a type of group intelligence algorithms, whose main idea is to be able to randomly search for excellence, and whose proposers were inspired by the actions of birds that are constantly moving and converging when they are searching for food. During the process of searching for food, the foragers and joiners make up the whole sparrow colony. In order to increase safety during the search for food, some sparrows can be divided and assigned the task of detecting and warning other sparrows, these sparrows we call vigilantes. The discoverers constantly update their position during the foraging process, and when the alert threshold is less than the safety threshold, it indicates that the area around the sparrow's foraging area is safe. Conversely, when the alert threshold is greater than the safety threshold, it means that some sparrows in the group have realized the presence of a predator in the vicinity and warned the other sparrows in the sparrow population, and the other sparrows in the group quickly flew to other safer areas for foraging after receiving the warning. During each iteration, the location of the discoverer is updated as described below:

$$X_{i,j}^{t+1}=\begin{cases} X_{i,j}^{t}\cdot\exp\left(\frac{-i}{\alpha\cdot it_{max}}\right) & \text{if } R_2<ST \\ X_{i,j}^{t}+P\cdot D & \text{if } R_2\geq 0 \end{cases} \quad (1)$$

In the above equation, X_{ij}: position information of the ith sparrow in the jth dimension; P: random number (obeying normal distribution); t: current iteration number; itmax: maximum number of iterations (constant); α: random number of (0, 1]; R_2: warning value ($R_2 \in [0, 1]$); ST: safety value ($ST \in [0.5,1]$); D: 1*d matrix (each element is all 1).

When the ith joiner with a small adaptation value is in a very hungry situation, it should go to other regions to feed in order to obtain more energy. The joiner location update is described as follows:

$$X_{i,j}^{t+1}=\begin{cases} P\cdot\exp\left(\frac{X_{worst}^{t}-X_{i,j}^{t}}{i^2}\right) & \text{if} \quad i>n/2 \\ X_P^{t+1}+\left|X_{i,j}^{t}-X_P^{t+1}\right|\cdot A^{+}\cdot D & \text{otherwise} \end{cases} \quad (2)$$

In the above equation, X_p: the optimal position where the finder is currently located; A: a 1*d matrix (each element is randomly assigned a value of 1 or -1); X_{worst}: the current global worst position.

In the usual case, it is assumed that the sparrows in the colony that have realized the threat make up 20% to 40% of the entire colony, and that the sparrows randomly change their initial position during the foraging process. When the existence of the worst fitness is less than the global best fitness value, it means that at this time a significant portion of individuals are on the edge of the population search area, very vulnerable to predators; and when the two are equal, it means that the sparrows in the middle of the population feel the proximity of the predator, and need to join with the sparrows in the other place to reduce the possibility of them being hunted and killed by predation, and the mathematical expression is as follows:

$$X_{i,j}^{t+1}=\begin{cases} X_{best}^{t}+\beta\cdot\left|X_{i,j}^{t}-X_{best}^{t}\right| & \text{if } f_i>f_g \\ X_{i,j}^{t}+K\cdot\frac{\left|X_{i,j}^{t}-X_{worst}^{t}\right|}{(f_i-f_w)+\varepsilon} & \text{if } f_i=f_g \end{cases} \quad (3)$$

2.3 Sparrow Search Algorithm for Optimizing BP Neural Networks

Although the BPNN itself can continuously adjust the input parameters in the neural network dynamically through multiple trainings to achieve the improvement of accuracy, the SSA can directly determine the optimal initial parameters in the neural network model, avoiding the possibility of over-training caused by randomization of the input parameters in the multiple trainings of the BPNN, and reducing the decrease in the accuracy of the prediction data due to the encounter of local optimal traps situation [10]. For this reason, in this paper, SSA is used to optimize the initial weights and thresholds of the BP neural network, so as to form the SSA-BP neural network model. The SSA-BPNN modeling process is shown in Figure 1 below.

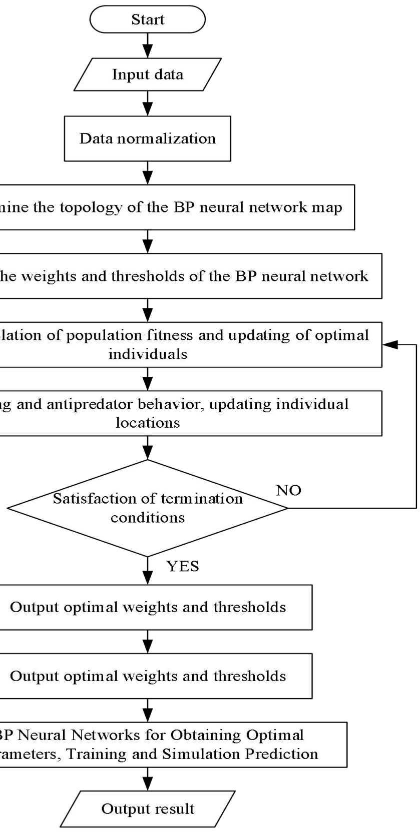


Figure 1. SSA-BP Neural Network Modeling Flow Chart

The main steps are as follows:

Step 1 Establish the network topology of BP neural network.

Step 2 Initialize the population and set the parameters.

Step 3 Start training the BP neural network

model.
Step 4 Calculate and update the positions of discoverers, joiners, and vigilantes.
Step 5 Obtain the current updated position and calculate to obtain the optimal individual as well as the best fitness value.
Step 6 When the trained result reaches the set parameters, stop the calculation and execute the output, otherwise return to step 3.
Step 7 Output the result.

3. Application Analysis in Medical Device Companies

3.1 Factors Affecting Stockpile Projections

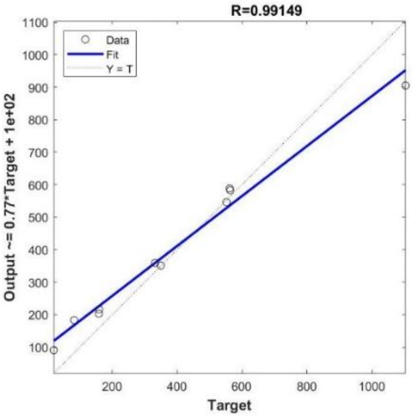
There are many factors that affect inventory setting, including but not limited to order quantity, order price, supply price, and repair rate. In this paper, eight quantifiable factors affecting inventory setting are selected as follows.
1) Order quantity. The order quantity of medical equipment of a medical equipment enterprise directly affects the quantity of inventory demand, which is the most direct key factor affecting inventory demand.
2) Order price. The order price directly affects the consumer's desire to buy, and the level of its setting affects the inventory setting.
3) Inventory cost. Inventory cost refers to the ordering cost of the product, overhead, reducing inventory cost is one of the main purposes of inventory forecasting.
4) Total orders. The total amount of orders for a product is an important indicator of a company's operating conditions, in terms of quantity equal to the number of orders and the multiplier of the unit price of the order is positively correlated, directly related to the number of sales.
5) the actual cost. The actual cost is to sell the product out of the total cost of Chan, including the actual value of the product and the intermediate links of various costs, in the number of sales with the number of products and the price of goods is positively correlated with the relationship between the pipe, which is an important factor in the shadow of the enterprise's inventory.
6) Supply price. The supply price of accessories with market price fluctuations, in low prices and high prices when the purchase cost is different, is to set the inventory needs to focus on a consideration of a factor.
7) Product repair rate. Good after-sales service is an enterprise in the industry can continue to develop the key ability, and after-sales service in the replacement of parts is also part of the inventory consumption.
8) Seasonal impact. The market demand of the product is affected by seasonality, different seasons, different demand, the profile affects the inventory setup.

3.2 Sparrow Search Algorithm Optimized BP Neural Network Inventory Forecasting Model Construction

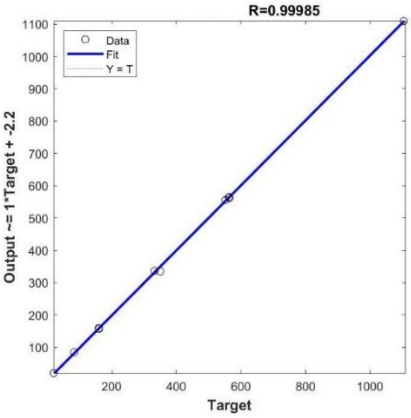
The relevant factor data of HX medical device enterprises for a total of 36 months from 2020 to 2022 is used as the dataset, and the training set is the data of the first 26 months, and the data of the last 10 months is used as the test set to test the predictive performance of the model.
Some of the raw data provided by HX medical device enterprises are shown in Table 1.
The network model was trained iteratively in Matlab software platform. The neural network has 8 neurons in the input layer, 1 in the hidden layer and 1 in the output layer, the gradient descent training method (function traingd) is used, the learning rate is 0.01, the minimum error of the training objective is 0.000001, the maximum number of training steps is 1000, and the size of the population is 30.The results of the network training are shown in Figure 2.

Table 1. Raw data of selected enterprises

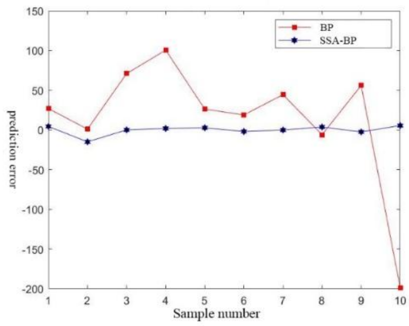
Season/month	Cost of inventory	order quantity	Order price	Total orders	actual cost	Supply price	Product repair rate	Actual inventory requirements
1	17195.75	285	26	7410.00	5269.67	18	0.7	317
2	25706.85	1001	27	27027.00	19523.94	19	0.3	1104
3	3375.75	143	25	3575.00	2501.20	17	0	160
4	11614.75	499	25	12475.00	8728.55	17	0.4	552
5	10627.00	510	23	11730.00	8160.00	15.5	0.2	564



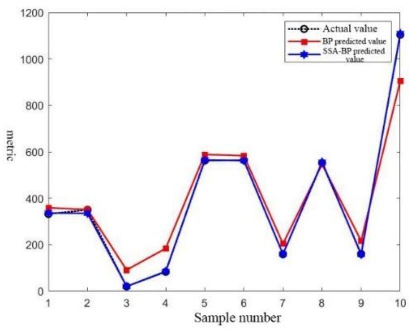
(a) BP neural Network Regression Plot



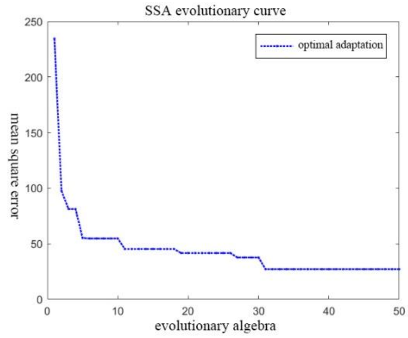
(b) SSA-BP Regression Plot



(c) Comparison Chart of Prediction Errors



(d) Plot of Projected Versus Actual Values



(e) Network Iterative Evolution Curve

Figure 2. Network Training Results

As can be seen from Figure 2(d), the conformity between the prediction curve of SSA-BPNN and the actual inventory volume curve is better than the prediction curve of BPNN, and there is Figure 2(e), it can be seen that the BPNN after combining with SSA jumps out of the local optimum many times, which proves that the algorithm optimization is effective. Taking the prediction error comparison of the results of 10 runs, the pre-average absolute percentage error of the BPNN prediction model is 39.5517%, and after the optimization of the SSA algorithm, the average percentage absolute error is reduced to 3.1808%, i.e., the prediction accuracy of BPNN is 60.4483%, and that of SSA-BPNN is 96.8192%, which proves that the optimization is effective. It can be seen that selecting the optimal threshold of the network through the sparrow algorithm can effectively improve the reliability and robustness of the BPNN prediction model and enhance the prediction performance.

4. Conclusion

In this paper, SSA-BP enterprise inventory prediction is applied to medical device inventory prediction, replacing human experience with machine learning, which is helpful for enterprise inventory prediction and efficiency.

In this paper, the eight basic factors affecting inventory setting are selected as neural network inputs, and if other influencing factors are added, principal component analysis is required, which is then sent to the network for training while increasing the number of training data, which can further improve the prediction accuracy. This paper establishes the inventory forecasting model of medical equipment manufacturing enterprises, which has certain reference significance for the establishment of inventory forecasting model of its similar enterprises.

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