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Optimization and Risk Assessment Model of Enterprise Supply Chain Management Mode Based on Simulation Algorithm

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ABSTRACT
The stability of the supply chain has a significant impact on both the strategic deployment and operational efficiency of the enterprise, in order to optimize the supply chain management model for the enterprise and resolve the major supply chain risks, this paper realizes the optimization management and risk assessment of the supply chain through Monte Carlo simulation algorithm and SVM. Taking the newsboy problem as an entry point, a supply chain management optimization model is constructed, and Monte Carlo simulation algorithm is used to solve it. Using SVM regression and assessment ideas, supply chain risk regression assessment is carried out by C-SVR. Applying the supply chain management optimization model, it is concluded that when the optimal inventory of prefabricated components of the selected construction unit is $2.55\times10^3 m^3$, the enterprise profit is the largest, which is $902.31\times10^3 m^3$ yuan. Supply chain risk assessment of a port, the training error and prediction error of the assessment model in this paper are only 0.043% and 1.76%, which are significantly better than the BP neural network assessment method. Therefore, it proves that the work in this paper achieves the optimization and risk assessment of enterprise supply chain management model through simulation algorithm.

Keywords: monte carlo simulation, newsboy model, SVM, supply chain management, risk assessment

1. Introduction

Supply chain management belongs to a kind of enterprise strategic means, the enterprise based on the overall perspective of the supply chain, through maintaining the cooperative relationship with the supply chain link suppliers, to maintain the supply chain operation, for the enterprise's own operation and development to provide more security support [1-3]. Supply chain management risk is a phenomenon that enterprises are bound to encounter in supply chain management, which is mainly

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manifested in the deviation of the results in the process of supply chain operation, and the uncertainty of the value generated by part of the link [4-6]. In order to give full play to the value of supply chain management and obtain more economic and social benefits, enterprises should strengthen the risk management and prevention and control of supply chain [7-8]. In actual operation, enterprises should analyze the supply chain risk according to their own situation, identify the common risks, and at the same time, respectively, strengthen the risk control from two perspectives: before and during the incident, so as to minimize the impact of supply chain risk on the development of the enterprise.

Supply chain simulation can effectively enhance the collaboration ability of the whole process of the supply chain in order to improve the overall effectiveness of the supply chain [9]. By modeling and simulation analysis of the supply chain system, it can make the enterprise management personnel from the consumer market to the raw material suppliers of the impact of a variety of decisions to carry out a more in-depth and intuitive analysis [10-12]. At the same time, different logistics management strategies and programs can also be quickly measured in the model, optimization, through the continuous optimization of the entire supply chain resources allocation to achieve the lowest total cost [13-14]. On this basis, the simulation of different decisions of managers, the simulation of the data obtained using statistical analysis methods can be used for enterprises to compare and analyze different control measures, to help enterprises to make the correct decision, so that enterprises can obtain market competitiveness and supply chain vitality, to fundamentally improve the competitiveness of enterprises and supply chain is of great significance [15-18].

Literature [19] designed a dual-objective optimization problem for cold supply chain with minimum total cost and minimum global warming impact, and used a hybrid simulation optimization method to solve the proposed mixed integer concave minimization problem, and verified that the method has certain effectiveness in real cases. Literature [20] shows that the simulation optimization algorithm can effectively solve the complexity and stochasticity problems in the enterprise supply chain, and is widely used in the decision-making of the enterprise supply chain, which has high practical value. Literature [21] focuses on the robustness of optimal solutions for supply chain management in uncertain environments, proposes to define the decision-making and environmental variables of the supply chain in order to reduce the solution space, and uses simulation optimization methods to optimize the supply chain problems that target supply chain operation cost and customer satisfaction. Literature [22] examined the role played by simulation optimization methods in supply chain risk management and found that for real-world supply chain risk management with dynamics and complexity, simulation optimization methods can effectively improve the decision-making process of enterprises. Literature [23] established a simulation optimization model for enterprise supply chain finance and logistics in an economic uncertainty environment, i.e., a fusion model of mixed-integer linear programming model and simulation-based optimization model, and the results of comparative study with a single model showed that the proposed fusion model has stronger robustness. Literature [24] investigated the optimization-simulation framework for integrating algorithms in a simulation-based optimization model for a dynamic control system of a supply chain, which fully considered the uncertainties expected in the planning stage and faced in the control stage of the optimization model and provided a theoretical basis for the supply chain design and planning problems of enterprises. Literature [25] proposes a disruptive simulation-based modeling approach to the enterprise supply chain digital copy of the roadmap, the real supply chain simulation model for managers to provide the ability to understand the decision-making behavior and complex dynamics to produce new supply chain coordination policy, to promote the development of the enterprise JIT control ahead of time.

The newsboy problem is the basic problem to realize the optimal management of supply chain. In this paper, a supply chain network equilibrium model is constructed based on the newsboy model by considering the factors of storage cost, product price, supply and demand at the same time, and the Monte Carlo simulation algorithm is used to solve the optimal inventory in the supply chain. The relationship between optimal inventory and factors such as demand factor and expected return under different marginal interest rates is examined in the arithmetic simulation. Using the idea of support vector machine regression and assessment, the input vectors are nonlinearly mapped to construct the objective function, the original nonlinear model is transformed into a linear regression model with high-dimensional feature space, and the C-SVR support vector regression machine is selected to carry out the supply chain regression assessment to realize the assessment work of the supply chain risk. Finally, a port supply chain is chosen as an example research object to test the application effect of the supply chain risk assessment model.

2. Supply chain management optimization model based on simulation algorithms

2.1. *Newsboy model*

The newsboy model is a fundamental problem in the field of supply chain management, and the management problem based on the newsboy environment is a popular research problem in the field of supply chain, as well as one of the research problems in this paper. The classical newsboy model portrays a single-cycle, two-level supply chain that requires the decision maker to minimize the expected cost by giving the optimal order quantity in the face of a given price but uncertain demand [26]. Assuming that the unit selling price of a product is p, the unit cost is c, and the unit salvage value is s, and based on the statistics of previous periods, the random demand $x(x \geq 0)$ of the product is a variable obeying a distribution function of $F(x)$, and its corresponding probability density function is $f(x)$. The retailer gains $(p-c)$ for each unit of the product sold, and loses $(c-s)$ for each unit of the product left over, so that when the retailer's order quantity is q, the profit is expressed as follows:

$$\Pi(q) = p\min(q,x) + s\max(q-x,0) - cq \tag{1}$$

Then the retailer's expected profit function is:

$$\begin{aligned} E[\Pi(q)] &= \int_0^q pxf(x)dx + \int_q^\infty pqf(x)dx + \int_0^q s(q-x)f(x)dx - cq \\ &= \int_0^\infty pxf(x)dx - \int_q^\infty pxf(x)dx + \int_q^\infty pqf(x)dx \\ &+\int_0^q s(q-x)f(x)dx - cq \\ &= pE[x] - \left[\int_q^\infty p(x-q)f(x)dx - \int_0^q s(q-x)f(x)dx\right] - cq \end{aligned} \tag{2}$$

The derivation of the above equation to obtain the retailer's optimal order quantity q^* should satisfy the following conditions:

$$F\left(q^*\right) = \frac{p-c}{p-s} \tag{3}$$

2.2. *Monte Carlo simulation algorithm*

Monte Carlo method is a numerical simulation computational method based on statistical principles to solve problems by random sampling and statistical analysis. The basic idea is to estimate the value function by sampling the actual experience several times. The Monte Carlo method can only estimate the true value of a state by sampling a number of sequences of states with complete experiences, by which is meant that the sequence must have reached an end point. With many sets of such complete state sequences, the algorithm can compute the approximate values of all states that occur throughout the process, and thus solve the prediction and control problems. At the end of each complete state sequence, the intelligence will update the value function based on the reward of the entire complete state sequence, and the valuation of each state depends on the reward value harvested in the time period k between the time step t in which the state is located and the end of the round of iteration [27]. Its cumulative reward G_t is shown in Equation (4):

$$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots + \gamma^k r_{t+k+1} \tag{4}$$

The valuation $V_\pi(S)$ of the current strategy for state S can be represented as the mean value of cumulative reporting G_t as shown in Equation (5):

$$V_\pi(S) = E_\pi\left[G_t \mid S_t = S\right] \approx \frac{\sum_{iS_t=-}^{N} G_t^i}{N} \tag{5}$$

Where: $\sum_{i,S_t^t=s}^{N} G_t^i$ denotes the sum of accumulated returns G_t at each visit to state S_t, and N is the visit count of the current state S_t. According to the law of large numbers, we can get the exact function expectation when N approaches ∞. The update process of its state valuation is shown in Equation (6):

$$V_\pi(S_t) = V_\pi(S_t) + \alpha\left(G_t - V(S_t)\right) \tag{6}$$

The Monte Carlo method updates based on the returns of the entire experienced complete sequence, i.e., after taking an action in a state, the intelligent body will keep interacting with the environment until it reaches the termination state, and then update the value function based on the returns. Since the Monte Carlo method estimates the value function based on actual experiences and each state will only be visited once in a sequence, it is closer to unbiased estimation, i.e., the expectation that the estimated value is equal to the true value, than the temporal difference method.

2.3. Enterprise supply chain management optimization model construction

2.3.1. Parameters and assumptions. The two-tier supply chain management optimization model constructed in this paper contains three components: raw material suppliers, product producers, and the entire demand market for the product. Assuming that all product producers in the supply chain network produce the same type of products, in the supply chain network topology, there is a total of m raw material supplier, there are n product producers, and all the products produced provide services for o demand markets, node i represents the raw material suppliers distributed in different regions, node j represents the product producers distributed in different regions, and the link between node i and node j represents the process of raw material production, manufacturing and transportation. Node k represents the demand market which is distributed in different regions and the link between node j and node k represents the process by which the product is produced from the producer of the product and transported to the demand market from where the target consumers of the product can buy the product they need.

In order to simplify the construction and study of the model, the following assumptions are made in this paper:

First, the demand fluctuation of the product obeys a known distribution. This paper focuses on the case where the demand fluctuation of the product obeys a normal distribution.

Second, it is assumed that customers' risk preferences are neutral and customers' unsatisfied demand does not affect customers' next purchase.

Third, the residual value of the unsold surplus product is zero.

Fourth, the cost functions of raw material suppliers and product producers are monotonically increasing convex functions of output:

$$\frac{\partial C_s}{\partial x_s} > 0; \frac{\partial^2 C_s}{\partial^2 x_s} < 0 \tag{7}$$

In order to describe the studied problem and mathematical model more clearly, this paper summarizes the relevant parameters and descriptions involved in the research process into Table 1.

Table 1. Parameter description

Parameter	Description
x	Supply chain yield
y	Demand for products
p	Product sales price
c_{ij}	The cost of the raw material supplier i to the product manufacturer j
c	The cost of the entire supply chain
$N(\mu,\sigma^2)$	μ :The expectation when demand is normally distributed σ^2 :The variance when demand is normally distributed
s	Unsold inventory processing price
C_H	Unit storage cost
Eg_e^*	Optimal expected return: $Eg_e^* = (p-s)\mu - (c-s)Q_e^* - (p-s)\sigma\varphi(\frac{Q_e^* - \mu}{\sigma}) - \frac{C_H}{2}$
Z	Profit margin: $\frac{p-c}{p-s}$
Q_e^*	Optimal reservoir:($Q_e^* = \mu + \sigma\varphi^{-1}(\frac{p-c}{p-s})$)

2.3.2. Modeling. The demand for the product is assumed to be y throughout the supply chain network, and it is assumed that the demand for the product y obeys a normal distribution of $N \sim \left(\mu,\sigma^2\right)$ and the value of the residual product is zero. Where, denote by c the total cost function of supply chain s, which is composed of two parts: the cost from raw material suppliers i to product producers j and the cost from product producers j to the demand market k (including production cost and transportation cost). Suppose that the selling price between the product producer and the demand market in supply chain s is p_s and the selling price p_s is related to the mean value of the product demand. The total revenue in supply chain s is π_s and the mean of the selling price of the product and the demand for the product obey the relationship between supply and demand.

Since the demand of the product is a random variable obeying normal distribution, when the demand of the product is smaller than the output of the producer, the revenue is $\pi_1 = \int_0^{x_s} p_s \cdot y \cdot f(y)dy$. When the demand of the product is larger than the output of the producer, the revenue is $\pi_2 = \int_{x_s}^{+\infty} p_s \cdot x_s \cdot f(y)dy$. The maximum revenue of the supply chain s should be the total revenue minus the total cost. All supply chains are assumed to be non-cooperative competitive game, in order to solve the variable inequality is convenient, this paper will turn the objective function to solve the minimum value, that is, when the demand for the product y obey the normal distribution of $N\left(\mu,\sigma^2\right)$, the objective function of supply chain s minimization conditions are:

$$\min C_H = C - \int_0^{x_s} p_s \cdot y \cdot f(y)dy - \int_{x_s}^{\infty} p_s \cdot x_s \cdot f(y)dy, \forall s \tag{8}$$

Equilibrium conditions of supply chain network based on newsboy model under normal distribution of demand: according to the knowledge of variational inequality, since the whole supply chain network has a total of S supply chains, the equilibrium conditions of the whole supply chain network under normal distribution of demand can be transformed into the following variational inequality:

$$\begin{aligned}&\sum_{s=1}^{S}\Big[-\int_0^{x_s} yf(y)dy - p_s^*\int_0^{x_s} yf(y)mdy - x_s \\ &+x_s\int_0^{x_s} f(y)dy - p_s^* x_s\int_{x_s}^{\infty} f(y)mdy\left(p_s - p_s^*\right)\Big] \\ &+\sum_{s=1}^{S}\left[\frac{\partial c_s}{\partial x_s{}^*} - p_s + p_s\int_0^{x_s} f(y)dy\right]\left(x_s - x_s^*\right), \forall s \forall i\end{aligned} \tag{9}$$

Eq. $m = -\dfrac{\partial \mu}{\partial p_s}\Big/\sigma^2\,(y-\mu)$.

The economic meaning of Eq. (9) is the optimal strategic equilibrium of price and output of raw material suppliers and product producers in the face of demand for normal distribution. That is, to determine p_s^* and x_s^* to meet the optimization objectives of the entire supply chain at the same time to achieve the optimal conditions, the equilibrium point for the Nash equilibrium, in the demand for the normal distribution of conditions, any supply chain unilateral adjustment decisions can not improve their own revenue.

3. Support vector machine-based supply chain risk assessment models

3.1. SVM model

SVM, known as Support Vector Machine, is a machine learning algorithm its, mathematically modeled as [28]:

$$\begin{aligned}&\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\left(\xi_i + \hat{\xi}_i\right) \\ &s.t.\begin{cases} f\left(x_i\right) - y_i \le \varepsilon + \xi_i \\ y_i - f\left(x_i\right) \le \varepsilon + \hat{\xi}_i \\ \xi_i \ge 0, \hat{\xi} \ge 0, i = 1,2,\ldots,m \end{cases}\end{aligned} \tag{10}$$

The Lagrange multipliers can be substituted into Eq. (10) to solve the SVM classification mathematical model as:

$$f\left(x,\hat{\alpha}_i,\alpha_i\right) = \operatorname{sgn}\left\{\sum_{i=1}^{m}\left(\hat{\alpha}_i - \alpha_i\right)K\left(x_i,x_j\right) + b\right\} \tag{11}$$

Where: $K\left(x_i,x_j\right)$ is the RBF kernel function:

$$K\left(x_i,x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2g^2}\right) \tag{12}$$

3.2. SVM-based supply chain risk assessment model construction

3.2.1. Definition of risk assessment model inputs and outputs. The purpose of constructing a supply chain risk assessment model is to assess whether the formed supply chain will be disrupted during its life cycle and the degree of impact of the disruption on the supply chain by utilizing the values of effective supply chain risk indicators based on the supply chain risk assessment indicator system. In this paper, the length of supply chain disruption time is used as a criterion to measure the magnitude of the impact of disruption. So the supply chain risk assessment model actually uses the values of the supply chain indicators to assess the disruption time after the formation of the supply chain. This time can be 0, i.e. no disruption occurred. It can also be ∞, i.e., a permanent disruption, where the customer order task fails.

Due to the difficulty of obtaining enterprise data, we conducted data collection through web crawlers and only obtained 20 complete typical samples of supply chains. In addition, there is an obvious nonlinear relationship between the individual samples of the supply chain. The support vector machine algorithm can well solve the small sample and nonlinear problem, so the support vector machine is used to model the supply chain risk assessment model.

The supply chain risk assessment system contains a training set and a test set. Sixteen of the samples are randomly selected as support vector machine training samples to train the model, and the remaining four samples are used as the test set to check the accuracy and error of the model assessment.

The supply chain risk assessment system consists of 16 training samples to form the sample set $x=\left[x_1,x_2,\cdots,x_i,\cdots,x_{45}\right]^T$. For ease of expression and computation, the sample is denoted as $x_i=\left[x_{i1},x_{i2},\cdots,x_{ik},\cdots,x_{i17}\right]\left(i=1,2,\cdots 45,k=1,2,\cdots,16\right)$ consisting of the 15 risk indicator data x_{ik} of the supply chain risk indicator system, y_i as the corresponding supply chain risk level value of the sample x_i, and $y_i \in Y$ as the risk level vector.

3.2.2. Selection of Risk Assessment Model Vector Machines and Kernel Functions. On the basis of defining the inputs and outputs of the supply chain risk assessment model, using the idea of regression and evaluation of support vector machine, we further find a nonlinear mapping that can map the input vector x_i of the model to the output value y_i of the model, i.e., it is the objective function of the supply chain risk assessment model. The process of solving the objective function for the supply chain model is as follows.

A nonlinear mapping φ maps the input vector x_i of the risk assessment model to a high-dimensional feature space, and the optimal decision function is constructed by applying the principle of structural risk minimization. The original nonlinear model is transformed into a linear regression model in the high-dimensional feature space as in equation (13):

$$f\left(x_i\right)=\omega^T\varphi\left(x_i\right)+b \tag{13}$$

where ω is the weight vector of the hyperplane and b is the bias term.

C-SVR is an extension of support vector regression, which adds C parameters to SVM and has better efficiency, robustness and flexibility. In this paper, C-SVR support vector regression machine is selected for supply chain regression evaluation, and regression with strong robustness is realized by introducing ε insensitive loss function, and the regression estimation is sparse [29]. The penalty parameter C and the relaxation variables ξ_i, ξ_i^* are also introduced. The regression problem is transformed into a convex quadratic programming problem with respect to ω and b as in equation (14):

$$\begin{gathered}\min_{\omega,b} L=\frac{1}{2}\omega^T\omega+C\sum_{i=1}^{45}\left(\xi_i^*+\xi_i\right)\\ \begin{cases} y_i-\omega^T\varphi(x)-b\le\varepsilon+\xi_i\\ \omega^T\varphi(x)+b-y_i\le\varepsilon+\xi_i^*\\ \xi_i^*,\xi_i\ge 0, i=1,2,\cdots,45\end{cases}\end{gathered} \tag{14}$$

The Lagrangian function and pairwise principle are used to transform the original problem of the above equation into its pairwise problem. The kernel function can transform the inner product operation in high-dimensional space into the kernel function calculation in low-dimensional input space, which solves the problem of "dimensional catastrophe" and other problems in high-dimensional eigenspaces, and introduces the kernel function $K(x_i,x_j)=\varphi(x_i)\cdot\varphi(x_j)$. The original problem is transformed into its dual problem as in Eq. (15):

$$\begin{gathered}\min_{\alpha,\alpha^*} D=\frac{1}{2}\sum_{i=1}^{45}\sum_{j=1}^{45}K(x_i,x_j)(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\\ -\sum_{i=1}^{45}y_i(\alpha_i-\alpha_i^*)+\varepsilon\sum_{i=1}^{45}(\alpha_i-\alpha_i^*)\\ \begin{cases}\alpha_i,\alpha_i^*\in[0,C], i=1,2,\cdots,45\\ \sum_{i=1}^{45}(\alpha_i-\alpha_i^*)=0\end{cases}\end{gathered} \tag{15}$$

Solve a_i and a_i^* by Eq. to get the regression estimation function that is the objective function of the supply chain risk assessment model, as in Eq. (16):

$$f(x)=\sum_{i=1}^{45}(\alpha_i-\alpha_i^*)K(x_i,x)+b \tag{16}$$

The kernel function $K(x_i,x)$ is a positive definite function that satisfies Mercer's condition. The choice of kernel function has a great impact on the accuracy of regression analysis when nonlinear regression modeling using support vector machines. The more commonly used kernel functions are: linear kernel function, polynomial kernel function, radial basis kernel function, Sigmoid kernel function, Gaussian kernel function and so on.

In the current research, the radial basis kernel function is the most widely used, and the accuracy and performance of the calculation are higher. The radial basis kernel function is chosen as the kernel function for the supply chain risk assessment model. The support vector regression machine model for supply chain risk assessment is trained using the training set, and the training process is shown in Figure 1.

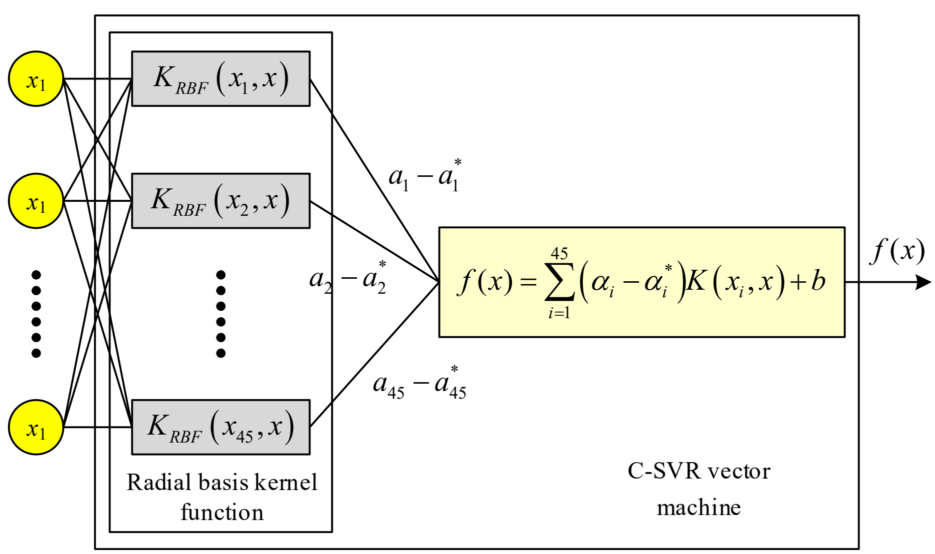


Fig. 1. The training process of the supply chain risk assessment model

3.2.3. Parameter optimization of risk assessment models. In the SVR model, the penalty parameter C and the kernel function parameter σ together affect the performance of SVR. A smaller value of C indicates a smaller penalty for empirical error, a smaller complexity of the learning machine and a larger value of empirical risk. A smaller value of σ means that the structural risk value of the optimal hyperplane is smaller while the empirical risk value is larger. Therefore choosing the optimal SVR parameters has a great impact on the accuracy of the model. The particle swarm optimization algorithm (PSO algorithm) is introduced to optimize parameters C and σ.

The PSO algorithm abstracts entities as particles, and the particle coordinates are the solution of the algorithm. In the SVR model for supply chain risk assessment, the parameters to be optimized are the penalty parameter C and the kernel function parameter σ, so the particle dimension is (σ, C) and the solution space is 2-dimensional. There are n particles and three d -dimensional vectors are used to represent the information of a particle. The particle information is shown in equation (17):

$$\begin{cases} \text{Current Position: } x_s = \left(x_{s1}, x_{s2}\right) \\ \text{All-time best Position: } p_s = \left(p_{s1}, p_{s2}\right) \\ \text{Speed: } v_s = \left(v_{s1}, v_{s2}\right) \end{cases} \tag{17}$$

The PSO algorithm is an optimization algorithm based on an iterative model. During each iteration, the position objective function of each particle is evaluated. If the current position of particle $s(s = 1, 2, \cdots, n)$ is better than its historical optimal position, it is updated p_s. The historical optimal position of the whole population is noted as $P_g = \left(P_{g1}, P_{g2}\right)$.

For the sth particle the tth dimension $(t = 1, 2)$ values are updated according to equation (18):

$$\begin{cases} v_{st}^{k+1} = \omega \cdot v_{st}^k + c_1 \cdot rand() \cdot \left(p_{st}^k - x_{st}^k\right) + c_2 \cdot rand\Big) \cdot \left(p_{st}^k - x_{st}^k\right) \\ x_{st}^{k+1} = x_{st}^k + v_{st}^{k+1} \end{cases} \tag{18}$$

In the formula k is the number of iterations. $c1$, $c2$ is the learning factor, which is positively related to the local search capability. $rand()$ is the random number belonging to $[0,1]$. ω is the inertia weight, which determines the degree of influence of the previous speed of the particle on the current speed, and can balance the global and local search ability of the algorithm.

The basic flow of the PSO optimization SVR model parameter algorithm is as follows:

Step1: Initialization. Iteration number $t = 0$, SVR The parameters to be optimized for the model are C and σ, and the set of particles is generated in the 2-dimensional space (C, σ).

Step2: Set the range of parameter values and set the range of particle update rate.

Step3: Calculate the fitness value $F\left(x_i\right)$ for each particle and compare it with the historical optimal fitness value for that particle. $F\left(pbest_i\right)$ compare it and if $F\left(x_i\right) < F\left(pbest_i\right)$ we replace the value of $pbest_i$ with x_i.

The PSO objective function is:

$$\min F_{mse}(C, \sigma) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left[y_i - \varphi\left(x_i, C, \sigma\right)\right]^2} \tag{19}$$

The PSO algorithm fitness function is taken:

$$F_{fitness} = F_{mse}(C, \sigma) \tag{20}$$

Step4: Compare the optimal evaluated value $pbest_i$ of the current position of each particle with the population global optimal value $gbest_i$, if $F\left(pbest_i\right) < F\left(gbest_i\right)$, we replace $gbest_i$ with $pbest_i$.

Step5: Make $t = t + 1$ and update the particle position and velocity. The particle position and particle velocity are updated according to equation (18).

Step6: Update the inertia weights.

Step7: Execute step3~step6 in a loop until the loop termination condition, iteration number requirement or best fitness requirement is satisfied.

Step8: Validate the SVR model using the optimal parameters obtained from the optimization search.

4. Supply chain management optimization and risk assessment simulation analysis

4.1. *Monte Carlo simulation solution*

A Monte Carlo simulation algorithm is used to optimize the inventory management model of a construction unit's supply chain as an example. In this work, the up and down fluctuations of the sample mean and standard deviation are correlated using the output factor information, and the effects of the fluctuations of the mean and standard deviation on the optimal inventory and the expected returns are analyzed.

It is assumed that a certain PC prefabricated component is used as the object of study. Where the price of prefabricated components unit production of finished products c=1628 (yuan/m^3), the price of sold units of products p=2211 (yuan/m^3) (the price of components transported to the construction site), and the price of unsold inventory units of products disposed of s=1,131 (yuan/m^3) (the disposal price of the components can not be lower than the cost price of raw materials at least). Unit product storage rate h = 2%. Maximum demand per cycle x = 2 thousand cubic meters.

According to the field research and study to determine the following distribution of uncertainty factors affecting the “zero inventory” parameters.

The demand for prefabricated components by construction units obeys a normal distribution, and the range of mean, standard deviation and other parameter values are shown in Table 2.The marginal profitability of prefabricated component firms is denoted by Z, which corresponds to Z=25%, Z=40%, Z=55% and Z=70%.

Table 2. Uncertainty factor parameter distribution

Uncertainty factor	Distribution	Computational standard
x	Normal distribution	μ=[1.5,3], σ=[0.1,2.5]
p	Triangular distribution	a=1982.3, m=2211, b=2438.3
c	Uniform distribution	a=1459.3, b=1782.9
s	Triangular distribution	a=1022.8, m=1131, b=1258.6

First, the standard deviation σ = 1 such that the mean μ varies between [1.5, 3], corresponding to the optimal inventory and expected return variations as shown in Fig. 2(a) and (b).

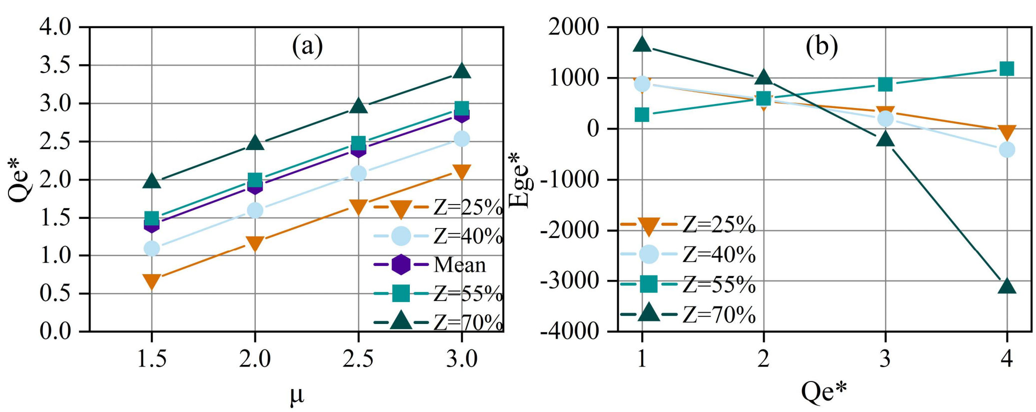
Figure 2(a) learns that the optimal inventory of components Q_e^* increases with the increase of the demand factor μ at different marginal rates. However, when the marginal profit rate Z = 55%, the firm's optimal inventory converges to the market demand, indicating that each increase in the sales volume of the precast component firm brings higher profits to the firm. When the marginal profit margin Z = 70%, the enterprise inventory is much larger than the average market demand, when the inventory storage is larger than the maximum demand, at this time, the components are stored too much, resulting in management costs as well as increased component loss. This makes the enterprise benefit plummet or even loss, according to the market demand to consider stopping the reproduction. When the marginal profit margin Z = 40% and Z = 25%, the enterprise's optimal inventory is less than the average market demand, at this time the enterprise should speed up production to reduce the opportunity cost lost.

Figure 2(b) shows that only under the condition of marginal interest rate Z=55%, expected return Eg_e^* and optimal inventory Q_e^* are positively correlated with respect to the mean value μ, while all other marginal interest rates are negatively correlated with expected return Eg_e^*. This indicates that, whether faced with high or low profit finished goods, the enterprise can not produce at the profit level, but only according to the market demand, and the production choice of optimal inventory is slightly larger than the market demand can be. Ensure that there will be no opportunity cost loss, while striving to realize the assembly prefabricated components enterprise inventory management close to “zero”. At this time, the stakeholders in the supply chain have high returns and the supply chain operation is relatively stable.

The mean value μ = 2.5, so that the standard deviation σ varies between [0.1, 2], which corresponds to the optimal inventory and the change of expected returns as shown in Fig. 2(c) and (b).

Figure 2(c) learns that the change in standard deviation affects optimal inventory differently at different marginal profit margins. Under higher marginal profitability, optimal inventory Q_e^* is positively correlated with respect to the standard deviation σ, indicating that as the standard deviation σ continues to increase, the range of market demand μ expands, and therefore the firm's inventory increases to ensure that the firm's supply of components is greater than the demand and to prevent the loss of customers. Under lower marginal profit margin, the optimal inventory Q_e^* is negatively correlated with respect to the standard deviation σ. The result shows that under lower marginal profit margin, with the unstable market demand, the precast component enterprise adopts a conservative production strategy to ensure the normal operation of the enterprise. At this time, the production of components gradually decreases and the inventory storage is lower than the market demand to prevent inventory backlog.

Figure 2(d) learns that expected returns Eg_e^* are negatively correlated about the standard deviation σ under the conditions of marginal interest rate Z=55% and Z=70%. As the standard deviation σ keeps changing, the market demand fluctuates greatly, the enterprise fails to accurately respond to the market changes, and the enterprise's returns are gradually decreasing. Therefore, the stakeholders in the supply chain to establish enterprise supply chain management optimization model for optimization, through data analysis, can timely and accurately grasp the demand for prefabricated components of the construction unit, so as to achieve the immediate supply of raw materials, the standardized production of prefabricated components, and the transportation time in place on time. Thus, the expected return of the enterprise can be improved. When the marginal interest rate is low, the expected return Eg_e^* about the standard deviation σ is positively correlated. As the standard deviation σ keeps changing, the market demand fluctuates. The enterprise adopts the strategy that the production of components is smaller than the market demand, reducing the storage loss of components and lowering the daily management cost to make the enterprise profitable.



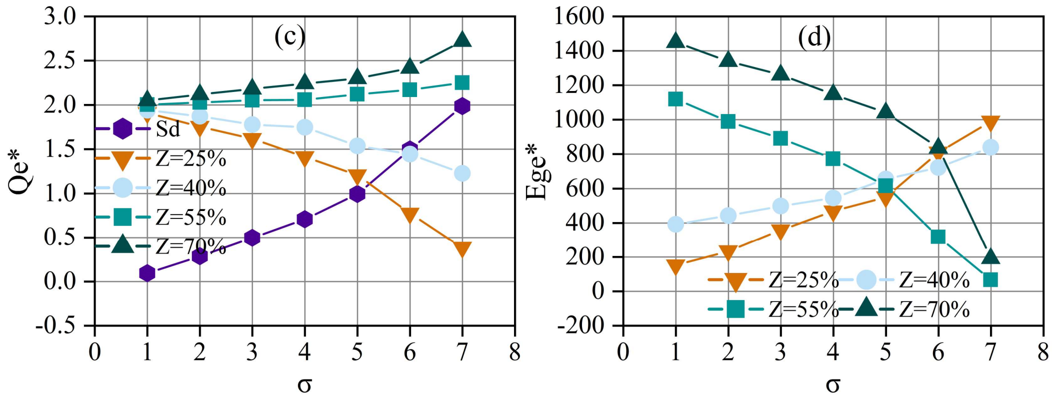


Fig. 2. The relationship between mean, inventory and expected return

To summarize, the enterprise's optimal revenue shows a growing trend in the case of high marginal interest rate and relatively stable market demand. Next, this paper applies Crystal Ball software to analyze and study the optimal inventory and optimal expectation of the enterprise's prefabricated components in 10,000 simulations, and finds that the statistical predictions and probability distributions under the conditions of marginal interest rate Z = 55%, μ = 2.5, and σ = 0.5 are obtained as shown in Fig. 3 (a), (b), and (c), respectively.

Under the condition that the average order quantity of components in a single cycle is $\mu=2.5\times10^3m^3$, through Monte Carlo simulation, the statistical results show that the optimal inventory of prefabricated components Q_e^* = $2.55\times10^3m^3$, and the inventory management of the enterprise basically realizes that the storage tends to be close to "zero", at this time, the optimal expected income of the enterprise Eg_e^* = $902.31\times10^3m^3$ yuan, the profit of the enterprise is also the largest, and it requires a high degree of cooperation between stakeholders in the supply chain. As inventory increases, expected returns are decreasing. When the optimal inventory Q_e^* = $3.2\times10^3m^3$, then the optimal expected return of the enterprise Eg_e^* = $482.31\times10^3m^3$ yuan. Due to the increase in inventory, the enterprise has to bear the corresponding warehousing costs and other forms of expenses, so the expected return is in a downward trend, while the whole supply chain operation is facing challenges. In short, the optimal inventory is based on the enterprise supply chain management optimization model to accurately analyze the market demand and decide.

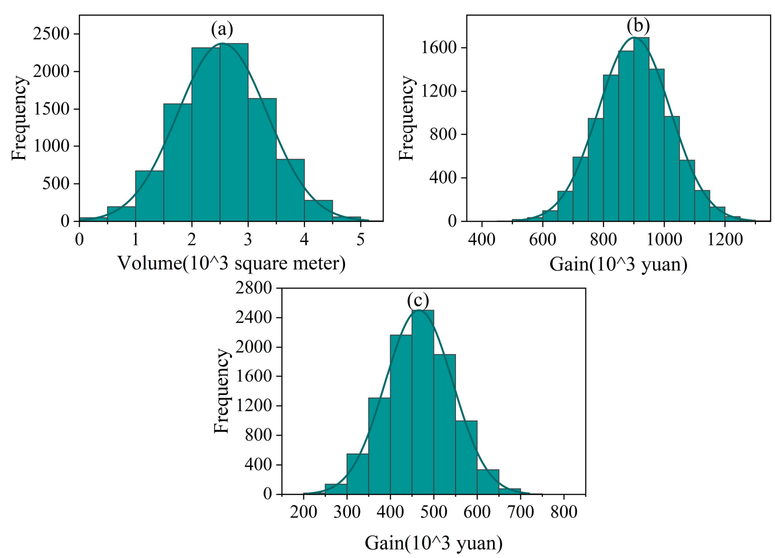


Fig. 3. The relationship between optimal inventory and expected gain

4.2. Example Analysis of Supply Chain Risk Assessment Based on Support Vector Machines

The risk assessment model in this paper is applied to a real case of a port to test the practical utility of the model.

4.2.1. Port Supply Chain Risk Assessment Indicator System Setting. To assess the risk of port supply chain firstly, we need to identify the supply chain risk so as to determine the indicators for risk assessment.

In this section, the Delphi method is used to set up the risk assessment index system of port supply chain, which assesses the risk of port supply chain from three major indexes, namely, external environment risk, supply chain internal operation process risk and supply chain cooperation risk. Each major indicator has multiple sub-indicators, so the port supply chain risk assessment indicator system consists of 15 indicators, see Table 3 for the specific indicator settings.

Table 3. Port supply chain risk assessment index system

Primary indicator	Secondary indicator
External environmental risk	Stock earnings(R1)
	Exchange rate fluctuation(R2)
	Government intervention(R3)
	Instability and other instability(R4)
	Impact of disaster(R5)
Internal operational process risk	Suppliers cannot deliver on time(R6)
	Lower demand for downstream customers(R7)
	Risk of shipping enterprise capability(R8)
	Port clearance efficiency(R9)
	Openness of information management(R10)
Cooperative risk	Management model(R11)
	Partner exits the supply chain(R12)
	Unequal distribution of benefits(R13)
	The existence of conversion costs(R14)
	Backward selection(R15)

The supply chain risk assessment results are within the interval [0,1], and it is stipulated that the risk assessment level is "large" when the risk score is 0.8∼1.0, the risk assessment level is "large" when the score is 0.6∼0.8, the assessment level is "fair" when the score is 0.4∼0.6, the risk level is "small" when the risk score is 0.2∼0.4, and the risk level is "small" when the score is less than 0.2.

4.2.2. Analysis of assessment results. The model takes the first 16 sets of data as the training sample set for sample fitting, and takes the last 4 sets of data as the extrapolation prediction samples to test its generalization ability. Each set of data has 15 inputs and 1 output, corresponding to 15 indicators and 1 desired output in the risk indicator system. The optimal kernel width parameter δ of 0.001 and C=120 is obtained by iterative testing using the cross-validation method.The results are analyzed below.

The risk assessment results and relative errors are shown in Table 4. The fitted image of the training sample set is shown in Fig. 4, where "◇" denotes the original data and "×" denotes the assessment data.

Assessed value minus the actual value and then take the absolute value is equal to the absolute error, the absolute error divided by the actual value of the relative error, i.e., relative error = | forecast actual value | / actual value. In this paper, the relative error is expressed as a percentage. As can be seen from the image, the fitting results to the training sample set are very good, the evaluation results are ideal, and the evaluation success rate is close to 100%. The flat coincident relative error of using support vector machine to predict the first 16 sets of training sample data is 0.043%, and the average relative error of predicting the last four sets of extrapolated sample data is 4.35%, which indicates that the support vector machine not only has high assessment accuracy, but also has a strong generalization ability, so it is completely feasible to use it for the port supply chain risk assessment. The average relative error of the extrapolated sample set will be even smaller if there are enough training data.

Table 4. The risk assessment results and the relative error based on SVM

Code	Actual value	Estimated value	Relative error (%)
1	0.52618	0.52624	0.01140
2	0.45918	0.45911	0.01524
3	0.65498	0.65465	0.05038
4	0.54383	0.54399	0.02942
5	0.38035	0.38059	0.06310
6	0.49310	0.49263	0.09532
7	0.55323	0.55289	0.06146
8	0.31306	0.31323	0.05430
9	0.42637	0.42672	0.08209
10	0.5226	0.52287	0.05166
11	0.42701	0.42717	0.00884
12	0.33928	0.33931	0.02018
13	0.64429	0.64416	0.04478
14	0.62521	0.62549	0.03599
15	0.30561	0.30572	0.03306
16	0.57477	0.57458	0.03306
17*	0.42637	0.45672	7.11823
18*	0.5226	0.53287	1.96517
19*	0.4643	0.43421	6.48072
20*	0.55399	0.54389	1.82314

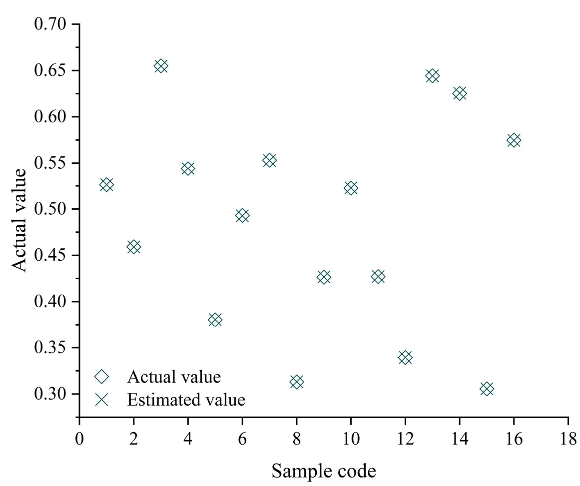


Fig. 4. The fitting image of the training sample set

4.2.3. Comparative analysis with other risk assessment methods. BP neural network can learn and store a large number of input and output pattern mapping relationships, without prior knowledge of the mathematical equations describing the mapping relationships, as long as enough sample pattern pairs can be provided for the network to learn and train, it will be able to complete the nonlinear mapping from the n-dimensional input space to the m-dimensional output space. At the same time, BP neural network also has strong fault tolerance and generalization ability, so BP neural network has a wide range of applications in pattern recognition, data compression, function approximation and so on.

Since the indicator system of port supply chain risk assessment contains 15 indicators, and the ideal output is only one, the BP neural network is set as a three-layer network, with a total of 15 neurons in the input layer, one neuron in the output layer, and the number of neurons in the hidden layer is 10.

In order to compare with the support vector machine method, the first 16 sets of data are still taken as the training sample set to train the network, and the last 4 sets of data are taken as the extrapolation sample set to test the generalization ability of the network. The risk assessment results obtained from the BP network are shown in Figure 5. From the image, it can be seen that the assessment results of the training sample set are average, and there are 3 sets of data with large differences.

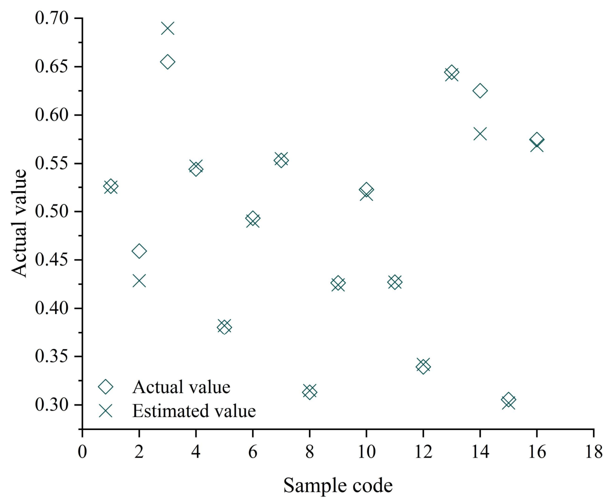


Fig. 5. The risk assessment results obtained by the BP network

The assessment results obtained from the BP neural network are compared with the support vector machine method to obtain a comparison table of risk assessment results as shown in Table 5.

For the BP neural network, the average relative error of the training sample set is 1.67%, and the average relative error of the test sample set is chemically 12.73%. This indicates that the BP neural network is not only less capable of generalization compared with the support vector machine, but also the evaluation results of the training sample set do not reflect its superiority. On the contrary, in the test set of SVM, the value of each test result is closer to the ideal value, so in a comprehensive comparison, it can be considered that the network performance of the supply chain risk assessment model based on the Support Vector Machine is better, and has a greater superiority than the BP neural network.

Table 5. The comparison table of risk assessment results

Code	Actual value	SVM		BP	
		Assessment value	Error (%)	Assessment value	Error (%)
1	0.52618	0.52624	0.01140	0.52510	0.20525
2	0.45918	0.45911	0.01524	0.42866	6.64663
3	0.65498	0.65465	0.05038	0.68962	5.28871
4	0.54383	0.54399	0.02942	0.54738	0.65278
5	0.38035	0.38059	0.06310	0.38220	0.48639
6	0.49310	0.49263	0.09532	0.49007	0.61448
7	0.55323	0.55289	0.06146	0.55506	0.33078
8	0.31306	0.31323	0.05430	0.31487	0.57816

9	0.42637	0.42672	0.08209	0.42429	0.48784
10	0.5226	0.52287	0.05166	0.51769	0.93953
11	0.42701	0.42717	0.00884	0.42721	0.04684
12	0.33928	0.33931	0.02018	0.34180	0.74275
13	0.64429	0.64416	0.04478	0.64163	0.41286
14	0.62521	0.62549	0.03599	0.58079	7.10481
15	0.30561	0.30572	0.03306	0.30207	1.15834
16	0.57477	0.57458	0.03306	0.56862	1.06999
17*	0.42637	0.45672	7.11823	0.51264	20.23290
18*	0.5226	0.53287	1.96517	0.59260	13.39457
19*	0.4643	0.43421	6.48072	0.49430	6.46134
20*	0.55399	0.54389	1.82314	0.61399	10.83052

5. Conclusion

In this paper, based on the newsboy model and Monte Carlo simulation algorithm, the enterprise supply chain management mode was modeled and optimized to solve the problem, and the model used to assess the supply chain risk was established based on SVM.

The supply chain management model of a construction unit is analyzed, and it is found that the market demand profoundly affects the production management of the supply chain. Too high or too low a marginal profit margin will bring the problems of increased overhead and lost opportunity cost, respectively, and only when the enterprise produces according to the market demand can it ensure the stability of the supply chain. At the same time, it is concluded that the optimal inventory of prefabricated components of the construction unit is $2.55 \times 10^3 m^3$, and the profit of the enterprise is maximized.

Supply chain risk assessment of a port, the training error of the assessment model in this paper is only 0.043%, and the prediction error is 1.76%. While the training error and prediction error of BP neural network assessment method are 1.67% and 12.73% respectively. This indicates that the model in this paper has better assessment accuracy and generalization ability, and can provide decision support for enterprise supply chain management model optimization and risk control.

The shortcoming of this paper is that it does not consider the impact of demand uncertainty changes on the optimal inventory of enterprises under different lead times, which is the work that can be continued in this paper.

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