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Research on the Supply Chain Risk Assessment Based on the Improved LSSVM Algorithm

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Abstract

In the increasingly fierce market competition, the survival environment that enterprises are facing is increasingly harsh. This makes the supply chain is facing more and more uncertainly factors gradually on the operating environment. In addition, this increases the likelihood of the risk. Therefore, the research on the supply chain risk assessment has the important practical significance. In this paper, we put forward the assessment indexes of the supply chain risk. Then, we use the improved ACO method to optimize the parameters of the LSSVM method and we propose the improved LSSVM method. After that, we use the method to assess and study the risk of the supply chain. Finally, the experiment indicates that the reliability and validity of the evaluation system.

Keywords*: LSSVM, supply chain, risk assessment*

1. Introduction

The supply chain management is a new management mode and method [1]. However, due to the sensitivity and the vulnerability of the modern supply chain, the supply chain management brings the value and the competitiveness to the enterprises while it brings many kinds of the new risks [2-3]. It is a big problem for the supply chain members to identify these risks and assess the risks effectively [4-5]. Therefore, many scholars have conducted the research on the supply chain risk.

Marjorie Windelberg recommended a set of objectives for cyber supply chain risk management. Then, the author examined the tradeoffs among the various objectives that acquirers and suppliers made [6]. Faisal Aqlan and Sarah S. Lam presented an approach and a software application for supply chain optimization under risk and uncertainty [7]. The proposed approach helped decision makers identified the best risk mitigation strategies and allocated inventory and customer orders effectively. Sónia R. Cardoso and other people proposed a mixed integer linear programming (MILP) formulation. This formulation integrated financial risk measures into the design and planning of closed-loop supply chains and it considered demand uncertainty of final products [8]. Yuan-Hsu Lin and Ming-Lang Tseng adapted a hierarchical structure and linguistic preferences to identify the competitive priorities under SSCM in electronic focal manufacturing firms in Taiwan [9]. Faisal Aqlan presented a software application framework for rapid risk assessment (RRA) in integrated supply chains. The proposed framework combined qualitative and quantitative methods to assess and prioritize the risks [10]. Yan Bo, Shi Ping and Ding Delong studied the risk assessment and the control of the agricultural product supply chain under the networking environment [11].

Firstly, the author identified the risks of the whole agricultural product supply chain according to the operation mode of the agricultural product supply chain under the networking environment and the three levels of the Internet of things. Then, they summed up the agricultural product supply chain risk factors under the networking environment. These supply chain risk factors included the perceived layer risk, the network layer risk, the application layer risk and other risks. At last, the author used OWA operator to

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evaluate quantitatively and ordered the risk factors. According to the results of the previous model, the author proposed the measures and the suggestions of the agricultural product supply chain risk management under the networking environment. Liu Weiguo analyzed the formation cause of the supply chain risk. Finally, the author established an operational supply chain risk assessment model [12]. In addition, there were many scholars studying the supply chain risk [13-15].

LSSVM is a classification method. In recent years, it is widely applied in the direction of the prediction. Reza Gholgheysari Gorjaei and other people applied the LSSVM predicted liquid flow rate in two-phase flow through wellhead chokes [16]. The author applied Particle swarm optimization (PSO) to optimizing tuning parameters of LSSVM model. Yunguang Gao *etc.*, proposed a novel Nonlinear Autoregressive with Exogenous (NARX) method for the cooling dehumidifier FDD based on LSSVM [17]. The experiment result indicated this method was effective for cooling dehumidifier FDD. Xu Juncai and other people used the grid search algorithm to optimize the parameters of the LS-SVM on the basis of traditional prediction methods for conventional concrete [18]. In addition, there were many scholars studying the LSSVM method [19-20].

The supply chain has the characteristics of the sudden danger. Once occurred, it will bring the huge loss to the whole supply chain. Therefore, this paper studies the assessment for the supply chain risk. In this paper, aiming at the characteristics of the supply chain risk, we build the evaluation system of the supply chain risk firstly. Then, we apply the improved ACO algorithm to optimize the LSSVM algorithm and propose the improved LSSVM algorithm. Finally, we apply the improved LSSVM algorithm to assess the supply chain risk. The structure of this paper is as follows. The first part is the introduction. The second part is the establishment of the evaluated indexes. In the second part, we construct the evaluated indexes of the supply chain risk. The third part is the LSSVM. The fourth part is the improved LSSVM algorithm and the final part is the conclusion.

2. The Construction of the Evaluated Indexes

The supply chain risk assessment is necessary to take the appropriate measures on the risk factors that we identify. It includes the potential loss frequency and the loss degree. In the supply chain risk assessment, it is the premise for the risk evaluation to establish the scientific and reasonable risk assessment index system. It needs a series of different dimensionless index group. The supply chain risk assessment indexes is as the Table 1.

Table 1. The Supply Chain Risk Assessment Indexes

<table>
<tr><td rowspan="15">supply chain risk assessment index</td><td rowspan="2">Partner risk</td><td>Contractual Risk</td></tr>
<tr><td>Cooperative Partners risk</td></tr>
<tr><td rowspan="3">Information risk</td><td>Bullwhip effect risk</td></tr>
<tr><td>Data storage and transmission security risk</td></tr>
<tr><td>Information technology and equipment failure rate risk</td></tr>
<tr><td rowspan="4">Demand risk</td><td>Price risk</td></tr>
<tr><td>Demand fluctuations risk</td></tr>
<tr><td>Customer satisfaction risk</td></tr>
<tr><td>Customer churn risk</td></tr>
<tr><td rowspan="4">External risk</td><td>Natural disaster risk</td></tr>
<tr><td>Policy risk</td></tr>
<tr><td>Economic cycle risk</td></tr>
<tr><td>Political risk</td></tr>
<tr><td rowspan="2">Logistics risk</td><td>Delay in delivery risk</td></tr>
<tr><td>Product loss risk</td></tr>
</table>

		Inventory risk
	Purchasing and sales risk	Procurement quality risk
		Market forecast and management decision risk
		Price risk
		Distribution channel risk
	Industry risk	Macro environmental risk
		Industry development prospects risk
		Enterprise basic quality risk

3. LSSVM

We assume that the training set is $(x_i, y_i), i = 1, 2, \cdots, N$. x_i is the input vector and y_i is the output vector. According to a nonlinear mapping function, $\varphi(\cdot)$ maps the samples to the high dimensional feature space. Then it does the linear regression.

$$y = f(x, \omega) = \omega^T \phi(x) + b \tag{1}$$

$\omega \in Z, b \in R$

Where, ω is the weight and b is the skewness.

According to the principle of the structural risk minimization, we use the LSSVM to regress the function. The optimization objectives are as follows.

$$\begin{aligned} &\min_{\omega,\xi} \frac{1}{2}\omega^T \omega + \frac{\gamma}{2}\sum_{i=1}^{N} \xi_i^2 \\ &s.t.\ y_i = \omega^T \varphi(x_i) + b + \xi_i \\ &\qquad \gamma > 0 \\ &\qquad i = 1, 2, \cdots, N \end{aligned} \tag{2}$$

γ is the penalty factor. It uses to balance the training error and the algorithm complexity. ξ_i is the slack variable.

According to the Lagrange multiplier, we transform the above constrained optimization problem into the unconstrained dual space optimization problem.

$$L(\omega, b, \xi_i, \beta) = \frac{1}{2}\omega^T \omega + \frac{1}{2}\gamma \sum_{i=1}^{N} \xi_i^2 - \sum_{i=1}^{N} \beta_i \left[\omega^T \varphi(x_i) + b + \xi_i - y_i\right] \tag{3}$$

Where β_i is the Lagrange multiplier.

According to KKT conduction, we can get,

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \quad \rightarrow \quad \omega = \sum_{i=1}^{N} \beta_i \varphi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \quad \rightarrow \quad \sum_{i=1}^{N} \beta_i = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \quad \rightarrow \quad \beta_i = \gamma \xi_i \\ \dfrac{\partial L}{\partial \beta_i} = 0 \quad \rightarrow \quad \omega^T \varphi(x_i) + b + \xi_i - y_i = 0 \end{cases} \tag{4}$$

We eliminate the ω and ξ_i. And we can transform the formula (4) into a linear equation set:

$$\begin{bmatrix} 0 & E^T \\ E & \Omega + \gamma^{-1} E \end{bmatrix} \begin{bmatrix} b \\ \beta \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{5}$$

Where, $E = [1,1,\cdots,1]^T$ is the matrix that all of the factors are 1. I is $N \times N$ matrix. β and b are the parameters of the model. Ω is an $N \times N$ kernel function symmetric matrix. We get

$$\Omega_{ij} = \varphi(x_i)^T \varphi(x_j) = K(x_i, x_j), i, j = 1, 2, \cdots, N \tag{6}$$

Where $K(x_i, x_j)$ is the kernel function. We assume $\Phi = \Omega + 2\gamma^{-1}E$ and we can get

$$\begin{pmatrix} 0 & E^T \\ E & \Phi \end{pmatrix}\begin{pmatrix} b \\ \beta \end{pmatrix} = \begin{pmatrix} 0 \\ y \end{pmatrix} \tag{7}$$

The corresponding parameters can be obtained by the following formulas.

$$\begin{cases} b = \dfrac{E^T \Phi^{-1} y}{E^T \Phi^{-1} E} \\ \beta = \Phi^{-1}\left(y - E \cdot \dfrac{E^T \Phi^{-1} y}{E^T \Phi^{-1} E}\right) \end{cases} \tag{8}$$

$$\Phi = \begin{bmatrix} K(x_1, x_1) + \dfrac{1}{2\gamma} & K(x_1, x_2) & \cdots & K(x_1, x_N) \\ & K(x_2, x_2) + \dfrac{1}{2\gamma} & \cdots & K(x_2, x_N) \\ & & & \\ K(x_N, x_1) & K(x_N, x_2) & \cdots & K(x_N, x_N) + \dfrac{1}{2\gamma} \end{bmatrix} \tag{9}$$

Where Φ is the feature matrix of the LSSVM and Φ^{-1} is the inverse matrix of Φ.

We can express the regression equation of this model according to the formula (8) and (9)

$$y(x) = \omega^T \varphi(x) + b = \sum_{i=1}^{N} \beta_i K(x, x_i) + b \tag{10}$$

Where $K(x, x_i)$ is the kernel function.

The flow chart of the LSSVM is as follows.

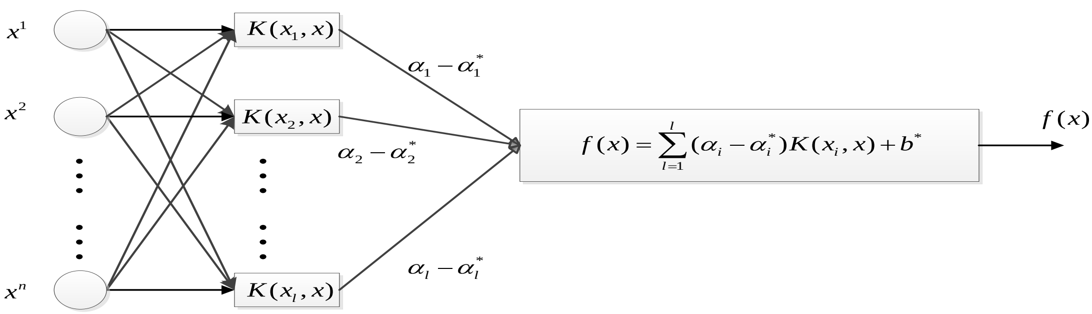

Figure 1. The Flow Chart of the LSSVM

The types of the kernel function are the key to the success that the LSSVM achieve the high performance. The types of the kernel function are as follows.

(1) Radial basis function.

$$K(x_i, x_j) = \exp\left(-\frac{\left\| x_i - x_j \right\|^2}{2\sigma^2}\right) \tag{11}$$

(2) Exponential radial basis function.

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

(3) Polynomial kernel function.

$$K(x_i, x_j) = (x_i \cdot x_j + r)^d \tag{13}$$

(4) Morlet kernel function.

$$K(x_i, x_j) = \cos\left[1.75\frac{\left\| x_i - x_j \right\|}{\sigma}\right] \cdot \exp(\frac{\left\| x_i - x_j \right\|^2}{2\sigma^2}) \tag{14}$$

(5)Meyer kernel function.

$$\begin{aligned} K(x_i, x_j) = {} & 35(\frac{\left\| x_i - x_j \right\|}{\sigma^2})^4 - 84(\frac{\left\| x_i - x_j \right\|}{\sigma^2})^5 \\ & +70(\frac{\left\| x_i - x_j \right\|}{\sigma^2})^6 - 20(\frac{\left\| x_i - x_j \right\|}{\sigma^2})^7 \end{aligned} \tag{15}$$

3. Improved LSSVM Algorithm

In this paper, we propose the improved ACO algorithm. Then, we use this algorithm to optimize the LSSVM algorithm. Finally, we get the improved LSSVM algorithm.

The ant colony algorithm is a novel simulated evolutionary algorithm. The algorithm is used to find the probability of the optimal path algorithm in the graph. It is inspired by the ants looking for food in the process of behavior path discovery. The parameters of the ant colony algorithm are shown in the following table.

Table 2. Parameters of the Ant Colony Algorithm

The parameter	The meaning of the parameter
M	the number of the ants
m	$m-th$ ants
τ_{ij}	The pheromone concentration of path $i \to j$
$\tau_{\max}$	the maximum value of the pheromone concentration
$\tau_{\min}$	the minimum value of the pheromone concentration
θ_{ij}^{α}	the probability of the path that the ants select from i to j
η_{ij}^{β}	inspired value
ρ	constant evaporation rate
N	iterations
$N_{\max}$	the maximum iterations

π_{1b}	the optimal value after one iteration
π_{gb}	the global value after the iterations
$\Delta(\tau_{ij})$	the changed value of the pheromone concentration of τ_{ij}
d_{ij}	Euclidean distance between $i \to j$
η_{ij}	the inspired function
P_{ij}	the state transition probability from i to j

In the ant colony algorithm, there are m ants distributed randomly in m cities. Each ant will move randomly to the next city. At t time, the state transition probability that the ant transforms from the element city i to the element city j is as follows.

$$\begin{cases} j = \arg\max_{I \in N_i^k} \{\tau_{ij}(t)\eta_{ij}^{\beta}\}, q \le q_o \\ p_{ij}^k = \dfrac{\tau_{ij}(t)\eta_{ij}^{\beta}}{\sum_{I \in N_i^k} \tau_{ij}(t)\eta_{ij}^{\beta}}, \quad else \end{cases} \tag{16}$$

α is the information elicitation factor. β is the expected heuristic factor. α and β are used to set the relative importance of the pheromone trail and the heuristic value. When α is close to zero, pheromone becomes less important. The ants tend to choose the nearest city. At this time, the behavior of the ants is similar to the greed search. When β is close to zero, heuristic value is not important any longer. The ant will stagnate when it meet the first good solution. In TSP problem, $\eta_{ij} = 1/d_{ij}$. q_o is the assumed threshold $(0.8 \sim 0.9)$

The initial position of the ant is $X_i(x_{i1}, x_{i2}, \cdots, x_{id})$. The initial pheromone of the ant i is,

$$\Delta\tau(i) = \exp(-f'(x_i)) \tag{17}$$

The fitness is as follows.

$$f'(X_i) = \begin{cases} f(X_i)/avg, avg > avg0 \\ f'(X_i), otherwise \end{cases} \tag{18}$$

avg is the evaluated value of $f(X_i)$. $f(X_i)$ is expressed the fitness before corrected and $f'(X_i)$ is expressed the fitness after corrected.

At the initial time, m ants will transform to the next city according to the state transition probability $P_{ij}(t)$. After n iterations, the ants will end their tours. If the distance that the ants move is short, the ants will leave more pheromone on the road. Therefore, the trail levels are updated as on a tour each ant leaves pheromone quantity by $1/L^k$. L^k is the length of the distance. On the other hand, the pheromone will volatile with the time. Therefore, the update formula of the pheromone is as follows.

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) - \varepsilon\frac{L_{worst}}{L_{best}} \tag{19}$$

$$\Delta\tau_{ij} = \sum_{m=1}^{M} \Delta\tau_{ij}^{k} \tag{20}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{1}{L^{k}}, if \quad edge(i,j) \quad is \quad solution \quad of \quad ant \quad k \\ 0, \quad otherwise \end{cases} \tag{21}$$

Where, t is the iteration counter. L_{best} is the shortest route at the current cycle. L_{worst} is the longest route at the current cycle. ρ expresses the pheromone residue coefficient. The affected degree among the ant individual is reflected. $(1-\rho)$ expresses the pheromone evaporation degree between t and $t+n$. $\Delta\tau_{ij}$ is the amount of information that the ant leaves in the path.

In order to prevent the distance between the optimal solution and other solutions of the pheromone is too large, the density of pheromone is set $[\tau_{\min}, \tau_{\max}]$.

In the actual operation, if the pheromone density is greater than $\tau_{\max}$, the density is automatically adjusted $\tau_{\max}$. Similarly, if the pheromone density is less than $\tau_{\min}$, the density is automatically adjusted $\tau_{\min}$.

The formula of $\tau_{\max}$ is as follows.

$$\tau_{\max} = \frac{1}{1-\rho} \cdot \frac{1}{L^{k}} \tag{22}$$

The formula of $\tau_{\min}$ is as follows.

$$\tau_{\min} = \frac{\tau_{\max} \cdot (1 - \sqrt[n]{p_{best}})}{Avg \cdot \sqrt[n]{p_{best}}} \tag{23}$$

Avg is the average number of the visited cities that the ants complete one cycle. p_{best} is the probability that the ants structure the optimal solution.

The steps of the improved ant colony algorithm are as follows.

1.initialize

Set time:=0% is time counter. $edge(i,j)$ sets the initial value. We set $\tau_{ij}(t) = c$ and $\Delta\tau_{ij} = 0$.

2. Set t:=0%. t:=0% is travel step counter. Place ant k on a city randomly and place the city in $visited_k$. Place the group of the city in tabu.

3. Repeat until tabu list is full.

Set t:=t+1

For k:1=1 to m do

According to the state transition probability $P_{ij}(t)$, the ants will search the next city. We put the selected city into $visited_k$ and put the group of selected city into tabu.

4.For k:=1 to m do

The $k-th$ ant moves from $visited_k(n)$ to $visited_k(1)$. We calculate the length that the $k-th$ ant moves. Then, we get the updated shortest route.

For every $edge(i,j)$ do

For k:=1 to 1 do

According to the formulas 19-21, we update the pheromone.

Time:=time+1

5.If(time<TIME_MAX), we empty $visited_k$ and tabu. Then, we return to the step 2. Else, we output the shortest route.

End

Then, we define the objective function as follows.

$$\min f(C,\sigma) = \sum_{i=1}^{M} (y - y)^2$$
$$st.\begin{cases} C \in [C_{\min}, C_{\max}] \\ \sigma \in [\sigma_{\min}, \sigma_{\max}] \end{cases} \tag{24}$$

Where, y is the output value of the ith sample. y is the predicted output value of the ith sample.

The idea of the LSSVM parameters optimization is to make the objective function minimize according to the iterative algorithm to search a set of the parameters (C,σ). We use the ACO to optimize and make a set of the parameter sequence (C,σ) on the domain as the position vector of the ant in the ACO.

The improved LSSVM algorithm is as follows.

Firstly, according to the historical data we collected, we establish the training sample set and the prediction sample set.

The second step is to set the parameters and initialize the position of the ants. Each position is corresponding to a group of parameter (C,σ) of the LSSVM algorithm. Then we establish the LSSVM prediction algorithm by the parameters and the training samples.

Thirdly, we input the training set into LSSVM. We take the prediction error of the training set as the fitness value of the ants and calculate the pheromone concentration of the ants.

The fourth step is to select randomly p ants. Then, according to the pheromone concentration of the position that the ant is in, we find out the position X_{best} of the ant and make is as the targeted Individual X_{obj}.

Where,

$$X_{obj} = \begin{cases} X_j, if \quad \tau(X_i) < \max(\tau(X_i)) \\ X_{best}, otherwise \end{cases} \tag{25}$$

Fifthly, the non-optimal ant does the global search according to the following formula.

$$X_i = (1-\lambda)X_i + \lambda X_{obj} \tag{26}$$

Sixthly, according to the following formula, the optimal ant does the search in the neighborhood.

$$X_{best} = \begin{cases} X_i', if \quad f(X_i') < f(X_{best}) \\ X_{best}, otherwise \end{cases} \tag{27}$$

The seventh step is to update the pheromone concentration.

Eighthly, if it reach to the maximum number of the iterations, we can encoding the position of the optimal ant and get the optimal value of the LSSVM parameter (C,σ).

Lastly, according to the optimal LSSVM model, we calculate it.

4. Experiment

When we construct the training samples and test samples of the support vector machine model, we must emphasize the typical and representative of the sample. It can fully represent the characteristics of the supply chain risk research of the enterprise. We evaluated 20 enterprises in the supply chain risk. We divide the output value into 5 levels. The risk interval is $[0,1]$. The risk interval of each level is $(0,0.2]$, $(0.2,0.4]$, $(0.4,0.6]$, $(0.6,0.8]$ and $(0.8,1]$. We use the collected data as the experiment. The first sample data is the training set and the last five data is the test set. The experimental result is shown as follows.

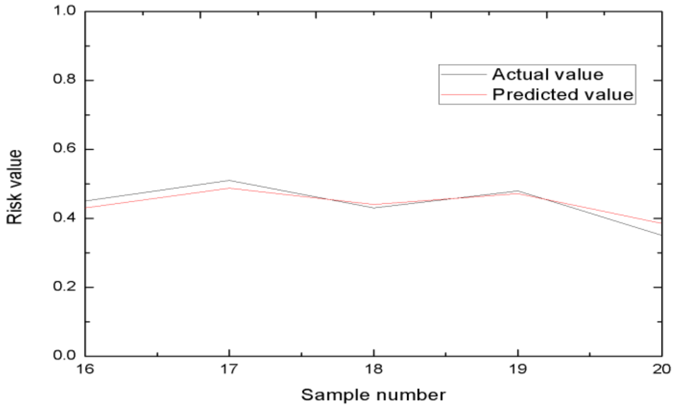

Figure 2. Comparing the Results of Actual Value with the Predicted Value

The error between the true value and predictive value is as follows.

Table 3. The Error Result of the Improved LSSVM Method

Sample number	Predicted value	Risk level	Actual value	Risk level	Error
16	0.4303	general	0.45	general	4.4%
17	0.4875	general	0.51	general	4.4%
18	0.4406	general	0.43	general	2.5%
19	0.4718	general	0.48	general	1.7%
20	0.3852	lower	0.35	lower	1%

From the Figure 1, we can see that the curve between the predictive value and the actual value is very similar. It means that the prediction accuracy of this method is relatively high. From Table 3, we can see that the changed range of the method is small for each test sample. It shows that the evaluation model has good generalization performance. Above all, the evaluation system has the good feasibility and effectiveness.

5. Conclusion

The uncertainty of the supply chain makes the supply chain risk increasing and causes the huge losses on the supply chain. Therefore, it is very necessary to assess the risk of a supply chain. Supply chain risk assessment is an important part in the supply chain risk management. It can help the enterprise to statistics the cause of the risk and adopt the preventive measures. This paper has the following works. Firstly, this paper briefly introduces the research background of the supply chain risk. Secondly, this paper put forward supply chain risk assessment evaluation indexes. Thirdly, this paper applies the improved ACO method to optimize the parameters for the LSSVM method and proposes the improved LSSVM method. Fourthly, this paper uses the improved LSSVM method to evaluate the risk of the supply chain. The experimental result shows the validity and reliability of the system.

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