CHEMICAL ENGINEERING TRANSACTIONS
VOL. 51, 2016

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Tichun Wang, Hongyang Zhang, Lei Tian

ISBN 978-88-95608-43-3; **ISSN** 2283-9216

DOI: 10.3303/CET1651059

Research on the Supply Chain Risk Prediction Based on the Improved Intelligent Algorithm

Jie Tao

Entrepreneurship Academy, Yiwu Industrial & Commercial College, Yiwu, Zhejiang 322000, China
84302588@qq.com

The uncertainty of the supply chain restricts improvement of the overall ability of the supply chain and brings great risks to the supply chain. The supply chain risk has the characteristic of the transmissibility. Once a node in the supply chain occurs the risk, the risk will spread to the whole supply chain and brings great risks to the supply chain. Therefore, it is very necessary to predict the supply chain risk. In this paper, we have to improve the performance of the PSO algorithm in order to improve the algorithm. Then, we use the algorithm to study the prediction of the supply chain risk. Finally, the experimental results show that the algorithm is effective and reliable.

1. Introduction

With the continuous development of the modern management, the supply chain has been in a constant change (Choi and Messinger, 2016). Compared with the traditional enterprises, the supply chain is the enterprise structure mode which has a broader, more complex structure. It contains all node enterprises which join. In the modern supply chain management, the supply chain developed towards to the trend of the agility supply chain (Lin and Wu, 2016). In addition, the modern supply chain logistics, the information flow and the capital flow transferred more quickly. All of these reasons not only made the supply chain more vulnerable, but also made the whole supply chain be faced with a huge risk (Marjorie, 2016).

In fact, the risk has been lurking in the supply chain. In the past, people had been keen on the pursuit of the efficiency and ignored the risk. When some unexpected events occurred and exposed these risks, the supply chain risk has been caused by people's attention (Cardoso et al., 2016). At present, the research on supply chain risk mainly includes two aspects. They are the qualitative research and the quantitative research. The current research focuses are the sources of the supply chain risk and the coping strategies (Frank Wiengarten et al., 2016) and the supply chain risk management (Mangla et al., 2015).

PSO is an efficient parallel optimization algorithm (Merkert and O'Fee, 2016). The algorithm can be used to solve a large number of nonlinear, non-differentiable and the multi peak complex optimization proposition. Moreover, the algorithm itself is simple and there is little parameter to be adjusted (Pandit et al., 2015). Therefore, the PSO algorithm has developed rapidly. After that, there are a large number of the improved algorithms being developed rapidly and applying to many fields of science and engineering.

In this paper, firstly, we classify the supply chain risk. In order to obtain the better prediction results, we propose an improved PSO algorithm. After that, we use the algorithm to predict the supply chain risk. The prediction results show that the algorithm is reliable and effective.

2. Supply chain risk classification

In order to predict the supply chain risk, we first classify the supply chain risk. We divide the supply chain risk into 6 second indexes and 20 third indexes. The specific categories are shown in the following table.

Please cite this article as: Tao J., 2016, Research on the supply chain risk prediction based on the improved intelligent algorithm, Chemical Engineering Transactions, 51, 349-354 DOI:10.3303/CET1651059

Table 1: Supply chain risk classification

The first level index	The second level index	The third level index
Supply chain risk	Supply chain structure risk	The number of nodes in supply chain
		The structure of the supply chain
		Supply chain quantity
		Supply chain enterprises
	Information risk	Information transfer risk
		bullwhip effect
		Information security risk
		Information fluctuation risk
	Supply chain operation risk	Manufacturer operational risk
		Supplier operational risk
		Retailer operational risk
	Cooperation risk	Partner selection risk
		Trust risk
	Logistics risk	Inventory risk
		The risk of transportation
		Distribution of risk
	Other risks	Legal risk
		Market risk
		Natural factors
		The development prospects of the industry risk

3. PSO algorithm

In recent years, PSO algorithm is a hot research topic. PSO algorithm has proposed by Kennedy and Eberhart in 1995. The rules of the PSO algorithm can be described as follows. When the whole groups are searching for a target, for one of the individuals, it adjusts its next search according to the optimal individual in the group and the optimal position that it achieves.

In PSO algorithm, each bird is as an individual in a group. It is abstracted as a particle which has no the mass and volume. Then, it is be extended to *d* dimension.

If the number of the groups are *n*,

$x_i = (x_{i1}, x_{i2}, \cdots, x_{id})$ is the current position for the $i(i = 1, 2, \cdots, n)$ particle.

$v_i = (v_{i1}, v_{i2}, \cdots, v_{id})$ is the speed of the $i(i = 1, 2, \cdots, n)$ particle.

The PSO algorithm is initialized to a random solution. Then, it begins to search the optimal solution according to the iteration. During the process of one iteration, each particle will update itself according to the local extremism and global extremism.

After finding out the two optimal values, the speed and the position of the particle updates by the function(1)and function (2).

$$v_i(t+1) = wv_i(t) + c_1 r_1(t)(pbest_i(t) - x_i(t)) + c_2 r_2(t)(gbest_i(t) - x_i(t)) \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

Where, c_1 is cognitive parameter. C_2 is social parameter. We adjust the effect of the own information and global information of the particle during the process of the movement according to c_1 and c_2. In general, we give,

$$c_1 = c_2 = 2 \tag{3}$$

r_1 and r_1 give *U(0,1)*. Where, *U(0,1)* is the random number in [0,1].

According to the fitness value of the particle, we update the global extremism $gbest$ and individual extremism *pbest*. The function is as follows.

$$pbest_i(t+1) = \begin{cases} x_i(t+1), & x_i(t+1) \geq pbest_i(t) \\ pbest_i(t) & x_i(t+1) < pbest_i(t) \end{cases} \tag{4}$$

In addition,

$$gbest_i(t) = \max(pbest_i(t+1)) \tag{5}$$

We assume that the maximum speed of the algorithm is v_{max}. That is, the speed of the particle is less than v_{max}.

If $v_i(t+1) > v_{\max}$, $v_i(t+1) = v_{\max}$. (6)

If $v_i(t+1) < -v_{\max}$, $v_i(t+1) = -v_{\max}$. (7)

4. The improved PSO algorithm

In order to improve the performance of the PSO algorithm and achieve the good results of the prediction of the supply chain risk, we improve the PSO algorithm and propose the improved algorithm. In this paper, we combine the LSSVM algorithm with the PSO algorithm. Then, we improve the algorithm and get the improved PSO algorithm.
LSSVM was developed in 1990s. It is the data mining tool which is based on the statistical learning theory. It can solve the nonlinear problem in order to obtain the optimal global solution and have s wide application range.
The flow chart of LSSVM is shown as follows.

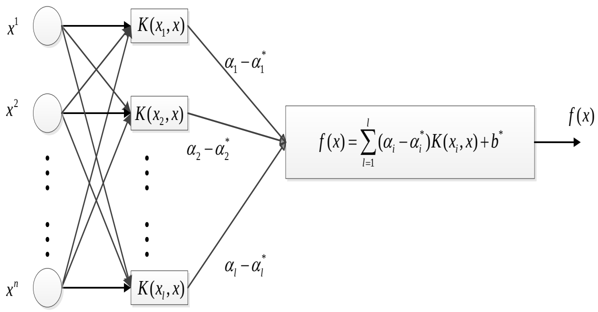

Figure 1: The flow chart of LSSVM

Kernel function method (KFM) is a new machine learning algorithm which combines the statistical learning theory with the support vector. With the rapid development of the science and technology, the research object is from the low dimension to high dimension. The statistical analysis method is more and more important to solve the complex high dimension object. Some methods can successfully solve the low dimensional problems. However, it has a variety of problems when solving the high dimensional data objects. Therefore, for the multivariate statistical analysis problem, dimensionality reduction is very important and the KFM appears.
KFM maps the original sample of the nonlinear. It maps from the data space to the feature space. Then, it can make the corresponding linear operation in the feature space. The application of the kernel function method achieves the nonlinear transformation between the feature space and the data space. We assume that ϕ is the nonlinear mapping function. Its function is to map the sample from the data space to the feature space. x_i and x_j are the original sample data. The core of the KFM is to make the inner transform for the vectors.

$$(x_i, x_j) \rightarrow K(x_i, x_j) = \phi(x_i)(x_j) \tag{8}$$

When making the inner product transform, the kernel function must satisfy the Mercer condition [50]. For any arbitrary symmetric function $K(x_i, x_j)$, The necessary and sufficient conditions of the inner product operation in a feature space is that $\int K(x,x)g(x)g(y)dxdy \geq 0$ for any $g(x)$.

In the application of the KFM, it is the key and the difficult problems to select the kernel function and determine the corresponding parameters. Now, the several common used kernel functions are following.
(1) Radial Basis Function

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2}) \tag{9}$$

(2) Exponential Radial Basis Function

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|}{2\sigma^2}) \tag{10}$$

(3) Polynomial kernel function

$$K(x_i, x_j) = (x_i \cdot x_j + r)^d \tag{11}$$

(4) Sigmoid kernel function

$$K(x_i, x_j) = \tanh(a \cdot x_i \cdot x_j + r) \tag{12}$$

(5) Gaussian kernel function

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

(13)

In this paper, we combine the RBF function with the sigmoid kernel function and propose the mixed kernel function.

$$K(x_i, x_j) = \alpha(x_i \cdot x_j + r)^d + (1-\alpha)\tanh(a \cdot x_i \cdot x_j + r) \tag{14}$$

α is the mixed weight coefficient and $\alpha \in$ [0,1].

During the evolution process, the diversity of the standard PSO algorithm cannot be well maintained. In the initial stage of the evolution, the individual particles in the particle swarm are relatively dispersed. Some particles may be far away from other particles. The high diversity leads to the slow process of the initial iterative process. With the process of the iteration, the particles are all moving to the direction of the global extreme *pbest* value and the individual extreme value *pbest*. When the diversity of the population has dropped to a low level, it is not conducive to the search to the global optimal solution. According to the characteristics and the status, we improved the PSO algorithm.

(1) System initialization

We set the particle population and produce a set of (c, γ, q, a) as the initial range of the particle/

(2) Determine the range of parameters to be optimized and set the maximum speed.

Penalty factor *c* reflects the model complexity and approximation error. The bigger the *c* is, the higher the fitting degree. *y* reflects the strength of the relationship among the support vectors.

(3) Calculate the fitness value $F(x_i)$ of each particle and compare with $F(pbest_i)$. If,

$$F(x_i) < F(pbest_i) \tag{15}$$

We use x_i to instead of $pbest_i$. The fitness value function is as follows.

$$F(x_i) = \frac{1}{m}\sum_{i=1}^{m}\frac{|f_i - y_i|}{y_i} \tag{16}$$

Where, y_i is the actual value of the i sample. f_i is the predicted value of the i sample.

(4) Compare the fitness value of each particle $F(x_i)$ with $F(gbest_i)$. If,

$$F(x_i) < F(gbest_i) \tag{17}$$

We use x_i to instead of $pbest_i$.

(5) Judgment the stagnation step the individual extremism evolution T_i of the i particle. If T_i is more than the preset value, we update the speed according to the following function.

$$v_i(t+1) = wv_i(t) + c_1 r_1(t)(r_3 \cdot pbest_i(t) - x_i(t)) + c_2 r_2(t)(gbest_i(t) - x_i(t)) \tag{18}$$

Where, r_3 is the random number in $(0,1)$.

Otherwise, we update the speed according to the function (1).

(6) Judgment the stagnation step the global extreme evolution. If it is more than the preset value, we update the speed according to the following function.

$$v_i(t+1) = wv_i(t) + c_1 r_1(t)(\cdot pbest_i(t) - x_i(t)) + c_2 r_2(t)(r_4 gbest_i(t) - x_i(t)) \tag{19}$$

Where, r_4 is the random number in (0,1).

(7) Update the inertia weight coefficient *w*.

(8) Determine whether to meet the termination conditions, if satisfied, end.

5. Experiment

For validate the reliability and validity of the improved PSO algorithm, we use this algorithm to predict the supply chain risk. We chose 5 enterprises for 20 years data to study on. The first 15 years data is the training set and the last 5 years data is the test set. Then, we use the improved PSO algorithm to predict the supply chain risk of these 5 enterprises. We divide the 5 levels of the output of the supply chain risk, namely [*very low, low, normal, high, very high*]. The risk interval [0,1] and the risk interval that the each level corresponds to is (0,0.2), (0.2,0.4), (0.4,0.6), (0.6,0.8), (0.8,1). The experimental result is shown as the table 2.

Table 2: The experimental result

Enterprise	Actual value	Grade	Predicted value	Grade
A_{16}	0.478	Normal	0.485	Normal
A_{17}	0.451	Normal	0.474	Normal
A_{18}	0.460	Normal	0.451	Normal
A_{19}	0.491	Normal	0.480	Normal
A_{20}	0.488	Normal	0.502	Normal
B_{16}	0.521	Normal	0.523	Normal
B_{17}	0.547	Normal	0.551	Normal
B_{18}	0.589	Normal	0.593	Normal
B_{19}	0.591	Normal	0.612	High
B_{20}	0.587	Normal	0.601	High
C_{16}	0.603	High	0.601	High
C_{17}	0.611	High	0.612	High
C_{18}	0.595	Normal	0.587	Normal
C_{19}	0.583	Normal	0.586	Normal
C_{20}	0.582	Normal	0.579	Normal
D_{17}	0.528	Normal	0.527	Normal
D_{18}	0.511	Normal	0.514	Normal
D_{19}	0.505	Normal	0.501	Normal
D_{20}	0.508	Normal	0.511	Normal
E_{16}	0.623	High	0.618	High
E_{17}	0.681	High	0.674	High
E_{18}	0.652	High	0.642	High
E_{19}	0.617	High	0.596	Normal
E_{20}	0.594	Normal	0.580	Normal

From the table 1, we can see that the predicted values of the supply chain risk through the improved PSO algorithm are similar to the actual values. This demonstrates that the experimental results are accurate. From this experiment, we can get the conclusion that it is feasible that use the improved PSO algorithm to predict the supply chain risk.

6. Conclusion

The occurrence of supply chain risk always brings a huge loss to the whole supply chain. To predict the risk of the supply chain can warm the supply chain risk early and avoid the occurrence of supply chain risk. In this paper, we propose the improved PSO algorithm to study on the prediction of the supply chain risk based on the classification of the supply chain risk. In this paper, we have done the following work. (1)we introduce the related background; (2)we establish the classification of the supply chain risk; (3)we introduce the PSO algorithm; (4) we propose the improved PSO algorithm and use this algorithm to predict the risk of the supply chain.

References

Cardoso S.R., Barbosa-Póvoa A.P., Relvas S., 2016, Integrating financial risk measures into the design and planning of closed-loop supply chains, Computers & Chemical Engineering, 85: 105-123, DOI: 10.1016/j.compchemeng.2015.10.012

Choi S., Messinger P.R., 2016, The role of fairness in competitive supply chain relationships: An experimental study, European Journal of Operational Research, 251: 798-813, DOI: 10.1016/j.ejor.2015.12.001.

Lin D.Y., Wu M.H., 2016, Pricing and inventory problem in shrimp supply chain: A case study of Taiwan's white shrimp industry, Aquaculture, 451: 24-35, DOI: 10.1016/j.aquaculture.2016.01.021

Merkert R., O'Fee B., 2016, Managerial perceptions of incentives for and barriers to competing for regional PSO air service contracts, Transport Policy, 47: 22-33, DOI: 10.1016/j.tranpol.2015.12.002

Mangla S.K., Kumar P., Barua M.K., 2015, Prioritizing the responses to manage risks in green supply chain: An Indian plastic manufacturer perspective, Sustainable Production and Consumption, 1:67-86, DOI:

Pandit M, Chaudhary V., Dubey H.M., Panigrahi B.K., 2015, Multi-period wind integrated optimal dispatch using series PSO-DE with time-varying Gaussian membership function based fuzzy selection, International Journal of Electrical Power & Energy Systems, 73: 259-272, DOI: 10.1016/j.ijepes.2015.05.017

Wiengarten F., Humphreys P., Gimenez C., McIvor R., 2016, Risk, risk management practices, and the success of supply chain integration, International Journal of Production Economics, 171:361-370, DOI: 10.1016/j.ijpe.2015.03.020

Windelberg M., 2016, Objectives for managing cyber supply chain risk, International Journal of Critical Infrastructure Protection, 12: 4-11, DOI: 10.1016/j.ijcip.2015.11.003