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Research Article

A Hybrid Support Vector Machines and Two-dimensional Risk Matrix Model for Supply Chain Risk Assessment

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Abstract: In recent years, the supply chain managements have been paid more and more attention. The supply chain risk management is an important content for enterprises implementing supply chain management. Therefore, how to measure the risk of supply chain is quite important. In this study, a supply chain risk evaluation model based on support vector machines and two-dimensional risk matrix is proposed. The index system of supply chain risk assessment which includes 14 indices is established. The case study shows that the proposed model is reasonable, effective and it can provide an important reference for supply chain risk management.

Keywords: Risk assessment, Supply Chain (SC), Support Vector Machines (SVMs), two-dimensional risk matrix

INTRODUCTION

As an integrated management mode under the globalization background, supply chain management has been widely adopted in various fields. Supply chains are considered as co-operative and dynamic networks, which link suppliers, manufacturers, third-party logistics, distributors, retailers and customers together. They merge enterprise production, material procurement, logistic, merchandise sales and other sectors into an organic whole, which benefits the related businesses. Due to the unpredictability of the operating environment and the complexity of the supply chain system itself, risks exist almost everywhere and can be spread through the supply chain network, which will eventually give rise to the supply chain risk. Even little risk occurred in a small corner in a supply chain can bring about catastrophe and badly damage the supply chain. Hence, it has a great significance to study supply chain risk management.

The practices of supply chain management around the world have proved that the ability to effectively identify and control the risk of supply chain operation is a major issue related to whether we can obtain the desired results from supply chain management. So the supply chain risk assessment is of great significance. The research on supply chain risk assessment has become an important research direction. Zhou (2008a) established a Diffusion Model (DM) of a supply chain risk which consisted of risk networks and a diffusion calculation process. The risk of the entire supply chain was assessed from three angles including risk factors, node enterprise and supply chain network. Neiger *et al.* (2009) proposed the Value-Focused Process Engineering (VFPE) methodology that combined process-based and objectives-based business modeling approaches into a model that enabled holistic representation of the business. It can be used for identifying the supply chain risk resulted from the integration of existing goal modeling and process modeling approaches and was therefore easily extended to include a multi-disciplinary view of risk that was flexible enough to accommodate variances arising from specific requirements of a supply chain structure being modeled. Tuncel and Alpan (2010) presented a high-level Petri Net (PN) based modeling methodology and a rule based approach for risk management in supply chains. This methodology could be applied for designing, analyzing, specification and evaluation of SC as well as for solving uncertainty and risk related problems using a real-time decision-making tool. Wu and David (2008) considered three types of risk evaluation models for supply chains: Chance Constrained Programming (CCP), Data Envelopment Analysis (DEA) and Multi-Objective Programming (MOP) models. Various risks are modeled and simulated according to specific probability distribution in risk-embedded attributes by these three types of risk evaluation models. The results showed that the proposed approach allowed decision makers to perform trade-off analysis among expected costs, quality acceptance levels and on-time delivery distributions. Amanda and Singh (2012) presented a numerical analysis using a simulation model motivated by an actual consumer packaged goods supply chain. The results demonstrated the importance of considering risk quantitatively and it's helpful for risk-informed decisions making. They also demonstrated that a

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systematic approach was necessary for control the downside of a disruption. Reducing risk at a single location in the network may not be helpful if the rest of the network was too vulnerable. Improving the strength of the weakest links in a chain would increase a chain's strength overall. Mary and Norbis (2011) developed a two-part assessment methodology, which includes a scoring system for assessing each participant of the supply chain in turn and an aggregation mechanism based on graphic modeling that results in a single supply chain risk index value for a specific supply chain of interest. Adhitya *et al*. (2009) thought that supply chain networks were in many ways similar to chemical plants, therefore well-established methods and concepts from chemical process risk management can be adapted for supply chains. Following the Hazard and Operability (HAZOP) analysis method in process safety, risk identification could be performed by systematically generating deviations in different supply chain parameters and identifying their possible causes, consequences, safeguards and mitigating actions.

However, some of the studies above are not visual for us to see the degree of risk and this does not help us to recognize the supply chain risk. Although some others of them can solve this problem by conducting a comprehensive risk evaluation model on the foundation of the sub-risks "risk value". That is to say, the first is to determine the scoring methods and then the result is obtained based on the scoring methods and the sub-risks. Unfortunately, this may lead to a deviation and the magnitude of the deviation which can hardly be known because of human's subjectivity. Besides, as for the risk degree and the risk's likelihood, the so-called "risk value" only takes one into consideration while the other is ignored. Support Vector Machines (SVMs) proposed by Vapnik in the middle of 1990s are a novel machine learning technology based on Statistical Learning Theory (SLT) and can solve a series of practical problems like classification and multivariate regression and have been widely used in many fields. Comparing with the traditional neural network learning methods, SVM can effectively solve the model selection and over learning problems, non-linear and dimension disaster, as well as issues such as local minima by solving a quadratic optimization problem to be the global optimal solution. In this study, the SVMs method is proposed and utilized to evaluate the supply chain's risk and the accuracy of the risk assessment can be improved. In addition, the supply chain's risk by the degree of harm and the likelihood of risk based on the two-dimensional matrix is analyzed, which enables the assessment system to adapt to the operating environment (e.g., time and space) and makes the result more reliable.

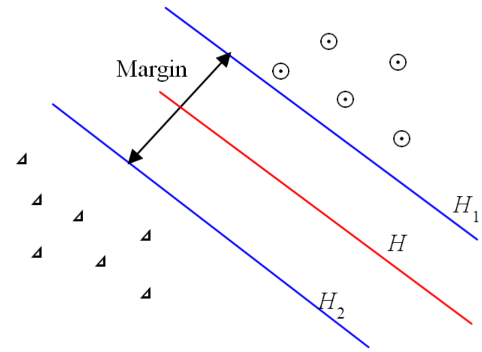

Fig. 1: The optimal hyper plane split of SVM

METHODOLOGY

Support vector machines: The SMVs is a novel machine learning theory that first developed by Cortes and Vapnik (1995) on the basis of Statistical Learning Theory (SLT). The SVMs adopt the Structure Risk Minimization (SRM) principle and have been shown to outperform the traditional Empirical Risk Minimization (ERM) principle used by conventional artificial neural networks. The SVMs have been widely used because of their excellent generalization performance, robustness in higher dimensions and efficiency in computation. SVMs are originally developed for binary classification intending to find out the optimal hyper-plane that makes the margin of separation between two different data sets maximized. The basic idea of SVMs is: when the linearly inseparable data sets map nonlinearly to a high dimensional feature space through the inner product kernel function, it becomes linearly separable data sets; and in the high dimensional feature space, we can establish the optimal classification hyper plane i.e., the so-called optimal hyper plane which can not only make the two types separate correctly but also maximize the margin (Li *et al*., 2009; Karim and Mahmoud, 2008). The basic idea of SVMs can be expressed in Fig. 1. In Fig. 1, ⊿ and ⊙ respectively represents a different class. H is the so-called optimal separating hyper plane. H_1 and H_2 respectively represents a straight line through the point closest to H and they parallels to H (the distances from H_1 and H_2 to H are the same).

Given the sample set $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, $y_i \in [+1, -1]$, for both situations i.e., linearly separable or linearly inseparable, these data can be separated by a hyper plane. The hyper plane satisfies:

$$\begin{aligned} &\min \frac{1}{2}(w\ )^T w \\ &s.t.\ \ y_i[(w \cdot x_i)+b]-1+\xi_i \geq 0, \\ &\quad \xi_i \geq 0, i=1,2,\cdots,n \end{aligned} \tag{1}$$

where,
w = The coefficient of the optimal hyper plane
b = The threshold value
ξ = The non-negative slack variable

when, $\xi_i = 0$, it is linearly separable while $\xi_i>0$ is inseparable.

According to the theory of SVMs, the input vector X can be mapped to a high dimensional feature space by a given nonlinear mapping. And then the optimal separating hyper plane can be found in this high-dimensional space, the problem to seek the optimal classification is transformed:

$$\begin{aligned} &\min_{\alpha} \ \frac{1}{2}\sum_{i=1}^{n}\sum_{i=1}^{n} x_i y_j \alpha_i \alpha_j K(x_i \cdot x_j) - \sum_{j=1}^{n}\alpha_j \\ &s.t. \ \sum_{i=1}^{n} y_i \alpha_i = 0 \\ &\quad 0 \le \alpha_i \le C, i = 1,2,\ldots\ldots,n \end{aligned} \tag{2}$$

where,
$K(u, v)$ = The kernel function
C = The penalty coefficient

$C>0$ and the larger C means the greater penalty for misclassification. According to the Eq. (2), we can get the optimal solution $\alpha^* = (\alpha_1^*,\ldots,\alpha_n^*)$ and $b^* = y_j - \sum_{i=1}^{n} y_i \alpha_i^* K(x_i, x_j)$, so the decision-making function is $f(x) = \mathrm{sgn}(\sum_{i=1}^{n} y_i \alpha_i^* K(x_i, x_j) + b^*)$.

SVMs are well applied to classification problems. It's critical to pre-determined kernel function and set the appropriate parameters for in order to find out the optimal hyper plane. In this study, Radial Basis kernel Function (RBF) is used:

$$K(x_i, x_j) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right) \tag{3}$$

Due to the robustness and the global optimization ability of the Genetic Algorithm (GA), it is particularly suited to deal with the complex and nonlinear problems. So, the GA is used to optimize the SVM's parameters (Huang and Wang, 2006; Avci, 2009).

The main feature of the genetic algorithm is the exchange of information between the group search strategy and the individuals of populations. Due to the robustness of the genetic algorithm, it is particularly suited to deal with the complex and nonlinear problems. The mainly steps are as follows:

Step 1: Generate an initial random population, a set of groups randomly and encoded in the parameter space

Table 1: Index system of supply chain risk assessment

Target layer	Criterion layer	Index layer
Overall risk (U)	System risk (U_1)	Natural disasters (U_{11})
		Instability of laws and policies (U_{12})
		Economic crisis (U_{13})
		Changes in market demand (U_{14})
	Cooperation risk (U_2)	Structure of the supply chain risk (U_{21})
		Requirement forecast accuracy rate risk (U_{22})
		Risks of benefits distribution (U_{23})
		Partners trust risk (U_{24})
		Coordinated control risk of the focal company (U_{25})
	Self-risk (U_3)	Quality safety risk (U_{31})
		Innovation capability risk (U_{32})
		Financial risk (U_{33})
		Risk of production and processing security (U_{34})
		Logistics risk (U_{35})

Step 2: Calculate the fitness value of individuals

Step 3: Judge whether it meets the pre-set stop criterion and if it meets the criterion, goes to Step 6; else, go to Step 4-5

Step 4: Determine the number that should be copied based on the fitness value of individuals and then do crossover and mutation operations to generate a new population

Step 5: Calculate the fitness value of individuals of the new generated population and then return to Step 3

Step 6: Get a new GA optimized parameters and establish GA-SVM model

Step 7: Judge whether the accuracy of GA-SVM model meets the pre-set stop criteria, if it meets the criterion, go to Step 8; else, return to Step1-6

Step 8: Determine the SVM optimal penalty factor C and the kernel function parameter G

Index system of supply chain risk assessment: In this study, the supply chains in which the manufacturing enterprises are as the core enterprises are studied. According to literatures (Wang *et al*., 2012; You *et al*., 2009; Zhou, 2008b; Oehmen *et al*., 2009; Moeinzadeh and Hajfathaliha, 2009; Tang *et al*., 2012) and experts' inquiries, the risk factors related to the supply chain mainly including the sectors of production, management and consumption etc. The main risk sources in the supply chain system include three aspects, i.e., System Risk, Cooperation Risk and Self-Risk. According to the principle of systemic, importance, as well as universality, we establish the index system combining the expert's investigation. The index system of supply chain risk evaluation in this study is as shown in Table 1.

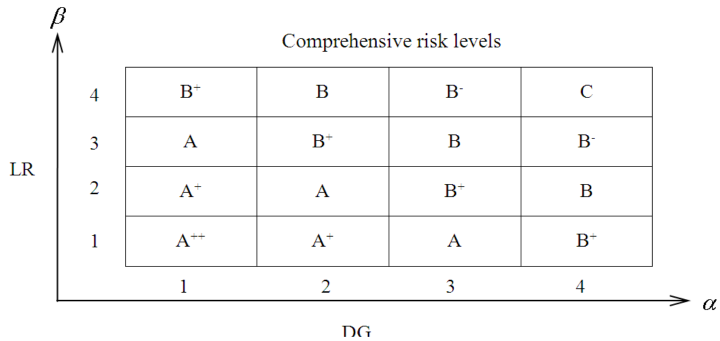

Fig. 2: Two-dimensional risk matrix

Table 2: Scores and descriptions

	Scores				
Dimensions	0.9	0.7	0.5	0.3	0.1
Risk harm degree	Catastrophic	Serious	Moderate	Acceptable	Mild
Risk likelihood	Almost certain	Probable	Uncertain	Doubtful	Not likely

Table 3: Risk levels and output vectors

Comprehensive risk levels		
Description	Levels	(α, β)
High	C	(4, 4)
	B^-	(4, 3), (3, 4)
	B	(4, 2), (3, 3), (2, 4)
	B^+	(4, 1), (3, 2), (2, 3), (1, 4)
	A	(3, 1), (2, 2), (1, 3)
Low	A^+	(2, 1), (1, 2)
	A^{++}	(1, 1)

Table 4: Experts scoring card

	Scores	
Index	DG	LR
Natural disasters (U_{11})	0.9	0.1
Instability of laws and policies (U_{12})	0.5	0.1
Economic crisis (U_{13})	0.7	0.3
Changes in market demand (U_{14})	0.7	0.5
Structure of the supply chain risk (U_{21})	0.5	0.5
Requirement forecast accuracy rate risk (U_{22})	0.3	0.7
Problems of distribution of benefits (U_{23})	0.3	0.5
Partners trust risk (U_{24})	0.7	0.5
Coordinated control of the core enterprise risk (U_{25})	0.9	0.7
Quality safety risk (U_{31})	0.5	0.3
Innovation capability risk (U_{32})	0.5	0.3
Financial risk (U_{33})	0.7	0.3
Risk of production and processing security (U_{34})	0.3	0.3
Logistics risk (U_{35})	0.3	0.5
Levels	3	2

Two-dimensional risk matrix: In this study, we use the Delphi method to obtain the risk evaluation data of the supply chain in a variety of circumstances by consulting experts (James and John, 2001). Referring to the study of Hallikas *et al*. (2002, 2004), we use five-level grading method and respectively measure Likelihood of Risk (LR) and Degree of Harm (DG). This grading method is as shown in Table 2.

After processing each sample data by SVMs, We can get a two-dimensional output vector, represented by (α, β). And α represents the DG level, β represents the LR level. We use 1, 2, 3, 4 four levels to measure them and the comprehensive risk levels that consists of the DG levels and the LR levels can be obtained. This approach to measure risk levels is shown in Table 3 and a two-dimensional risk matrix Fig. 2. We mark various kinds of supply chain risk in this matrix according to the likelihood of risk and the degree of harm. According to the results, decision makers can come up with corresponding strategies and control the risk.

CASE STUDY

In this study, 30 supply chain samples in which manufacturing enterprises are core enterprises are chosen. The samples are divided into two parts, 25 samples as training data and the others are as test samples. Various experts in the supply chain field are invited to assess each index of supply chains for 30 samples. Index values were determined by related experts according to the grading method shown in Table 2. Besides, experts should also use the Delphi method to give the 25 scores of the DG level and LR level of each supply chain by considering the overall operational status and trends (Ma *et al*., 2004; Saleh *et al*., 2011; Member and Swarup, 2011; Chen and Li, 2010). The scoring card is shown as Table 4.

The training samples and test samples are selected and the data are normalized according to Eq. (4):

$$X^* = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{4}$$

The LibSVM, which is a toolkit developed by Lin and can be used for classification and regression quickly and efficiently according to the principle of SVM, is used to train the SVMs with the training samples (Chang and Lin, 2011). In this study, the Radial Basis Function (RBF) as kernel function is used

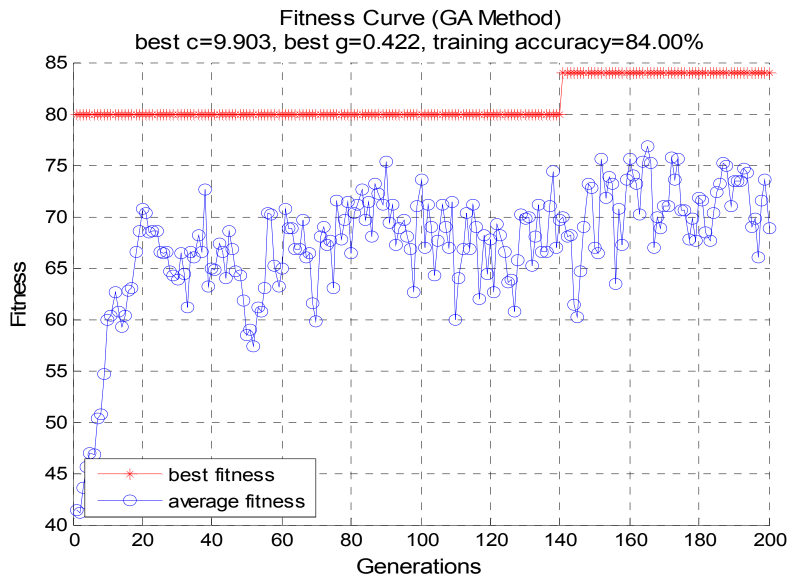

Fig. 3: Parameter-optimization result (DG)

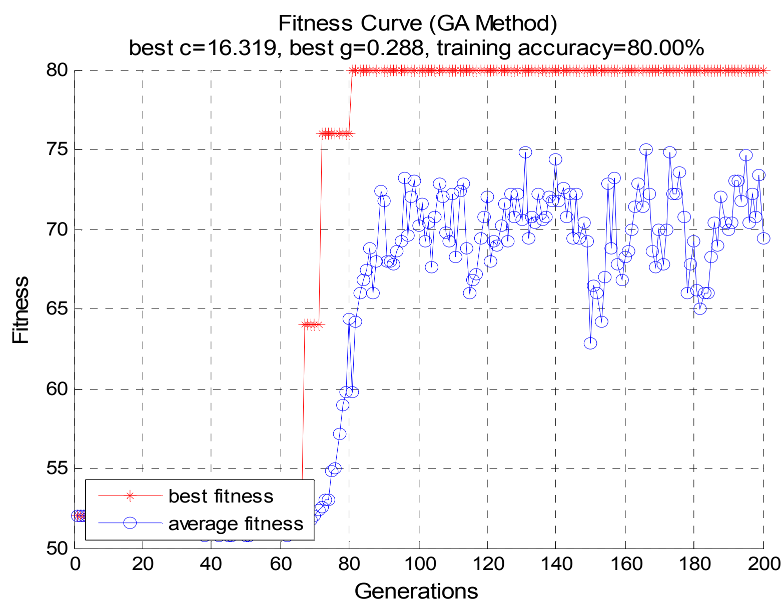

Fig. 4: Parameter-optimization result (LR)

and the Genetic Algorithms (GA) which has the global optimization ability is used to find the best penalty factor C and kernel function parameter γ. According to the calculation steps in above section, we can establish a contact between the fitness function and the objective function. And with the increase of generations, the fitness value of individuals shows a rising trend (Fig. 3 and 4). The larger the fitness value is, the stronger the viability of population will become. That means the parameters will be more suitable. During the process, we can grasp at the biggest fitness value among all we have calculated and can determine the optimum parameters.

Here, for DG, the best $C = 9.903$ and the best $\gamma = 0.422$, while the accuracy of classification (fitness value) is 84%. For LR the best $C = 16.319$, the best $\gamma = 0.288$ and the accuracy of classification (fitness value) is 80%.

The test samples are predicted by the trained SVMs and the levels of DG and LR can be obtained, as shown in Table 5.

Table 5: Levels of DG and LR

No.	26	27	28	29	30
Levels of DG	2	3	1	2	4
Levels of LR	3	4	1	2	2

Table 6: Comprehensive risk levels

No.	26	27	28	29	30
Comprehensive risk	(2, 3)	(3, 4)	(1, 1)	(2, 2)	(4, 2)
Levels	B^+	B^-	A^{++}	A	B

Finally, according to Table 3 and Fig. 2, we integrated the predicted results of DG and LR above and obtained the comprehensive risk level, as shown in Table 6.

As we know, DG represents the degree of harm and the levels of DG largely reflect the characteristics of industries in supply chains and the reasonableness of supply chain structures. Likewise, LR represents the likelihood of risk and the levels of LR are reflections of the external conditions of supply chains and can be regarded as descriptions of management level and operation status of supply chains. So, we can obtain a lot of information from DG level and LR level and we can take targeted measures to control DG level and LR level so as to control comprehensive risk levels.

Based on the above understanding, we can obtain some results as following according to the result of Table 6. Firstly, Supply Chain No. 28 is at a lowest level in terms of both DG and LR, its comprehensive risk level is A^{++}, which indicates that No. 28 is in good and safe condition. Secondly, the risk levels of No. 26 and No. 29 are B^+ and A respectively, which can be regard as a moderate level. But it is still necessary to strengthen the supply chain management and cooperation in order to further reduce the likelihood of risk. Thirdly, for Supply Chain No. 30, whose risk level is B, it is important to reconsider the rationality of its supply chain structure because of its high DG level. Before that, should figure out where the defects are and whether they originate from characteristics of the industry. This risk may be difficult to be eliminated completely because the risk is accompanied by the birth of the industry. If possible, the development of the technology and theory will be the best way to solve the problem. But managers should firstly take steps to adjust the structure of the supply chain to make it appropriate and reasonable as far as possible. And it is still necessary to make the supply chain management and cooperation more effectively and efficiently. Fourthly, the comprehensive risk level of Supply Chain No. 27 is high, reaching B^- level, which implies that this supply chain means enormous risk. It is urgent to take measures to control the overall risk level of the supply chain; otherwise it will cause great harm to all enterprises of the supply chain. And managers must choose a holistic way to think about it. However, to suppliers, manufacturers, retailers, consumers, etc., once they realize the risk, they may choose other cooperators instead of looking for change. In other words, to quit from the original supply chain is the most direct way to solve the problem if the cost of the change can be accepted. So, it is of great significance to asses the overall risk in time.

CONCLUSION

Along with the quickly development of theory and application about supply chain management, the supply chain risk management become an important content for enterprises. In this study, SVMs are used to the field of supply chain risk assessment. Using the multi-classification function of SVMs, the problem of supply chain risk assessment is transformed into risk rating problem. Besides, a two-dimensional risk matrix consisting of the degree of harm and the likelihood of risk is established, which can be more visually to demonstrate the risk levels of the supply chain and enable decision makers to take more targeted measures to control the supply chain risk. Finally, a case is studied and the results show the feasibility of this method. However, there are still some special attentions which we will pay attention to when we apply this method. The index system may be different for different supply chains. In addition, the supply chain risk evaluation is a complex system evaluation problem and the further studies are certainly desirable on risk assessment and control.

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