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Risk Assessment of Automotive Manufacturing Supply Chain Based on Combined Weighting—Fuzzy Comprehensive Evaluation

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Abstract: The automotive industry is one of the pillar industries of the Chinese economy and still has excellent development potential. However, due to the complex structure of automobiles, the riskiness probability in the automotive manufacturing supply chain is greatly increased compared with other manufacturing supply chains. Thus, this paper proposes a risk assessment model integrating the combined weighting method and the fuzzy comprehensive evaluation method. Firstly, risk factors are identified according to the improved SCOR model. Second, the combined weights of risk factors are calculated using the Lagrange multiplier method. Finally, the risk factors are evaluated through the fuzzy comprehensive evaluation method. The first-level risk factors, in order of their impact on the supply chain, are: Procurement process risk, Production process risk, Planning process risk, Reverse process risk, Delivery process risk, Research and development process risk, and Operation and maintenance process risk. In addition, this paper also ranks the impact of second-level risk factors within each process. The results of the risk assessment model provide theoretical support for the supply chain risk management of automotive manufacturing-related companies.

1. Introduction

With the universality of the concept of supply chain, supply chain management has penetrated the enterprise management of various industries in China. Supply chain management stresses cooperation and coordination among members to maximize the overall interests of the whole supply chain. This approach enhances resource utilization and operational efficiency but also heightens risk probabilities. Once risks happen in one member of the supply chain, the regular operation of other nodes in this supply chain will also be affected. The automotive supply chain, a typical discrete manufacturing supply chain, is particularly prone to risks due to its regional dispersion, complexity, and numerous node enterprises. This risk impact is more significant in manufacturing than in service supply chains [1].

In recent years, risk management in the automotive industry has also been studied by many scholars from different perspectives. Zhang et al. empirically analyzed risks in Shanghai Automotive Industry Co., using the Confirmatory Factor Analysis and the WBS-RBS method for evaluation [2]. Junaid M et al. combined the neutrosophic (N) theory with the AHP method to identify the automotive supply chain risk management standard [3]. Pan et al. applied a back propagation neural network to determine risk factor weights [4], while Hu constructed a Bayesian network-based risk factor assessment model [5]. Tian & Li investigated the risk factors weight of intelligent networked vehicles through variable-weight hierarchy analysis method [6]. Since the automotive industry is one of the pillar industries of China's national economy, many scholars have studied risk management in the automotive industry from a financial perspective. Li researched the financial credit risk assessment model of the automotive supply chain by logistic regression analysis method [7]. With the promotion of new energy vehicles, Li assessed the financial credit risk of the new energy automotive supply chain, using an improved DEMATEL model [8]. From the perspective of supply chain vulnerability, Zhang combined the AHP method with the TOPSIS model for automotive supply chain risk management [9]. Seyedamir et al. integrated the best-worst method with the rough strength-relation analysis method to research automotive supply chain risks during disruptions [10].

In summary, in risk management of automotive industry, most studies employ a single method to analyze risk factor weights in assessment models. Although some studies have combined methods, they did not take actual project data into consideration when weighting the risk factors. In order to make the results of the risk assessment more realistic, when researching the objective weight of supply chain risk factors, this paper use the entropy weight based on two actual projects in automotive manufacturing industry, the project data is obtained through enterprise research.

Taking the automotive manufacturing supply chain as the research object, this paper proposes the combined weighting-fuzzy comprehensive evaluation model for risk assessment. The entropy weight method and the DEMATEL model are used to analyze the weight of risk factors from objective and subjective perspectives, respectively. Then, the Lagrange multiplier method is used to carry out the combination of weights to reduce the personal influence of the expert's opinion. The remainder of this paper is organized as follows. In section 2, a risk assessment model for the automotive manufacturing supply chain is constructed. In section 3, risk factors are assessed based on the enterprise project data and the working experience of enterprise personnel. Section 4 conclude this paper.

2. Risk Assessment model formulation

2.1 Risk factor identification

The supply chain operations reference (SCOR) model is a tool proposed by the Supply Chain Council that can be used for risk diagnosis and as a reference tool for constructing a risk evaluation index system [11]. The SCOR model divides the activities in the supply chain into five processes: Planning, Procurement, Production, Delivery, and Return. The improved SCOR model (Figure 1) adds the Research and Development (R&D) process and the Operation and Maintenance (O&M) process to the traditional SCOR model and expands the original return process into a reverse process [6]. Combined with the characteristics of the automotive manufacturing supply chain, this paper identifies the risk factors in the automotive manufacturing supply chain based on the above improved SCOR model and establishes a risk evaluation indicators system.

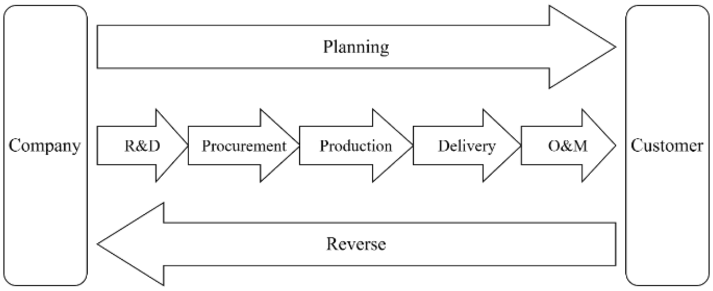

Figure 1: Supply chain management process based on improved SCOR model.

According to the improved SCOR model, the complete automotive manufacturing supply chain risk evaluation factors system is shown in Table 1.

Table 1: Automotive supply chain risk evaluation factor system.

The first level risk factors	The second level risk factors
Planning process risk U_1	Quality of planners U_{11}
	Impact of unexpected events U_{12}
	Macroeconomic fluctuations U_{13}
Research and development process risk U_2	Quality of research and development staff U_{21}
	R&D process specification U_{22}
	Information security construction U_{23}
Procurement process risk U_3	Quality of procurement staff U_{31}
	Procurement price fluctuations U_{32}
	Fluctuations in the quality of procurement U_{33}
	Supplier quality management U_{34}
Production process risk U_4	Performance of production equipment U_{41}
	Production safety management U_{42}
	Quality of producing products U_{43}
	Material storage specifications U_{44}
Delivery process risk U_5	Changes in product requirements U_{51}
	Quality of carrier services U_{52}
	Environment of transport routes U_{53}
Operation and maintenance process risk U_6	Quality of operations and maintenance personnel U_{61}
	Hardware and Software Performance U_{62}
	Legal disputes and society reputation U_{63}
Reverse process risk U_7	Reverse system management U_{71}
	Product quality traceability U_{72}

2.2 Calculation of risk factor objective weights

The entropy weight method is often used to determine the weights of factors in the case of multiple factors and samples. The entropy represents the information entropy, which indicates the degree of uncertainty of the information, and the greater the entropy of the risk factors, the smaller the weight in the system [12]. In this paper, the data for the entropy weight method is from research in automotive manufacturing enterprises, and the specific calculation steps are as follows:

● Standardization of data. Suppose the amount of samples is n and the number of risk factors is m. The data a_{ki} is standardized using the extreme value difference method to obtain a'_{ki}. The forward factor a_{ki}^{forward} signifies a decrease in overall automotive manufacturing supply chain risk with its augmentation. Conversely, the backward factor a_{ki}^{backward} indicates an increase in risk with its increase [12]. The calculation equations are:

$$a_{ki}^{\text{forward}} = \frac{max a_i - a_{ki}}{max a_i - min a_i} \tag{1}$$

$$a_{ki}^{\text{backward}} = \frac{a_{ki} - min a_i}{max a_i - min a_i} \tag{2}$$

$$A = \begin{pmatrix} a'_{11} & a'_{12} & \cdots & a'_{1m} \\ a'_{21} & a'_{22} & \cdots & a'_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a'_{n1} & a'_{n2} & \cdots & a'_{nm} \end{pmatrix} \tag{3}$$

● Calculation of the percent of factors. The percent of the ith risk factor in the kth sample P_{ki} is:

$$p_{ki} = \frac{a'_{ki}}{\sum_{k=1}^{n} a'_{ki}}, k = 1, 2, \ldots, n, i = 1, 2, \ldots, m \tag{4}$$

● Calculation of the information entropy value. Information entropy value of the ith risk factor e_i is:

$$e_i = -\frac{1}{\ln n} \sum_{k=1}^{n} p_{ki} \ln p_{ki}, i = 1, 2, \ldots, \mathrm{m} \tag{5}$$

● Calculation of objective weights for risk factors.

$$\omega_i^e = \frac{1 - e_i}{\sum_{i=1}^{m} 1 - e_i} \tag{6}$$

2.3 Calculation of risk factor subjective weights

DEMATEL is a system analysis method, which can be used to analyze the degree of interaction between factors in complex systems [13]. Traditional weight calculation methods, such as hierarchical analysis, assume that the factors are independent and do not consider the interactions between the factors. Therefore, this paper uses the DEMATEL method to analyze the mutual influence between each risk factor, with the following steps:

● Identify the risk elements in the system. Suppose that system P have j elements, denoted as $P = \{P_1, P_2, \ldots P_j\}$, in this paper, P represents each subsystem of the automotive manufacturing supply chain, i.e., first-level factors, a total of 7. P_j is the risk elements contained in the subsystems, i.e., the second-level factors.

● Construction of a direct impact matrix. The value b_{ij} in the direct impact matrix is obtained from the two-by-two comparison between the factors in the subsystem, and b_{ij} indicates the influence degree of factor i on factor j in the subsystem. Define a 0-9 scale to represent the influence degree, the closer to 0, the smaller the influence; the closer to 9, the larger the influence. If the amount of factors in the subsystem is m, the direct impact matrix B is constructed as:

$$B=\begin{pmatrix} 0 & b_{12} & \cdots & b_{1m} \\ b_{21} & 0 & \cdots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & 0 \end{pmatrix} \tag{7}$$

● Direct impact matrix normalization.

$$N=\frac{B}{max\sum_{j=1}^{m} b_{ij}} \tag{8}$$

● Calculation of the integrated impact matrix. The integrated impact matrix T represents the indirect impact between the risk factors, where I is a unit matrix of the same order as N.

$$T=N\left(I-N\right)^{-1} \tag{9}$$

● Calculate the degree of influence D_i, the degree of influenced C_i, the degree of centre M_i and the degree of cause R_i, where t_{ij} is the value of row i and column j in the integrated impact matrix T.

$$D_i=\sum_{j=1}^{m} t_{ij}, i=1,2,\ldots,m \tag{10}$$

$$C_i=\sum_{i=1}^{m} t_{ij}, i=1,2,\ldots,m \tag{11}$$

$$M_i=D_i+C_i \tag{12}$$

$$R_i=D_i-C_i \tag{13}$$

● Calculation of subjective weights.

$$\omega_i^d=\frac{M_i}{\sum_{i=1}^{m} M_i} \tag{14}$$

2.4 Calculation of combined weights

In the above sections, the application of one single method cannot fully consider all the information of the factors. Therefore, many scholars use the combination of weights for a more reasonable assessment. Ji et al. used geometric mean combined with fuzzy hierarchical analysis and entropy weighting to determine the mixed weights [14]. Xiao introduced game theory to find a balance between subjective and objective weights to get the composite weights [15]. This paper use the Lagrange multiplier method to combine the objective and subjective weights. According to the principle of minimum discriminative information, in order to shrink the gap between the optimal combination weights ω_i and ω_{1i}; ω_i and ω_{2i}, it can be calculated by the following equation:

$$\min F = \sum_{i=1}^{m} \omega_i \left(\ln \frac{\omega_i}{\omega_i^e} \right) + \sum_{i=1}^{m} \omega_i \left(\ln \frac{\omega_i}{\omega_i^d} \right) \tag{15}$$

Using Lagrange multiplier method to solve equation (15), the optimal combination weights can be obtained as follows:

$$\omega_i = \frac{\omega_i^e \omega_i^d}{\sum_{i=1}^{m} \omega_i^e \omega_i^d} \tag{16}$$

2.5 Risk factor assessment

The fuzzy comprehensive evaluation method has been widely applied to the risk assessment process in engineering and technology, economy and finance, supply chain and so on [16-17]. Methods such as AHP and entropy weight method are often used together with the fuzzy comprehensive evaluation method for risk assessment. In the process of risk assessment, the former is used to determine the weight of risk evaluation factors, while the latter is used to classify the risk level [18]. The steps are:

- Determine the set of evaluation factors for assessing projects $U = \{U_1, U_2, U_3, U_4, \cdots\}$;
- Determine the rubric level set $V = \{V_1, V_2, V_3, V_4, \cdots\}$;
- Determine the fuzzy relationship matrix. The evaluation vector $Frm(U_i)$ of each single risk factor for automotive supply chain risk can be derived by some methods;
- Determine the fuzzy weight sets for assessment factors ω;
- Establishment of a mathematical model for fuzzy comprehensive evaluation

$$F = \omega \cdot Frm \tag{17}$$

After normalization is carried out, the results of the fuzzy comprehensive evaluation can be derived according to the principle of affiliation.

3. Case study

3.1 Calculation of automotive manufacturing supply chain risk factor objective weights

The objective data required by the entropy weight method were obtained through research on automotive enterprises, and 2 valid project samples were recovered.

This section takes the production process risk factor as an example to illustrate the calculation process of the subsystem corresponding to the first-level risk factor. The production process risk contains four second-level risk factors. Among them, the objective criterion for the performance of production equipment is set as the proportion of the number of entries in which the period of regular maintenance of the equipment differs from the industry standard. The objective criterion for production safety management is the frequency of accidental injuries to staff. The objective criterion for the quality of producing products is the proportion of products that do not comply with the requirements in the production process. And the objective criterion for the specification of materials storage is the frequency of cost increases due to the extrusion and stacking of materials and semi-finished products. The four second-level risk factors are all backward factors.

Thus, according to equations (1)-(6), evaluation matrix of production process risk factors A_4 is:

$$A_4 = \begin{pmatrix} 0.083 & 0.100 & 0.133 & 0.189 \\ 0.200 & 0.200 & 0.001 & 0.010 \end{pmatrix}$$

P_4 is obtained by normalizing the evaluation matrix A_4:

$$P_4 = \begin{pmatrix} 0.294418 & 0.333333 & 0.930233 & 0.949721 \\ 0.705882 & 0.666667 & 0.069767 & 0.050279 \end{pmatrix}$$

Production process risk information entropy is:

$$e_4 = \begin{pmatrix} 0.376403 & 0.395488 & 0.157221 & 0.123855 \end{pmatrix}$$

The objective weight of production process risk:

$$\omega_4^e = \begin{pmatrix} 0.211602 & 0.205125 & 0.285976 & 0.297297 \end{pmatrix}$$

3.2 Calculation of automotive manufacturing supply chain risk factor subjective weights

The subjective weights are calculated using the DEMATEL method. The data is obtained through the questionnaire method, and 21 valid data are recovered. This section also takes the production process risk factor as an example to illustrate the calculation process.

According to equations (7) - (14), the data are weighted to obtain the direct impact matrix B_4:

$$B_4 = \begin{pmatrix} 0 & 6.523810 & 7.333333 \\ 5.952381 & 0 & 6.952381 \\ 5.952381 & 5.666667 & 0 \\ 3.952381 & 5.761905 & 5.952381 \end{pmatrix}$$

N_4 is obtained by normalizing the evaluation matrix B_4:

$$N_4 = \begin{pmatrix} 0 & 0.335784 & 0.377451 \\ 0.306373 & 0 & 0.357843 \\ 0.306373 & 0.291667 & 0 \\ 0.203431 & 0.296569 & 0.306373 \end{pmatrix}$$

Integrated impact matrix T_4 is:

$$T_4 = \begin{pmatrix} 1.876414 & 2.289227 & 2.51440 \\ 2.240910 & 2.184432 & 2.662449 \\ 2.040324 & 2.191329 & 2.158579 \\ 1.874836 & 2.081466 & 2.268809 \end{pmatrix}$$

The centrality degree M_4 and the causality degree R_4 of the production process risk are:

$$M_4 = \begin{pmatrix} 16.701967 & 18.044262 & 17.966922 & 15.725904 \end{pmatrix}$$

$$R_4 = \begin{pmatrix} 0.636998 & 0.551355 & -1.241553 & 0.053201 \end{pmatrix}$$

Thus, the subjective weight of the production process risk is:

$$\omega_4^d = \begin{pmatrix} 0.244041 & 0.263654 & 0.262524 & 0.229780 \end{pmatrix}$$

3.3 Calculation of automotive manufacturing supply chain risk factor combined weights

Based on (15) - (16), the combination weights of each second-level risk factor in the production process risk are:

$$\omega_4 = \begin{pmatrix} 0.207296 & 0.217102 & 0.301375 & 0.274228 \end{pmatrix}$$

3.4 Automotive manufacturing supply chain risk factor assessment

3.4.1 Identification of risk factor sets and weights

The automotive supply chain risk factors are identified by the improved SCOR model as Table 1. The weights of risk factors are shown in section 3.1.

3.4.2 Determine the risk factor rubric level and fuzzy relationship matrix

Categorization of risk factor rubric levels into 5: $V = \{V_1, V_2, V_3, V_4, V_5\}$. Among them, V_1 indicates the highest degree of risk influence; V_2 suggests a high degree of risk influence; V_3 indicates a medium degree of risk influence; V_4 represents a weak degree of risk influence, and V_5 indicates the weakest degree of risk influence. The automotive industry managers and employees were invited to evaluate the automotive supply chain risk factors, and 21 valid data were recovered. Due to space constraints, this paper only shows the production process risk data. Thus, the fuzzy relationship matrixes for the production process risk are:

$$Frm_4 = \begin{pmatrix} 0.142857 & 0.52381 & 0.238095 & 0.047619 & 0.047619 \\ 0.142857 & 0.333333 & 0.428571 & 0.047619 & 0.047619 \\ 0.238095 & 0.428571 & 0.285714 & 0 & 0.047619 \\ 0 & 0.380952 & 0.380952 & 0.142857 & 0.095238 \end{pmatrix}$$

According to the principle of maximum affiliation, we can rank the second-level factors which belong to the same first-level factors in order of their influence on the supply chain. For example, the second-level factors within production process risk are ranked in descending order of impact: Performance of production equipment U_{41}, Quality of producing products U_{43}, Material storage specifications U_{44}, Production safety management U_{42}.

From the perspective of the degree of cause R_4, Performance of production equipment U_{41}, Production safety management U_{42}, and Material storage specifications U_{44} are causal factors. Quality of producing products U_{43} is affected by the above factors. Thus, in production department, managers should focus first on the production equipment performance, followed by material storage specifications and production safety management. These factors could affect the quality of products.

3.4.3 Determine the fuzzy comprehensive evaluation results

There are two commonly used fuzzy synthesis operators, one is the "big-small" mode of operation, and the other is matrix operation. Since taking "big-small" will lose an amount of information, the form of matrix operation is used to calculate the final result in this paper. According to Equation (17), based on the weights calculated in Section 3.1, the affiliation degree corresponding to the impact of each first level risk factor can be weighted. For the production process risk, the affiliation degree vector $F_4 = (0.132 \quad 0.415 \quad 0.332 \quad 0.059 \quad 0.061)$. The complete results are shown in Table 2.

After summing up the affiliation degree of each first level risk factor according to five rubric levels, normalization processing is conducted. Then we can obtain the comprehensive evaluation result of the automotive manufacturing supply chain $F = (0.148 \quad 0.362 \quad 0.292 \quad 0.132 \quad 0.066)$. Due to the principle of maximum affiliation, the level of risk impact on the automotive manufacturing supply chain is relatively high. This indicates that enterprises within the automotive manufacturing supply chain need to prioritize risk management in their daily operations.

According to the principle of maximum affiliation, in decreasing order of influence, the first-level risk factors in the automotive manufacturing supply chain are: Procurement process risk U_3, Production process risk U_4, Planning process risk U_1, Reverse process risk U_7, Delivery process risk

U_5, Research and development process risk U_2, Operation and maintenance process risk U_6. This provides reference basis for the risk management operations of automotive manufacturing-related enterprises.

Table 2: The affiliation degree corresponding to the impact of each first level risk factor.

The first-level risk factors	V1	V2	V3	V4	V5
Planning process risk U_1	0234	0.395	0.258	0.079	0.033
Research and development process risk U_2	0.185	0.295	0.368	0.103	0.048
Procurement process risk U_3	0.323	0.446	0.124	0.096	0.010
Production process risk U_4	0.132	0.415	0.332	0.059	0.061
Delivery process risk U_5	0.047	0.324	0.315	0.277	0.036
Operation and maintenance process risk U_6	0.069	0.283	0.336	0.155	0.156
Reverse process risk U_7	0.048	0.373	0.306	0.157	0.116

The result indicates that the procurement processes related to supplier quality management, price fluctuations of purchased goods, and quality fluctuations are the most important to be focused in the daily operations. This may be attributed to the extensive demand for a diverse range and significant quantity of components and raw materials within the automotive supply chain. Any delay in the supply of specific components can potentially disrupt the production processes of manufacturing enterprises. Consequently, to enhance the reliability of procurement processes, enterprises can rationally increase the number of suppliers, elevate the criteria for selecting supply chain members, and establish a supplier evaluation system. Additionally, maintaining appropriate inventory reserves serves as a crucial measure in mitigating risks associated with procurement processes.

The affiliation degrees of production process and planning process are slightly less than that of procurement process. Thus, production issues such as production equipment performance and planning issues such as quality of planners should also be given a certain attention. To mitigate production process risks, enterprises ought to establish rigorous norms for production processes, thereby ensuring standardized operations among personnel. Regarding planning process risks, enterprises must be well-prepared to respond to emergencies. Firstly, enterprises can establish warning thresholds, as not all abnormal information necessarily indicates the occurrence of an emergency. Secondly, enterprises can prepare different warning decisions in advance for different emergencies. Lastly, enterprises must prioritize the cultivation of risk awareness among employees.

In addition, with limited enterprise resources, companies can pay remaining attention to processes in order of reverse process work; delivery process work; R & D process work; O & M process work.

4. Conclusion

This paper studies the risk assessment of the automotive manufacturing supply chain. The risk evaluation factor system of the automotive manufacturing supply chain is constructed by an improved SCOR model, and the risk assessment model is built by combining the combined weighting method with the fuzzy comprehensive evaluation method. Based on enterprise project data and the working experience of enterprise personnel to solve the model, the following conclusions are drawn:

1) From an overall perspective, the level of risk impact on the automotive manufacturing supply chain is high. Therefore, the enterprises should emphasis on the prevention, control and timely handling of risks.

2) The degree of affiliation of each second-level factor can be obtained and ranked according to its impact on the supply chain. Through the calculation process, the second-level factors within the

same first-level factors can be classified as cause factors and influenced factors. The results inform the focus and direction of work for each department.

3) By weighting the secondary risk factors, this paper calculates the corresponding degree of affiliation of the first-level risk factors, and then compares and ranks the first-level factors. The results provide a reference for automotive manufacturing enterprises to undertake supply chain risk management across different departments.

Owing to the confidentiality of enterprise data, only a limited number of samples can be obtained. Therefore, the objective weights of the automotive manufacturing supply chain have some limitations in their application. There is still a need to collect more project data in subsequent studies to enhance the objectivity of the assessment results.

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