International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 4650-4659

https://doi.org/10.70517/ijhsa464308

Supply Chain Resilience Assessment and Optimization Based on Ensemble Learning

Xuanshuang Wang[1], Quanpeng Chen[2,*], Jia Chen[1] and Xianying Pang[1]
[1] Southwest Jiaotong University Hope College, Chengdu, Sichuan, 610400, China
[2] Sichuan Vocational College of Finance and Economics, Chengdu, Sichuan, 610101, China
Corresponding authors: (e-mail: xueshunihao@163.com).

Abstract Improving supply chain resilience is crucial to the long-term success and sustainable development of enterprises. This paper designs the supply chain toughness evaluation index system from the actual situation, and constructs the supply chain toughness evaluation model based on the material element topable theory. Quantify the supply chain toughness index, realize the dynamic evaluation of toughness level, and mine the optimization direction. Dynamic selective integrated learning method is proposed to carry out multi-supply chain entity adaptive negotiation optimization, targeting to improve the toughness level of enterprise material supply chain. The study shows that there are 5 level I toughness indicators with correlation > 0 and average score < 80, which are concentrated in 2 level I indicators, namely, evolution capability and efficiency capability, and need to be optimized accordingly. The ratings of 4 first-level indicators, namely, readiness ability, efficiency ability, adaptive ability, and evolutionary ability, are decreasing according to level Ⅳ - level Ⅰ, and the correlation degrees are 0.758, 0.245, 0.119, and 0.145, respectively. The negotiation optimization of the toughness of the evolutionary ability is realized by using the integrated learning algorithm, and the agreement is reached after 6 times of negotiation.

Index Terms supply chain toughness evaluation, object element topology theory, quantitative assessment, integrated learning

I. Introduction

In recent years, global supply chains have been greatly affected and impacted by various events such as extreme weather, public health emergencies, geopolitical conflicts, and demand fluctuations, such as supply disruptions due to insufficient supply of raw materials or products, inventory buildups or stock shortages due to demand fluctuations, and prolonged timeframes for the transportation of goods due to constraints in the transportation network [1]-[4]. In the face of these challenges, it is particularly important to improve supply chain resilience. Supply chain resilience refers to the ability of a supply chain system to achieve buffering, rapid response and adaptation in the face of uncertainty [5]. In the early 21st century, the development of globalization and complex supply chain networks have brought uncertainty, emphasizing the importance of supply chain resilience and promoting diversified suppliers, optimized inventory, and enhanced information sharing [6], [7]. Increased supply chain resilience contributes to reducing the risk of supply chain disruptions, and it is crucial to recover quickly from crises and respond positively to changes brought about by environmental uncertainty [8], [9]. The improvement of supply chain resilience can guarantee that the supply chain can realize a high level of opening to the outside world under the premise of safe and stable operation [10].

The Chinese government report emphasizes the importance of “focusing on improving the resilience and security level of industrial chain supply chain”, which is regarded as a key point for promoting high-quality development, accelerating the construction of a modernized economic system, and safeguarding national industrial security. The study of supply chain resilience is not only crucial to the competitiveness and viability of individual enterprises, but also has a far-reaching impact on the economic development and social stability of the country [11]-[13]. As a result, the evaluation of supply chain resilience has become an important significance to analyze the short boards, advantages, development direction and development potential of supply chain, which can help the government, society and enterprises to better formulate industrial policies and development plans to enhance the resilience of supply chain [14], [15]. Supply chain resilience evaluation has gone through the three main stages of expert qualitative index evaluation, dynamic modeling, intelligent evaluation, expert evaluation methods and the actual supply chain impact resistance to a low degree of contact, dynamic modeling and intelligent evaluation to enhance the accuracy of supply chain resilience evaluation to intelligent evaluation is more accurate [16]-[18].

This paper constructs the enterprise material supply chain toughness evaluation index system, and collects relevant assessment data as the research basis through questionnaire survey and data statistics and other methods. The object element topable evaluation model is established, and the multidimensional index system is built by defining the object elements, combining the classical domain and section domain division, and constructing the object element matrix to quantify the toughness indexes. The weights are further calculated to determine the importance of each toughness indicator. And based on the correlation analysis to assess the deviation of the actual state of the supply chain from the ideal target, and diagnose the problems of the supply chain. A multi-agent adaptive negotiation optimization strategy is introduced to learn the concession magnitude law in the historical negotiation data by using dynamic selective integration support vector machine, and the model generalization ability is improved through integrated learning. Meanwhile, the utility function optimization mechanism is designed to combine the multi-agent collaborative decision-making to achieve supply chain resilience optimization.

II. Evaluation system construction and enterprise supply chain resilience evaluation

II. A. Construction and analysis of supply chain resilience evaluation index system

II. A. 1) Construction of the indicator system

Table 1 shows the supply chain resilience evaluation index system established in this paper. On the basis of relevant theories, this paper combines the results of word frequency statistical analysis, the structure and characteristics of enterprise supply chain, and selects the supply chain resilience evaluation indexes as 4 level 1 indexes and 16 level 2 indexes of readiness, efficiency, adaptability, and evolutionary capacity from the four time nodes of the latent period, triggering period, response period, and reconstruction period of the disruption event. The following is a detailed discussion of each level 1 indicator and the secondary indicators to which it belongs:

1) Preparedness capacity: the ability to take active preventive and planning actions when facing potential risks and uncertainties. Readiness is the core pillar of supply chain resilience, which significantly reduces the possibility of supply chain disruption due to external shocks by early warning of potential risks, formulating coping strategies in advance, and optimizing the allocation of resources to ensure the continuity, stability and responsiveness of the supply chain, which is crucial for maintaining supply chain security, improving overall efficiency and quickly adapting to market changes.

In enterprise supply chains, readiness capability not only includes forecasting and planning for common risks (e.g., seasonal demand fluctuations), but also emphasizes sensitivity to emerging risks (e.g., global public health events), and the supply chain should also have a high level of visualization and intelligence to cope with these risks. Therefore, this paper refines supply chain readiness capability into secondary indicators such as risk awareness, supply chain visualization, and supply chain intelligence.

2) Efficiency capability: the ability to react promptly to changes that occur in the supply chain when risks occur, and to act quickly to reduce or eliminate external shocks and improve the ability to cope with changes. In the supply chain, this capability focuses on the time and speed of recovery and is an important line of defense against disruptions. By acting quickly to reduce or eliminate the impact of internal and external shocks, the efficiency capability not only improves the adaptability and resilience of the supply chain, but also ensures that products can consistently and efficiently meet the diversified needs of consumers around the world, thus maintaining a leading position in global competition.

In business, rapid response in logistics and distribution is key to ensuring timely delivery of orders. Efficiency capabilities require companies to be able to quickly adjust inventory levels in the face of supply chain disruptions to ensure the timely availability of best-selling products while avoiding a backlog of slow-moving goods. It also requires the ability to build an efficient logistics network that can flexibly handle the logistics challenges of different regions and countries to ensure the rapid flow of goods. Enterprises' access to data such as popular elements and consumers' wishes is based on the corresponding network platforms, and the fine analysis and in-depth interpretation of big data is the basis for enterprises to adjust their strategies in a timely manner. Therefore, this paper refines the supply chain efficiency capability into contingency planning, supply chain agility, supply and demand management capability, cross-border logistics coordination and other secondary indicators.

3) Adaptive capacity: focuses on supply chain recovery from multiple homeostatic changes and supply chain resource reorganization. On this basis, this paper argues that adaptive capacity, in terms of enterprises, is the ability of an enterprise to adapt to changes caused by disturbances over a long period of time when the supply chain structure changes due to unexpected events. The adaptive capacity of the supply chain ensures that each enterprise can make timely and appropriate responses in the future development process, so as to achieve the expected competitive advantage.

For enterprises, they not only have to face the increasingly changing market demand, but also need to pay attention to the impact of global disruption events on logistics, inventory, production, and market, etc. Therefore, adaptive capacity is extremely important for such enterprises, and this paper refines the supply chain adaptive capacity into the secondary indicators such as supply chain redundancy, supplier flexibility, adaptive management, supply chain integration, and the ability to reconfigure resources.

4) Supply chain evolution capability focuses on supply chain recovery and renewal and improvement after restructuring. This means that companies and their supply chain partners need to be able to learn from past experiences, optimize strategies, and continuously improve their operations, as well as have the ability to quickly learn and implement new solutions. The ability to optimize strategies and continuously improve the way they operate.

In enterprise supply chains, this evolutionary capability is particularly important because it is directly related to the resilience and adaptability of the supply chain. In the face of a complex and changing international environment, exchange rate fluctuations, logistics delays and other challenges, a supply chain with strong evolutionary capacity can quickly adjust its strategy and respond flexibly to ensure that products are delivered to consumers on time, in quality and quantity. At the same time, through continuous learning and improvement, the supply chain can continuously improve efficiency and reduce costs, providing strong support for the rapid expansion of brands in the global market. Therefore, evolution capability is one of the indispensable core competencies of cross-border supply chain, which is of great significance to enhance the overall resilience of the supply chain and ensure the healthy development of brands. In this paper, supply chain evolution capability is subdivided into secondary indicators such as learning ability, financial strength, collaboration among partners, and trust among partners.

Table 1: Evaluation index system for supply chain resilience

First-level indicator	Number	Secondary indicator	Number
Preparation ability	A1	Risk awareness	B1
		Supply chain visualization	B2
		Intelligent supply chain	B3
Efficiency ability	A2	Emergency plan	B4
		Supply chain agility	B5
		Supply and demand management ability	B6
		Cross-border logistics coordination	B7
Adaptability	A3	Supply chain redundancy	B8
		Supplier flexibility	B9
		Adaptive management	B10
		Supply chain integration	B11
		Resource reconfiguration capability	B12
Evolutionary ability	A4	Learning ability	B13
		Financial strength	B14
		Collaboration among partners	B15
		Trust among partners	B16

II. A. 2) Sample descriptive statistics

Taking enterprises operating mainly fast fashion and cross-border e-commerce in Province A as the main distribution target, the questionnaire was focused on the relevant personnel in their supply chain departments, purchasing department, marketing department, warehouse department and organization department. The content of this questionnaire is divided into two aspects: the first is the cultural degree, the time of working in cross-border e-commerce or fast fashion, and the specific position of the respondents, and the second is the type of supply chain participating subjects and the size of the employees of the respondents' enterprises. The second aspect is the core of this paper, which focuses on the assessment of supply chain resilience of cross-border fast fashion enterprises, which mainly contains four primary indicators of readiness, efficiency, adaptability, and evolution, 16 secondary indicators, and a total of 32 entries, and utilizes a 5-level Likert scale to classify the degree of agreement of the respondents on the above issues as “strongly disagree” and “strongly agree”. Using a 5-point Likert scale, the respondents were categorized into “strongly disagree” and “strongly agree” on the above issues, and assigned values from 1 to 5 respectively.

The questionnaires were distributed through face-to-face interviews, questionnaire star links, emails and other methods, totaling 500 questionnaires. To ensure the representativeness and reliability of the data samples, this study regarded the questionnaires with too short an answer time, omitted questions, and the questionnaires with the same options for more than 8 consecutive questions as invalid questionnaires, and finally rejected 30 invalid questionnaires, resulting in 470 valid questionnaires recovered, with an effective rate of 94%.

The descriptive statistical analysis of the sample is mainly about the overall sample characteristics of the basic data of the respondents and their companies. In the personal data of the respondents, there are contents such as education, years of working experience, specific positions, and so on, and in the basic data of the company, it contains the category of the company to which the respondents belong to and the number of the company's personnel, and so on.

Table 2 shows the basic information of the questionnaire sample. In terms of the distribution of individual attributes, the education level of the 470 respondents was in the following order: 57.45% undergraduate, 17.02% below undergraduate, 11.70% master's degree, and 13.83% PhD. In terms of length of employment, 46.81% had worked for 8-10 years, 23.40% for >10 years, 17.02% for 4-8 years, and 12.77% for 1-4 years. Of these individuals, 43.62% were in management positions at the grassroots level or higher. Therefore, as far as the distribution of individual traits is concerned, the respondents' academic qualifications, years of working experience and positions basically coincide with the real situation, so the questionnaire is well representative. In terms of the distribution of enterprise traits, among the 470 samples, there are 200 manufacturers, accounting for 42.55%; 150 suppliers, accounting for 31.91%; 85 distributors, accounting for 18.09%; and others accounting for 7.45%. In terms of firm size, the largest number of firms with 1,500-4,500 employees was 205, or 43.62%; followed by firms with sizes between 450 and 1,500, with 135, or 28.72% of the total; and the combined percentage of firms with 450 or more than 4,500 employees was 27.66%. The sum of the percentage of the number of people who have experienced small and large incidents of supply chain performance decline is 77.66%. In conclusion, the overall sample composition is relatively reasonable, matches the current industrial situation, and has a certain degree of representativeness.

Table 2: Descriptive statistics of the sample

Name	Option	Frequency	Percentage (%)
Educational attainment	Doctor	65	13.83
	Master	55	11.70
	bachelor	270	57.45
	Below bachelor	80	17.02
Years of working experience	1-4 years	60	12.77
	4-8 years	80	17.02
	8-10 years	220	46.81
	>10 years	110	23.40
Specific job duties	Top leadership	10	2.13
	Middle-level leader	60	12.77
	Grassroots management	135	28.72
	General employee	265	56.38
Participating entities	Supplier	150	31.91
	Manufacturer	200	42.55
	Dealer	85	18.09
	Other	35	7.45
Company size	<450	85	18.09
	450-1500	135	28.72
	1500-4500	205	43.62
	>4500	45	9.57
Have experienced supply chain risk situations	No	25	5.32
	Have experienced a minor incident of a decline in supply chain performance	165	35.11
	Have experienced major events such as a decline in supply chain performance	200	42.55
	Have experienced supply chain disruptions	80	17.02

II. A. 3) Reliability analysis of the questionnaire

Questionnaire reliability reflects the correlation between each question in the scale. The reliability of internal consistency is generally measured by the Cronbach's alpha coefficient.The value of Cronbach's alpha ranges from 0.00 to 1.00, and a larger value indicates a higher degree of correlation between the entries of the scale, which means that the scale's internal consistency has a high degree of reliability. Usually, alpha coefficients above 0.85

represent good internal consistency, in the range of 0.75 to 0.85 is good, in the range of 0.65 to 0.75 is average, and below 0.65 is non-conformity, and the questionnaire scale should be revised.

Table 3 shows the results of this reliability analysis. The reliability coefficients of each level of indicators are 0.965, 0.947, 0.981, 0.973, which are within the range of [0.85,1.00], thus indicating that the scale used in this study has a good internal consistency, and that the obtained data have validity and can be used in subsequent algorithmic studies.

Table 3: Reliability analysis results

First-level indicator	Cronbach's α	Number of items
Preparation ability	0.965	6
Efficiency ability	0.947	8
Adaptability	0.981	10
Evolutionary ability	0.973	8

II. B.Enterprise material supply chain toughness object element topable evaluation model construction

II. B. 1) Determination of physical elements

Objective element analysis describes things in the form of an ordered triad of three elements: things, features, and quantitative values (denoted by N, C, and V, respectively), which is called the object element R. The thing to be evaluated is denoted as N, its features are denoted as, and the value of the eigenquantity is denoted as V, and it is assumed that N has more than one feature: $C_1, C_2, \cdots, C_n$. The corresponding quantities of these N features are $V_1, V_2, \cdots, V_n$. The total research object of this paper is the enterprise enterprise material supply chain toughness, that is, the total objective in the index system is the enterprise material supply chain toughness, and there are 16 secondary indicators. Thus the second-level indicators for the total research object, its corresponding material dollar is actually:

$$R = \begin{bmatrix} N & C_1 & V_1 \\ & C_2 & V_2 \\ & \vdots & \vdots \\ & C_n & V_n \end{bmatrix} = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{bmatrix} \tag{1}$$

where R is the n-dimensional object element, C denotes the 16 features of the object element to be evaluated: $C = \left(C_1, C_2, \cdots, C_{23}\right)$, and V denotes the measures of the 16 features: $V = \left(V_1, V_2, \cdots, V_{23}\right)$. In the enterprise material supply chain resilience evaluation, R_1 is readiness capacity resilience, R_2 efficiency capacity resilience, R_3 adaptive capacity resilience, and R_4 evolutionary capacity resilience. N denotes the classified enterprise material supply chain toughness level. C is the 16 enterprise material supply chain resilience level 2 indicators including risk awareness, supply chain visualization, etc. V is the specific quantitative value of the corresponding level 2 indicators.

II. B. 2) Determination of classical and sectional domains

1) Determine the classical domain

If the evaluation object is the object element matrix of the enterprise material supply chain toughness index, the classical domain is determined according to the interval in which the object element characteristics to be evaluated and their quantitative values are located. Assuming that the enterprise material supply chain toughness evaluation level is divided into m levels, with $N_j (j = 1 \cdots m)$ denoting the j th level, with $C_i (i = 1 \cdots 16)$ denoting the i th toughness evaluation index, with $V_{ji} (i = 1 \cdots 16)$ denoting the first toughness evaluation index under level j. The value range of the first i toughness evaluation index under the rank j, this value range is represented by the interval $\left(a_{ji}, b_{ji}\right)$, then the matrix formed by the three N, c, v is the classical domain object matrix R_j, which denotes the corresponding toughness evaluation indexes of the enterprise material supply chain It represents the value range of the grade interval corresponding to the evaluation index of enterprise material supply chain toughness:

$$R_j = \begin{bmatrix} N_j & C_1 & V_{j1} \\ & C_2 & V_{j2} \\ & \vdots & \vdots \\ & C_n & V_{jn} \end{bmatrix} = \begin{bmatrix} N_j & C_1 & (a_{j1}, b_{j1}) \\ & C_2 & (a_{j2}, b_{j2}) \\ & \vdots & \vdots \\ & C_n & (a_{jn}, b_{jn}) \end{bmatrix} \tag{2}$$

2) Determine the section domain

The section domain is the object matrix composed of the classical domain object elements and the expanded range of values of the evaluation index characteristics represented, that is, the range of values of the enterprise material supply chain resilience evaluation index, and its object matrix is expressed by R_p. N_p denotes the totality of all levels of the enterprise material supply chain toughness evaluation index. V_{pi} is the range of quantitative values of the section domain object element about the enterprise material supply chain toughness evaluation index C_i: $V_{pi}=\left(a_{pi},b_{pi}\right)\left(i=1\cdots n\right)$, where $\left(a_{pi},b_{pi},b_{pi}\right)$, is $\left(a_{ji},b_{ji}\right)j=1\cdots m$, the concatenated set of all ranges of the i th indicator. The section domain object element R_p can be expressed as:

$$R_p=\begin{bmatrix} N_p & C_1 & V_{p1} \\ & C_2 & V_{p2} \\ & \vdots & \vdots \\ & C_n & V_{pn} \end{bmatrix}=\begin{bmatrix} N_p & C_1 & (a_{p1},b_{p1}) \\ & C_2 & (a_{p2},b_{p2}) \\ & \vdots & \vdots \\ & C_n & (a_{pn},b_{pn}) \end{bmatrix} \tag{3}$$

II. B. 3) Constructing the Object Element Matrix

On the basis that the classical domain and the section domain have been determined, the matrix of to-be-evaluated object elements of enterprise material supply chain resilience is determined. If the enterprise material supply chain toughness evaluation grade is x, then N_x is a number of different evaluation grades, C_n is 16 enterprise material supply chain toughness evaluation indexes, and V_n is the range of values of the grade N_x corresponding to the toughness evaluation index C_i. Where the object element matrix is denoted as R_x:

$$R_x=\begin{bmatrix} N_x & C_1 & V_1 \\ & C_2 & V_2 \\ & \vdots & \vdots \\ & C_n & V_n \end{bmatrix} \tag{4}$$

II. C. Calculation of combined weights of evaluation indicators

The specific composite weights of the constructed supply chain resilience evaluation indicators are calculated, and Table 4 shows the final weight calculation results. Among the first-level indicators, the one with the largest weight is readiness capacity A1 (0.378), followed by efficiency capacity A2 (0.322). In the second-level indicators, the top five indicators with the largest weights are Risk Awareness B1 (0.148), Supply Chain Intelligence B3 (0.120), Supply Chain Visualization B2 (0.110), Contingency Planning B4 (0.105), and Supply Chain Agility B5 (0.092). From the results of weight calculation, it can be judged that the key to improve supply chain resilience is: good response planning for possible risks, and at the same time always pay attention to the goods in the supply chain to improve the real-time response ability.

Table 4: Weight calculation result

First-level indicator	Weight	Secondary indicator	Weight	Sorting
A1	0.378	B1	0.148	1
		B2	0.110	3
		B3	0.120	2
A2	0.322	B4	0.105	4
		B5	0.092	5
		B6	0.070	6
		B7	0.055	7
A3	0.155	B8	0.035	10
		B9	0.030	13
		B10	0.029	14
		B11	0.027	15
		B12	0.034	11
A4	0.145	B13	0.038	9
		B14	0.051	8
		B15	0.031	12
		B16	0.025	16

II. D. Calculation of the relevance of evaluation indicators

II. D. 1) Evaluation of relevance of secondary indicators

Combining the results of weight calculation and the supply chain resilience object element topological evaluation model, the corresponding correlation of indicators at all levels is solved, and according to the results of correlation calculation, the resilience level of enterprise supply chain is evaluated, and the optimization direction of enterprise supply chain resilience is searched. Table 5 shows the results of correlation degree calculation for the evaluation of secondary indicators. The toughness rating with an average score of 90 points or more and correlation > 0 is level IV, the toughness rating with an average score of 85-90 points and correlation > 0 is level III, the toughness rating with an average score of 80-85 points and correlation > 0 is level II, and the toughness rating with an average score of < 80 points and correlation > 0 is level I. The higher the level, the better the toughness. The higher the rating, the better the toughness. There are five indicators of rating Ⅳ, which are B1 Risk Awareness, B3 Supply Chain Intelligence, B4 Contingency Planning, B5 Supply Chain Agility, and B11 Supply Chain Integration, and the results of the rating indicate that the toughness of the enterprise material supply chain is better in these five indicators. There are also five indicators in rating level I, namely B9 Supplier Flexibility, B10 Adaptive Management, B14 Financial Strength, B15 Inter-partner Collaboration, and B16 Inter-partner Trust, which need to be strengthened in terms of resilience.

Table 5: The secondary indicators evaluate the correlation degree

Secondary indicator	Weight	Total score	Average score	Evaluate the correlation degree of the indicators				Toughness grade
				J=1	J=2	J=3	J=4	
B1	0.148	100	98	-0.815	-0.611	-0.210	0.351	IV
B2	0.110	100	86	-0.360	-0.202	0.287	-0.392	III
B3	0.120	100	91	-0.861	-0.714	-0.411	1.967	IV
B4	0.105	100	90	-0.786	-0.561	-0.113	0.102	IV
B5	0.092	100	92	-0.834	-0.665	-0.311	0.736	IV
B6	0.070	100	87	-0.563	-0.110	1.715	-0.321	III
B7	0.055	100	84	-0.831	0.636	-0.311	-0.766	II
B8	0.035	100	83	-0.816	3.587	-0.213	-0.344	II
B9	0.030	100	70	0.987	-0.761	-0.514	-0.882	I
B10	0.029	100	76	0.762	-0.563	-0.113	-0.136	I
B11	0.027	100	90	-0.913	-0.811	-0.610	0.985	IV
B12	0.034	100	86	-0.886	-0.760	0.487	-0.514	III
B13	0.038	100	80	-0.785	0.537	-0.111	-0.136	II
B14	0.051	100	77	0.786	-0.611	-0.213	-0.341	I
B15	0.031	100	74	0.262	-0.463	-0.246	-0.407	I
B16	0.025	100	73	0.787	-0.613	-0.213	-0.343	I

II. D. 2) Evaluation of relevance of first-level indicators

Table 6 shows the results of the correlation calculation of the first-level indicators.The toughness rating of A1 readiness ability is level IV (0.758), the toughness rating of A2 efficiency ability is level III (0.245), the toughness rating of A3 adaptive ability is level II (0.119), and the toughness rating of A4 evolutionary ability is level I (0.145). According to the rating results, in order to improve the enterprise supply chain toughness, it is necessary to optimize the relevant indexes of evolutionary capacity, adaptive capacity, efficiency capacity, and readiness capacity in turn.

Table 6: First-level indicator correlation degree

Overall goal	First-level indicator	Weight	Evaluate the correlation degree of the indicators				Toughness grade
			J=1	J=2	J=3	J=4	
Research on the Resilience Assessment of Enterprise Material Supply Chain	A1	0.378	-0.710	-0.521	-0.136	0.758	Ⅳ
	A2	0.322	-0.740	-0.216	0.245	-0.063	Ⅲ
	A3	0.155	−0.392	0.119	-0.193	−0.200	Ⅱ
	A4	0.145	0.512	-0.285	-0.196	-0.307	Ⅰ

III. Supply chain resilience optimization based on dynamic selective integrated learning

III. A. Adaptive Negotiation Optimization Strategy Based on Multiple Supply Chain Entities (Agents)

III. A. 1) Concession Magnitude Learning Based on Dynamic Selective Integrated Support Vector Machine (SVM)

The prediction performance of each sub-SVM learning machine is different for different data, and it is not appropriate to use the same model function to estimate the concession margin for different issues. According to the current issue values in the negotiation, the nearest neighbor sample set is used as the evaluation sample to evaluate the performance of each sub-model, and the sub-model with better performance is retained for integration. In the negotiation, K-means nearest-neighbor search algorithm is used for each negotiation issue to find the k subset of samples from the validation dataset that are nearest-neighbors to the current value of the issue to be predicted as the evaluation dataset, and the root-mean-square error is used as a criterion for the evaluation of the prediction performance of each sub-model, some sub-models that have poor prediction performance are excluded, and the combination weights of the sub-models are computed, to build the final dynamic selective integrated SVM model.

1) K-means to generate the evaluation dataset: To predict the negotiation sequence P_q, set the number of its closest neighboring negotiation sample sets in the validation dataset P_L as k, and compute the distance between P_q and each negotiation data sample point P_i in P_L to obtain the previous sample set P_k.

$$P_D(P_q, P_i) = \sqrt{\sum_{i \in L} (p_q - p_i)^2} \tag{5}$$

2) SVM sublearning machine screening: input P_k sample sets, use the root mean square error as the screening criterion, select the corresponding first $\bar{k}$ sublearning machine as the integrated sub-model of the set to be predicted P_q, and the i th sub-model root mean square error is shown in equation (6).

$$E_{ij} = \sqrt{\frac{\sum_{i=1}^{k} (\tilde{c}_{ij} - C_{ij})^2}{k}} \tag{6}$$

where $\tilde{c}_{ij}$ denotes the predicted value of the next round of concession magnitude of issue j by the i th sublearning machine; C_{ij} denotes the real concession magnitude of issue j in the next round.

3) Calculate the combination weight of each sub-model: according to the root mean square error value E_{ij} of the i th sub-model, the combination weight of the sub-model is derived as:

$$\alpha_i = \left(\frac{1}{E_{ij}^2}\right) \Bigg/ \left(\sum_{i=1}^{\bar{k}} \frac{1}{E_{ij}^2}\right) \tag{7}$$

When k sublearning machines are all trained successfully, combined with the current issue selection error of the smallest $\bar{k}$ sublearning model, input the former t round of manufacturers, distributors Agent on the conflict issue j the average concession magnitude of the average value, the first t round manufacturer Agent, distributor Agent proposal value difference and other variables, to get the first $t+1$ round of A_{fac}, A_{dis} concession magnitude prediction value, for each issue concession magnitude prediction output is:

$$C_{t+1,j}^{fac/dis} = \alpha_1 C_{1j} + \alpha_2 C_{2j} + \cdots + \alpha_{\bar{k}} C_{\bar{k}j} \tag{8}$$

III. A. 2) Utility function optimization

1) Current global utility

The global utility indicates that for positive issues it is desirable to have a larger value of the opponent's issue, and vice versa for negative issues, and the utility evaluation function for the issue value of the negotiation object at t rounds of negotiation is shown in Eq. (9) and Eq. (10), respectively.

$$U_{t,all}^{+} = \sum_{j=1}^{n} w_{t,j} \left(\frac{p_{t,j}^{opp} - p_{t,j}^{min}}{p_{t,j}^{max} - p_{t,j}^{min}}\right) \tag{9}$$

$$U_{t,all}^{-} = \sum_{j=1}^{n} w_{t,j} \left(\frac{p_{t,j}^{\max} - p_{t,j}^{opp}}{p_{t,j}^{\max} - p_{t,j}^{\min}}\right) \tag{10}$$

$$U_{t,all} = U_{t,all}^{+} + U_{t,all}^{-} \tag{11}$$

where $p_{t,j}^{opp}$ denotes the current offer value of the opponent; $p_{t,j}^{max}$ denotes the maximum value of the current offer. Taking A_{fac} as an example, the global utility with each A_{dis} is calculated according to Eq. (11) during the t-round of negotiation, and the larger $U_{t,all}$ indicates that the larger the utility obtained from the negotiation with the current A_{dis} is, the smaller the impact on the concession margin, and the larger the concessions are made.

2) Current local utility

The difference between the local utility of the 2 previous and 2 previous negotiations is used to determine whether to stop the current negotiation process, as shown in equation (12). Based on the predicted value of the concession margin of A_{fac} on issue j in the round of $t+1$ as $C_{t+1,j}^{dis\to fac}$, the value of the distributor's proposal of $A_{t,j}^{dis\to fac}$ on issue j in the round of consultation of t is $p_{t,j}^{dis\to fac}$. The predicted proposed value for its $t+1$th round issue j is shown in equation (13).

$$U_{t,area}=\sum_{j=1}^{J}w^{j}p_{j}^{dis\to fac} \tag{12}$$

$$p_{t+1,j}^{dis\to fac}=p_{t,j}^{dis\to fac}+C_{t+1,j}^{dis\to fac} \tag{13}$$

Coordination A_{md} combines Eq. (12) and Eq. (13) to calculate the difference between the predicted value of utility of A_{dis} in the $t+1$th round and the actual value of utility in the tth round, and when the difference $\Delta U_{t+1,t}>0$, continue to negotiate that the utility of A_{fac} will still be increased, and that utility is not maximized yet, and vice versa to end the negotiation.

III. B. Negotiated simulation results for evolutionary capacity toughness optimization

In order to improve the resilience of the evolutionary capability of the enterprise material supply chain, Matlab, a high-performance mathematical computing language, is used to simulate and analyze the collaborative negotiation process between the manufacturer Agent1 and the seller Agent5 as an example based on the multi-agent adaptive negotiation optimization strategy proposed in this paper. Table 7 shows the process and final results of 6 negotiations. It can be seen that the optimal solution of (8.501,68) is obtained after 6 times of negotiation, which achieves the result that both parties are satisfied, the partnership and trust between the manufacturer and the seller are closer, and the resilience of the supply chain evolution capability is enhanced. This also indicates the effectiveness of the dynamic selective integration learning method in optimizing the resilience of enterprise supply chain.

Table 7: Negotiate the simulation process and results

Number of negotiations	Manufacturer 1		Salesperson 5	
	Price	Quantity	Price	Quantity
1	8.583	65	8.318	67
2	8.461	68	8.058	69
3	8.118	65	8.083	68
4	8.153	69	8.588	70
5	8.645	67	8.585	69
6	8.501	68	8.493	68

IV. Conclusion

In this paper, we use the object element topable evaluation model and integrated learning algorithm to realize the resilience evaluation and optimization adjustment of enterprise material supply chain. In the second-level indicators, the level IV toughness indicators with an average score of >90 and a correlation of >0 are: risk awareness, supply chain intelligence, contingency planning, supply chain agility, and supply chain integration, and the enterprise supply chain has done a better job in these aspects. Among the first-level indicators, the readiness ability toughness is Ⅳ, with a correlation degree of 0.758; the efficiency ability toughness is Ⅲ, with a correlation degree of 0.245; the adaptability ability toughness is Ⅱ, with a correlation degree of 0.119; and the evolution ability toughness is Ⅰ, with a correlation degree of 0.145, and the toughness optimization needs to be carried out according to the hierarchical order of the order of the smallest to the largest. Through integrated learning negotiation optimization, finally after 6 negotiations the manufacturer and seller reach (8.501,68) price and quantity optimization solutions to improve the evolutionary ability toughness of the enterprise supply chain. In the future, the scope of the questionnaire survey can be expanded to collect data related to supply chain resilience evaluation from multiple industries and multiple enterprises, so as to improve the applicability breadth of the model and algorithm.

Funding

This work was supported by 2025 National Project for Logistics Education and Education Reform of the National University and Vocational College (Project No.: JZW2025007)

References

[1] Bag, S., Rahman, M. S., Chan, H. L., & Sharma, J. (2025). Effect of Supply Chain Flexibility and Supply Chain Endurance on Supply Chain Resilience in Extreme Weather Events: An Empirical Study. IEEE Transactions on Engineering Management.

[2] Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2022). Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Annals of operations research, 319(1), 1159-1196.

[3] Bednarski, L., Roscoe, S., Blome, C., & Schleper, M. C. (2025). Geopolitical disruptions in global supply chains: a state-of-the-art literature review. Production planning & control, 36(4), 536-562.

[4] Kobayashi, M., Tomino, T., Shintaku, J., & Park, Y. (2017). Demand fluctuation and supply chain integration: case studies of Japanese firms. Perspectives on Global Development and Technology, 16(5), 564-586.

[5] Novak, D. C., Wu, Z., & Dooley, K. J. (2021). Whose resilience matters? Addressing issues of scale in supply chain resilience. Journal of Business Logistics, 42(3), 323-335.

[6] Kazancoglu, Y., Lafci, C., Berberoglu, Y., Upadhyay, A., Rocha-Lona, L., & Kumar, V. (2024). The effects of globalization on supply chain resilience: outsourcing techniques as interventionism, protectionism, and regionalization strategies. Operations Management Research, 17(2), 505-522.

[7] Chowdhury, M. M. H., Quaddus, M., & Agarwal, R. (2019). Supply chain resilience for performance: role of relational practices and network complexities. Supply Chain Management: An International Journal, 24(5), 659-676.

[8] Um, J., & Han, N. (2021). Understanding the relationships between global supply chain risk and supply chain resilience: the role of mitigating strategies. Supply Chain Management: An International Journal, 26(2), 240-255.

[9] Laguir, I., Choi, T. M., Stekelorum, R., Gupta, S., & Kumar, A. (2022). Roles of mobilized controls and environmental uncertainty on supply chain resilience: An empirical study from dynamic-capabilities-view and levers-of-control perspectives. IEEE Transactions on Engineering Management, 71, 2296-2309.

[10] Ivanov, D. (2022). Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. Annals of operations research, 319(1), 1411-1431.

[11] Pu, G., Li, S., & Bai, J. (2023). Effect of supply chain resilience on firm’s sustainable competitive advantage: a dynamic capability perspective. Environmental Science and Pollution Research, 30(2), 4881-4898.

[12] Queiroz, M. M., Fosso Wamba, S., & Branski, R. M. (2022). Supply chain resilience during the COVID-19: empirical evidence from an emerging economy. Benchmarking: An International Journal, 29(6), 1999-2018.

[13] Silva, M. E., & Ruel, S. (2022). Inclusive purchasing and supply chain resilience capabilities: lessons for social sustainability. Journal of Purchasing and Supply Management, 28(5), 100767.

[14] Yang, C., Tian, K., & Gao, X. (2023). Supply chain resilience: Measure, risk assessment and strategies. Fundamental Research.

[15] Moosavi, J., & Hosseini, S. (2021). Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context. Computers & industrial engineering, 160, 107593.

[16] Pavlov, A., Ivanov, D., Dolgui, A., & Sokolov, B. (2017). Hybrid fuzzy-probabilistic approach to supply chain resilience assessment. IEEE Transactions on Engineering Management, 65(2), 303-315.

[17] Ma, C., Zhang, L., Gao, X., & Liu, C. (2025). Modelling and evaluating wood supply chain resilience factors based on system dynamics. Scientific Reports, 15(1), 1-16.

[18] Mittal, U., & Panchal, D. (2023). AI-based evaluation system for supply chain vulnerabilities and resilience amidst external shocks: An empirical approach. Reports in Mechanical Engineering, 4(1), 276-289.