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Risk Identification and Network Optimization of Regional Supply Chains Based on Multi-Source Data Fusion

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Abstract: ***In response to increasingly complex global economic dynamics, enterprises are encountering heightened supply chain challenges, including transportation disruptions, frequent shifts in international trade regulations, and the demand for greater supply chain autonomy. This study proposes a network optimization framework based on multi-source risk data fusion and the multi-objective evolutionary algorithm NSGA-III. Four core indicators—logistics efficiency, regulatory adaptability, historical disruption frequency, and substitution costs—are integrated, and node risk features are extracted through graph convolutional networks (GCNs) to provide quantitative assessments of supply chain elements. A simulation was conducted within a multinational component group with an annual procurement volume exceeding USD 800 million, systematically evaluating centralized, zoned, and regionalized collaborative supply chain layouts. The results demonstrate that the "3 Centers + 6 Radiations" regionalized collaborative model achieves a 34.5% reduction in average delivery cycle fluctuations and a 26% decrease in annual plan adjustments, compared to traditional structures. Furthermore, the dynamic elasticity adjustment mechanism developed in this study enables scenario-based simulations under varying geopolitical and economic disruptions, providing robust decision support for resilient supply chain optimization.***

Keywords: Regionalized supply chain; Multi-source risk data fusion; NSGA-III; Graph convolutional network; Supply chain resilience; Layout optimization.

1. INTRODUCTION

In the process of deepening economic globalization, the global supply chain network has developed into a highly complex and interdependent system [1]. According to data from the World Bank, in recent years, the share of global supply chain trade in total world trade has remained stable within the range of 75% to 80%, fully demonstrating its core position in the global economic system [2]. However, in recent years, a series of destabilizing factors have continuously and strongly impacted this system, causing its complexity and uncertainty to reach unprecedented levels [3]. In the transportation sector, extreme weather events leading to natural disasters have increasingly impacted transportation routes [4]. Between 2023 and 2024, there were over 400 annual incidents worldwide where floods, snowstorms, hurricanes, and other disasters caused disruptions to road and rail transportation. In 2024 alone, 94.13 million people in China were affected by natural disasters to varying degrees, resulting in the forced disruption of many transportation routes [5]. Port operations also face severe challenges, with congestion and strikes frequently occurring. In 2024, the average congestion duration at major global ports increased by 35% compared to 2022, with the average waiting time for ships extending from 2.5 days to 3.8 days. By the end of 2024, major ports in Northern Europe, such as Rotterdam and Antwerp, had high berth occupancy rates, and some ships arriving in Rotterdam were delayed by up to 4 days. The congestion at Mediterranean ports such as Valencia and Barcelona also continued to worsen [6]. Additionally, the increase in export demand from Asia and the geopolitical situation in the Red Sea region forced many shipping routes to be adjusted, further exacerbating the pressure on the supply chain [7]. In the first half of 2024, freight volume increased by 6.7% year-on-year, but fuel consumption increased by 18%, leading to a significant rise in operational costs. The dynamic adjustment of international trade rules has also posed significant challenges for enterprises [8]. Trade protectionism has been on the rise, with countries introducing targeted tariff policies and non-tariff barriers [9]. According to a report from the World Trade Organization, between October 2023 and October 2024, its member countries implemented 169 trade-restrictive measures, covering a trade volume of 887.7 billion USD, a 163% increase compared to the previous 12 months. Since the outbreak of the Sino-US trade dispute in 2018, more than 12,000 product categories have been subjected to additional tariffs, forcing many multinational enterprises to reassess and adjust their global procurement and production layouts [10]. Research shows that trade friction has caused enterprises' average operating costs to increase by 15% to 20%, significantly raising market risks. At the same time, governments are paying increasing attention to supply chain controllability to safeguard industrial security and stabilize employment [11]. Surveys indicate that over 85% of enterprises have increased their investment in supply chain stability over the past 5 years, aiming to reduce reliance on high-risk regions and ensure the stable operation of supply chains under various disruptions [12].

In this context, regionalized supply chains have gradually emerged as an innovative strategic model. Taking the European Union as an example, by establishing a unified market and supply chain system, intra-regional trade has grown at an annual rate of 5% over the past 10 years. Regionalized supply chains address the drawbacks of traditional global supply chains, such as excessive dispersion and slow response times, by integrating resources within specific regions [13]. This integration significantly improves the responsiveness of the supply chain and allows for quick adaptation to changes in market demand. Shortening transportation distances not only reduces transportation costs by 20% to 30% on average under the regionalized supply chain model, but also allows for better adaptation to dynamic regulatory and policy adjustments within the region, thereby enhancing risk resilience [14]. However, the construction and optimization of regionalized supply chains face many challenges. On one hand, accurately identifying and assessing potential risks in the supply chain is a highly challenging task [15]. Traditional risk identification methods, relying on a single data source or simple empirical judgment, are inadequate for addressing the complex and dynamic risk landscape [16]. On the other hand, during the process of supply chain network reconstruction, enterprises must seek a balance between conflicting objectives such as reducing costs, improving service levels and enhancing supply chain resilience [17]. This presents high demands on the performance of optimization algorithms. Based on this, this study uses multi-source data fusion technology to accurately identify risks in regionalized supply chains and employs multi-objective evolutionary algorithms to optimize and reconstruct the supply chain network. The goal is to provide enterprises with a scientific and efficient regionalized supply chain optimization strategy to help them achieve stable development in a complex market environment.

2. METHODS

2.1 Multi-source Risk Data Collection and Organization

This study collects four types of core indicator data to comprehensively evaluate the risk of supply chain nodes. The specific data collection scope is shown in Table 1.

Table 1: Details of Multi-source Risk Data Collection.

Indicator Category	Specific Operation	Data Source Quantity
Logistics Efficiency Indicator	Track and monitor 120 major transportation routes globally over 3 years, collecting data on average transportation time and fluctuations (transportation time dimension)	120 transportation routes
Logistics Efficiency Indicator	Collect cost data from 600 logistics companies across different routes and transportation methods (transportation cost dimension)	600 logistics companies
Logistics Efficiency Indicator	Analyze inventory management data from 400 manufacturing companies (inventory turnover rate dimension)	400 manufacturing companies
Regulatory Adaptability Indicator	Review policy changes in 60 major trade countries and regions over the past 10 years and build a regulatory adaptability evaluation system	60 countries and regions
Historical Disruption Frequency Indicator	Analyze over 2,500 disruption events across 250 supply chain nodes in the past 10 years, including natural disasters, supplier bankruptcies, transportation accidents, and other disruptions, to obtain historical disruption frequency data for each node	250 supply chain nodes
Substitution Cost Indicator	Conduct a detailed survey of 200 companies on the costs of substitution measures taken during supply disruptions	200 companies

2.2 Risk Feature Extraction and Scoring Based on Graph Convolutional Network (GCN)

In this study, the supply chain network is abstracted as a graph structure, where nodes represent supply chain entities and edges represent business relationships. The four types of risk indicator data—logistics efficiency, regulatory adaptability, historical disruption frequency and substitution costs—are collected and preprocessed into feature vectors before being input into the Graph Convolutional Network (GCN). The GCN, through multi-layer convolution operations, automatically combines the risk features of the nodes and their adjacent nodes, generating risk feature embeddings that reflect the node's position and degree of association within the network [18,19].

Finally, the node risk scores are calculated using a fully connected layer and softmax function, with higher scores indicating a higher level of risk. During model training, 1,200 supply chain network samples are used, achieving an accuracy of over 88%.

2.3 Supply Chain Network Optimization Based on Multi-objective Evolutionary Algorithm NSGA-III

The optimization of regionalized supply chain networks requires balancing multiple conflicting objectives, such as cost minimization, service level maximization, and supply chain resilience maximization [20,21]. In this study, the multi-objective evolutionary algorithm NSGA-III is used. First, an initial population of supply chain network layout plans, including node positions and connection relationships, is randomly generated. The cost, service level and supply chain resilience for each plan are calculated [22]. Non-dominated sorting is performed based on Pareto dominance, and the distance and crowding degree of individuals from the reference point are calculated to obtain reference point association degrees [23]. Based on this, certain individuals are selected for crossover and mutation operations, generating a child population. After merging the parent and child populations, sorting and association degree calculations are performed again, and individuals are selected to form a new parent population for further iterations, until the pre-set termination conditions are met [24]. The Pareto optimal solutions under different objective trade-offs are output as the optimized layout plan. During the algorithm operation, the maximum number of iterations is set to 600 and the population size is set to 250 individuals.

3. RESULTS AND DISCUSSION

3.1 Simulation Case Description

To validate the effectiveness of the regionalized supply chain optimization strategy, this study conducted a simulation practice within a multinational component group with an annual procurement scale exceeding 800 million USD.

Table 2: Supply Chain Network Architecture of the Multinational Component Group.

Facility Type	Quantity
Production Bases	35
Distribution Centers	60
Major Suppliers	250

The simulation tested three layout models: centralized, zoned, and regional collaborative. The centralized layout places the main production bases and distribution centers in six geographically advantageous areas. It relies heavily on the transportation network, and disruptions in transportation can lead to a collapse of the supply chain [25,26]. The zoned layout establishes 12 independent production and distribution systems by region, improving regional response speed but leading to resource redundancy and higher costs. The regional collaborative layout builds a "3 Centers + 6 Radiations" network structure, where regional supply chain centers collaborate, combining the advantages of regionalization with the ability to optimize resource allocation [27].

3.2 Simulation Result Analysis

The simulation compared the service level, transportation timeliness and disruption resistance of the supply chain under the three layout models. A detailed comparison is shown in Table 3.

Table 3: Performance Comparison of the Three Supply Chain Layout Models.

Performance Indicator	Regional Collaborative "3 Centers + 6 Radiations" Structure	Centralized Layout	Zoned Layout
Average Order Delivery Cycle (days)	12.8	16	14.7
Order Fulfillment Rate	Over 98%	95.5%	96.8%
Average Cargo Transportation Time (days)	6	8	6.5
Performance Indicator	Regional Collaborative "3 Centers + 6 Radiations" Structure	Centralized Layout	Zoned Layout
Average Order Delivery Cycle (days)	12.8	16	14.7

In terms of disruption resistance, when faced with the same risks, the regional collaborative structure reduced the average delivery cycle fluctuation by 34.5% and the number of annual plan adjustments by approximately 26%. This improvement is due to the higher redundancy and flexibility of its supply chain network, which enables a quick response to disruptions in nodes or routes.

3.3 Application of the Elasticity Coefficient Dynamic Adjustment Mechanism

The elasticity coefficient dynamic adjustment mechanism proposed in this study can simulate and optimize the supply chain network layout strategy in real-time based on different geopolitical and economic disturbance scenarios [28]. The elasticity coefficient is an indicator that comprehensively reflects the supply chain's ability to respond and recover when facing various risk disturbances [29]. It is calculated by weighting key risk indicators, including logistics efficiency, regulatory adaptability, historical disruption frequency, and substitution costs.

In practical applications, when facing different geopolitical disturbance scenarios (such as sudden trade policy adjustments, natural disasters, geopolitical conflicts, etc.), the weight of the elasticity coefficient is dynamically adjusted based on changes in real-time risk indicator data, reflecting the changing importance of current risk factors [30,31]. Then, based on the adjusted elasticity coefficient, the NSGA-III algorithm is used to re-optimize the supply chain network layout, generating the optimal layout plan that adapts to the new risk scenario [32,33]. For example, when a significant trade policy change in a specific region causes a sharp decline in the regulatory adaptability indicator, the weight of the regulatory adaptability indicator in the elasticity coefficient calculation is increased [34]. This makes the algorithm focus more on the regulatory compliance risk of supply chain nodes in that region during the optimization process, adjusting the network layout by reducing production and procurement activities in that region and increasing supply chain resource allocation in regions with more stable regulatory policies [35]. In the 15 simulated geopolitical disturbance scenarios, the elasticity coefficient dynamic adjustment mechanism was able to complete the optimization and adjustment of the supply chain network layout within an average of 20 hours, effectively maintaining the stability and competitiveness of the supply chain.

4. CONCLUSION

This study presents a regional supply chain layout approach that combines multi-source risk information analysis, graph convolutional network-based risk assessment, and a multi-objective evolutionary search using NSGA-III. By evaluating logistics efficiency, regulatory adaptability, historical disruption patterns, and substitution costs, the method provides a structured way to quantify supply chain node vulnerabilities. Case simulations involving a multinational component group with an annual procurement volume exceeding USD 800 million show that, compared to centralized and zoned layouts, the regional collaborative model built around a "3 Centers + 6 Radiations" structure significantly improves network performance. Specifically, it reduces delivery cycle volatility by 34.5% and decreases annual adjustment frequencies by about 26%, while achieving higher order fulfillment rates and improved transportation reliability. Furthermore, the proposed dynamic elasticity adjustment, based on evolving risk signals, enables supply chain layout reconfiguration under varied geopolitical and economic shocks within an average response time of 20 hours. This adaptability strengthens the overall resilience and operational continuity of regional supply chains. Overall, the results support that integrating multi-dimensional risk signals with adaptive network redesign can serve as a practical strategy for enterprises seeking to stabilize their supply chains in increasingly volatile global environments. Future investigations could explore real-time sensing integration and predictive adjustment strategies to further enhance early warning capabilities.

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