



International Journal of Environment and Sustainable Development

ISSN online: 1478-7466 - ISSN print: 1474-6778

<https://www.inderscience.com/ijesd>

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Qiang Zhou

DOI: [10.1504/IJESD.2025.10074929](https://doi.org/10.1504/IJESD.2025.10074929)

Article History:

Received:	25 February 2025
Last revised:	17 July 2025
Accepted:	16 September 2025
Published online:	23 February 2026

Resilience enhancement in heterogeneous supply chain networks: complex network analysis and collaborative optimisation of intelligent systems

Qiang Zhou

New Epoch School of Tourism and Civil aviation Management,
Haikou University of Economics,
Haikou, 570000, Hainan, China
Email: genius785278@163.com

Abstract: This paper enhances supply chain resilience using complex network analysis and intelligent optimisation. A heterogeneous network model is built to identify node dependencies and vulnerabilities. Q-learning and PSO algorithms optimise resource allocation, inventory, and transportation paths while a dynamic adjustment mechanism based on fuzzy logic adapts to real-time feedback. Compared to existing methods, our approach shows shorter recovery times (18.4 h, 18.19 h, 17.35 h for supplier failure, transportation delay, and demand fluctuation), stronger network connectivity, and higher resource utilisation. This demonstrates improved proactive resilience and the ability to cope with external shocks.

Keywords: heterogeneous supply chain network; complex network analysis; intelligent collaborative optimisation; risk prediction; dynamic adjustment mechanism.

Reference to this paper should be made as follows: Zhou, Q. (2026) 'Resilience enhancement in heterogeneous supply chain networks: complex network analysis and collaborative optimisation of intelligent systems', *Int. J. Environment and Sustainable Development*, Vol. 25, No. 5, pp.24–43.

Biographical notes: Qiang Zhou is working as an Associate Professor at New Epoch School of Tourism and Civil aviation Management, Haikou University of Economics. He obtained his PhD in Transportation Planning and Management from Nanjing University of Aeronautics and Astronautics in China. His research expertise includes supply chain management, complex networks, evolutionary games and big data applications.

1 Introduction

With the deepening development of globalisation and the rapid changes in market demand, modern supply chains face increasingly complex and changing challenges (Mamasoliev, 2024; Nasereddin, 2024). The supply chain is no longer a linear and sequential process in the traditional sense but a complex network consisting of multiple heterogeneous nodes and their interconnections (Liu et al., 2022; Chen et al., 2024). These nodes form a dynamically evolving supply chain ecosystem through the interaction of information, material, and capital flows (Wang et al., 2023; Calzada et al., 2023).

Previous studies usually rely on simplified assumptions (Ameh, 2024; Agarwal et al., 2022b), ignoring the heterogeneity of these nodes and the complexity of the multi-level structure (Namdar et al., 2024; Gao et al., 2024), which makes it difficult to fully describe the vulnerability of the supply chain when faced with external shocks. Existing research has primarily focused on risk management (Yang et al., 2022, 2023) and post-disaster recovery strategies (Moosavi et al., 2022; Katsaliaki et al., 2022) of a single link but lacks in-depth exploration of the collaboration between various links in the supply chain. When responding to emergencies, many resilience-enhancing strategies remain at the reactive stage (Song et al., 2022; Syed et al., 2024) and fail to effectively conduct proactive risk prevention and dynamic optimisation, resulting in a slow response when faced with uncertainty. Therefore, improving the proactive resilience of the supply chain and optimising its collaborative capabilities have become key issues in current research.

In this context, scholars have conducted extensive explorations in supply chain resilience and risk management, especially regarding recovery capabilities in response to emergencies. Many studies have focused on achieving rapid recovery of the supply chain through optimal scheduling (Joel et al., 2024; Abaku et al., 2024), alternative resource allocation (Xu et al., 2023; Pan et al., 2022), and emergency plans (Chukwuka et al., 2023; Wang et al., 2022). However, most of these studies are limited to traditional simplified models and fail to fully consider supply chain networks' heterogeneity and multi-level complexity.

With the deepening of research, issues such as network structure optimisation, resource allocation, and multi-objective decision-making have gradually become hot topics in the academic community. Various intelligent optimisation algorithms have been applied to improve the collaborative optimisation capabilities of the supply chain (Nwagwu et al., 2023; Cui et al., 2022). These methods provide new perspectives for improving supply chain resilience but still have significant limitations. Especially in the collaborative optimisation of multi-level heterogeneous supply chain networks, existing research often ignores the complex interactive relationships and dynamic evolution between nodes. It cannot consider both reactive and proactive strategies in a dynamic environment. Therefore, comprehensively considering network heterogeneity, improving collaborative capabilities, and achieving enhanced proactive resilience in emergencies remain significant challenges in current research.

This paper adopts a comprehensive method of complex network analysis and intelligent system collaborative optimisation to solve these problems. A multi-level network model that can reflect the heterogeneity of the supply chain is constructed. The network structure is deeply analysed through indicators such as degree centrality. Each key node's vulnerability and potential risks in the supply chain are identified. This paper constructs an intelligent decision support system combining machine learning with optimisation algorithms. Through the Q-learning and PSO algorithms, resource allocation, inventory management, and transportation paths are collaboratively optimised, improving the supply chain's flexibility and ability to respond to emergencies. In addition, this paper also applies a dynamic adjustment mechanism to optimise the supply chain's response speed and recovery capacity through adaptive feedback. The main contributions of this paper are that the structural characteristics of heterogeneous supply chain networks are deeply studied by combining complex network analysis and intelligent optimisation technology. The proactive resilience and overall efficiency of the supply chain are improved through an intelligent decision-making system, providing a

new research perspective and methodological framework for enhancing the resilience of modern supply chains.

2 Related work

Enhancing the ability to resist emergencies (Ergun et al., 2023; Kamalahmadi et al., 2022), improving the adaptability, and optimising the response time of the system (Kazancoglu et al., 2022; Hussain et al., 2023) are key aspects of research in supply chain resilience and risk management. Traditional research methods mostly explore quickly resuming normal operations after an emergency through resource scheduling, inventory management, and optimisation of alternative plans. Moreover, many studies are based on linear models and simplified assumptions, ignoring the complexity and heterogeneity of the supply chain system and failing to accurately grasp the complex interactions and dependencies between nodes in the supply chain. Although traditional recovery strategies can effectively deal with known risks, their responsiveness and adaptability are still insufficient when faced with unpredictable events, and they cannot respond proactively.

In response to this, some studies have begun to apply complex network analysis methods to explore the issue of supply chain network structure optimisation (Baloch and Rashid, 2022; Tavana et al., 2022). Network analysis technology based on graph theory has been applied to assess the vulnerability and risk of each node in the supply chain (Agarwal et al., 2022a; Zhao et al., 2025). For example, by calculating indicators, such as the centrality and connectivity of nodes, key nodes in the system and their impact on the overall system's stability can be identified. However, this type of research ignores the dynamic characteristics and heterogeneity of the supply chain. It cannot cope with the variability and diversity of the supply chain in the real environment. Although optimising network structure can help improve the system's ability to resist risks, existing analysis methods fail to fully consider the collaborative optimisation problems in multi-level and heterogeneous networks.

Meanwhile, more and more studies are trying to apply machine learning and optimisation algorithms to supply chain management to enhance the supply chain's collaborative capabilities and dynamic response capabilities (Pasupuleti et al., 2024; Rolf et al., 2023). Intelligent optimisation methods such as reinforcement learning, genetic algorithms, and particle swarm optimisation (PSO) have achieved specific results in problems such as resource allocation, inventory management, and transportation path selection. These methods improve the supply chain's real-time response speed and optimisation efficiency through intelligent decision support systems and show good adaptability, especially in risk scenarios such as demand fluctuations and supply chain disruptions. However, existing intelligent optimisation methods usually focus on single-level or local decision optimisation, which makes it difficult to cope with multi-dimensional and multi-level collaboration problems in complex heterogeneous supply chains. Existing algorithms still have certain limitations in the collaboration and resource allocation optimisation between multiple nodes and multiple types of nodes.

Although current research has made some progress in supply chain resilience, network structure optimisation, and intelligent optimisation decision making, most methods still have limitations when faced with complex, heterogeneous supply chains. On the one hand, traditional recovery strategies and network optimisation methods have failed to effectively address the heterogeneity and complexity in the supply chain,

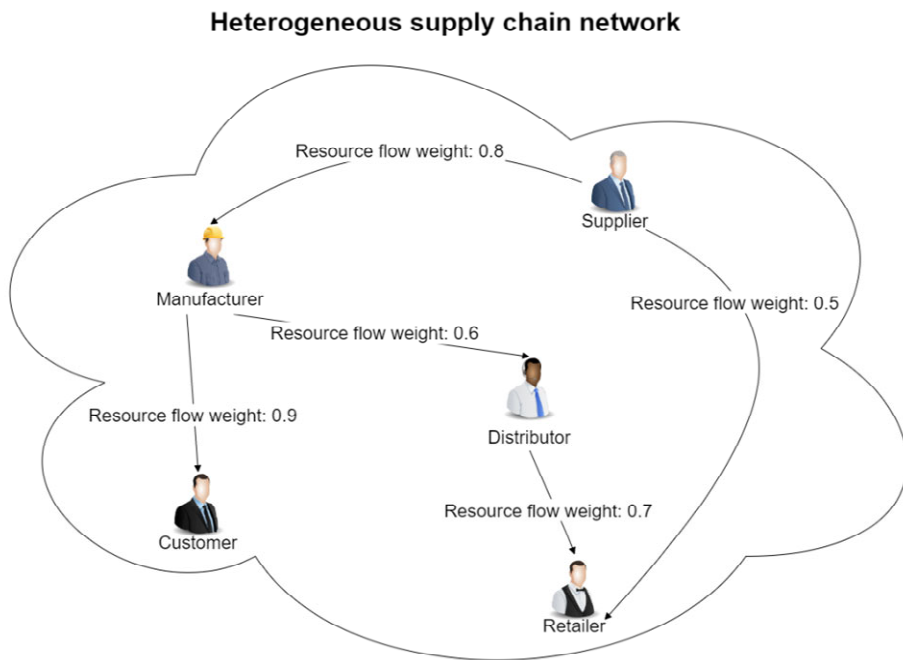
resulting in the inability to improve the resilience and adaptability of the system comprehensively. On the other hand, although the existing intelligent optimisation methods have achieved specific results in optimising a single objective, they are still insufficient in collaborative optimisation and dynamic adjustment in multi-level and heterogeneous supply chain networks. Therefore, combining complex network analysis and intelligent optimisation technology to improve the proactive resilience of heterogeneous supply chain networks in emergencies remains an essential challenge in current research.

3 Structure optimisation and intelligent collaboration of heterogeneous supply chain networks

3.1 Construction and analysis of heterogeneous supply chain networks

In constructing heterogeneous supply chain networks, network models with different node attributes and functions are built based on the differences in node types in the supply chain. Each node represents a component of the supply chain. Weighted edges connect nodes. The weight of the edge reflects the intensity of resource flow, interdependence, and closeness of information flow between nodes. Figure 1 presents the heterogeneous supply chain network structure.

Figure 1 Heterogeneous supply chain network structure (see online version for colours)



Firstly, the network topology analysis method in graph theory is used to clarify the role and position of each node. The connection relationship between nodes is represented by

the weight of the edge. The weight of the edge is set by the resource exchange frequency, dependency strength, production capacity, and delivery cycle between nodes. For production nodes, since they are directly related to the manufacturing and supply capabilities of products, their weights are mainly determined based on production capacity, production efficiency, and supply stability to downstream nodes; the weights of warehousing nodes focus on inventory capacity, cargo turnover rate, and logistics regulation capabilities; the weights of transportation nodes are allocated based on factors such as transportation capacity, transportation timeliness, and transportation costs. In actual scenarios, the calibration method of edge weights is as follows: first, collect historical data such as transaction records, logistics transportation data, and information interaction frequency between nodes; second, combine expert evaluation and field research to determine the contribution of each factor to the weight; finally, use statistical analysis and machine learning methods, such as regression analysis and neural networks, to dynamically calibrate and optimise the weights to accurately characterise the interaction intensity between supply chain links. These weighted connections can accurately characterise the interaction intensity between supply chain links. By constructing a network topology, you can intuitively understand the dependencies between nodes in the supply chain.

After the network structure is constructed, the role and importance of each node in the network are quantitatively analysed through three important indicators in graph theory: degree centrality, closeness centrality, and betweenness centrality.

The number of edges directly connecting a node to other nodes is called degree centrality, one of the indicators to quantify the importance of a node. Nodes with a high degree centrality usually play an essential role in the flow of information and resources, which is calculated by formula (1):

$$C_D(n_i) = \deg(n_i) = \sum_{j=1}^n A_{ij} \quad (1)$$

A_{ij} indicates whether there is an adjacency matrix element connected between nodes n_i and n_j .

The average reciprocal of the shortest path length between a node and every other node in the network is called closeness centrality. Nodes with higher closeness centrality can spread information faster or influence other nodes. The calculation formula is:

$$C_C(n_i) = \frac{n-1}{\sum_{j \neq i} d(n_i, n_j)} \quad (2)$$

$d(n_i, n_j)$ represents the shortest path length between node n_i and node n_j . Closeness centrality reflects the efficiency of connection between a node and other nodes.

Betweenness centrality reflects the intermediary role of a node in the shortest path between other nodes. The higher the betweenness centrality value of a node, the greater its bridging effect in the network. The calculation formula is:

$$C_B(n_i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(n_i)}{\sigma_{st}} \quad (3)$$

σ_{st} is the number of shortest paths from the node s to t , and $\sigma_{st}(n_i)$ is the number of paths that go through the node n_i . Nodes with high betweenness centrality play a vital role in the connectivity and stability of the network.

The key nodes and weak links in the network are identified by calculating the three indicators, and the changes in network performance after node failure are further evaluated. Assuming that a node n_k in the network fails, the connectivity of the entire network is then affected. The resource flow between n_k and its directly connected nodes is especially interrupted.

To quantitatively analyse network vulnerability, this paper uses the shortest path algorithm to calculate the shortest path between any two nodes and evaluate the impact of node failure on network connectivity. The effect of failed nodes on network performance is calculated using formula (4):

$$\Delta C = C_{before} - C_{after} \quad (4)$$

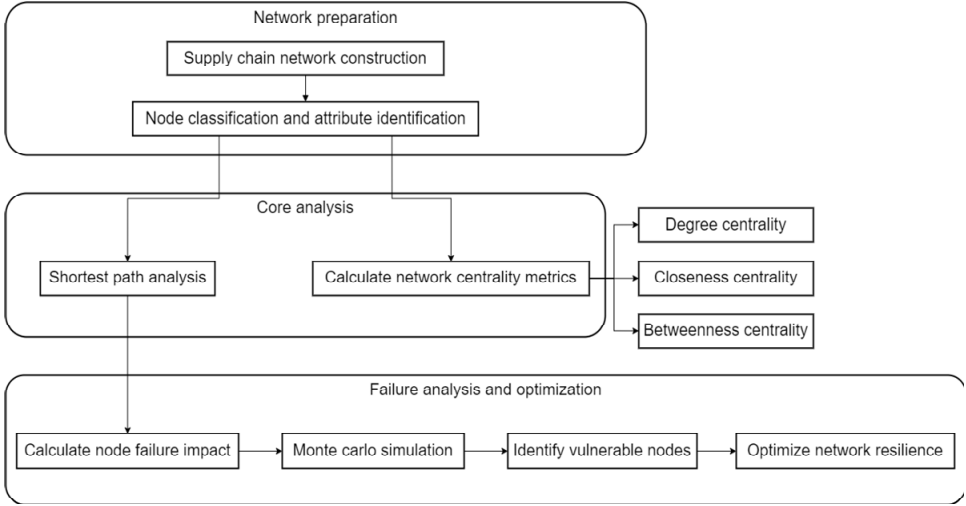
C_{before} represents the network connectivity before the failed node, and C_{after} represents the network connectivity after the failed node. If ΔC is large, it indicates that the node has a high importance in the network, and its failure may affect the stability of the entire supply chain. In order to more accurately assess the vulnerability of the network, this paper considers the compensatory effect of the node redundancy mechanism on connectivity loss when calculating ΔC . When a node fails, its neighbouring nodes or backup paths may take over some of the functions, thereby alleviating the connectivity loss.

To accurately reflect the heterogeneity of the supply chain, this paper adopts a hierarchical modelling approach to divide different nodes in the supply chain into levels. Nodes such as suppliers are divided into various levels, and nodes at each level play different roles under various conditions. Hierarchical modelling can more precisely describe the interdependencies between nodes and reveal the interactions between different levels.

Due to the supply chain network's dynamic characteristics, nodes' attributes and connection relationships are adjusted with factors such as market changes and demand fluctuations. To adapt to these changes, this paper applies real-time data streaming and dynamic feedback mechanisms to update the properties of nodes and connections continuously. Whenever a node in the network changes, the weights of the related connections are adjusted accordingly to ensure that the network structure always reflects the current supply chain status.

3.2 Network vulnerability identification and key node analysis

When identifying supply chain network vulnerabilities and analysing key nodes, each node is classified in detail based on the supply chain network topology. The nodes in the supply chain network include suppliers, manufacturers, distributors, and other roles. Each node plays a different function in the network and has various attributes and connection relationships. The node attribute dataset mainly comes from enterprise resource planning systems, supply chain management software, IoT sensor data, and historical operation records, etc. It covers multiple dimensions of information such as node type, production capacity, inventory level, transportation time, cost, etc., providing data support for accurately assessing the vulnerability of nodes. Figure 2 displays the framework for supply chain network vulnerability identification and key node analysis.

Figure 2 Framework for supply chain network vulnerability identification and key node analysis

Indicators such as degree centrality are used to quantitatively evaluate each node's role in identifying vulnerable nodes and weak links in the supply chain network. By analysing the centrality of nodes, nodes that play a key role in the network can be preliminarily identified, especially those playing a key bridge role in the flow of information and resources.

Next, the shortest path algorithm is used to perform connectivity analysis of the supply chain network. The shortest path algorithm evaluates the overall connectivity of the network by calculating the shortest path between any two nodes and considering the weights of the connections between nodes. In this process, the impact of node failure on the connectivity and performance of the network is analysed.

For each node v_i in the network, the shortest path $d(u, v_i)$ is calculated using formula (5):

$$d(u, v_i) = \min \left(\sum_{e_j \in P(u, v_i)} w(e_j) \right) \quad (5)$$

u and v_i are two nodes in the network. $P(u, v_i)$ represents the path from u to v_i . $w(e_j)$ is the weight of each edge in path $P(u, v_i)$. Based on the results of the shortest path calculation, it is further determined which nodes or connections whose failure significantly impacting the overall performance of the network.

The Monte Carlo simulation method is used to conduct multiple epochs of experiments on the network to comprehensively evaluate the vulnerability of the supply chain network in various failure scenarios. By randomly selecting one or more nodes or edges for failure processing, the connectivity and performance indicators of the network are recalculated.

In each simulation, a failed node v_k is first selected, and the change in network connectivity after the failure is calculated. If the failure of node v_k leads to a significant increase in the shortest path length $d'(u, v_i)$ of the network, the node's role in the network is identified as an essential node. Formula (6) is used to calculate the connectivity change after node failure to further quantify the impact of node failure:

$$\Delta d(v_k) = \sum_{u, v_i \in V} (d'(u, v_i) - d(u, v_i)) \quad (6)$$

The impact of each node failure on the network can be determined through multiple independent simulations and statistical analysis. Combining the results of shortest path analysis and Monte Carlo simulation, it is concluded which nodes are crucial to the stability of the supply chain network. By optimising key nodes, the resilience of the supply chain network can be improved. When conducting network vulnerability analysis, it is necessary to combine the specific supply chain business context and comprehensively consider each node's functions, dependencies, and role in resource flow.

3.3 Intelligent collaborative optimisation and decision support

In realising intelligent collaborative optimisation and decision support, the Q-learning algorithm is used to optimise resource scheduling, inventory management, and transportation path selection in the supply chain. PSO and genetic algorithm (GA) jointly participate in optimising resource scheduling and path planning to deal with multi-objective optimisation problems. In Q-learning, the state space specifically includes multiple dimensions such as inventory levels, production capacity, transportation capacity, demand forecasts, and the real-time operating status of each node, which are used to comprehensively characterise all possible resource configurations and operating conditions in the system.

Q-learning is used to optimise resource scheduling and management in supply chains. The state space S is set to represent all possible resource configurations and operation states in the system, including parameters such as inventory, production capacity, and transportation capacity. The action space A consists of all possible resource allocation decisions, such as inventory adjustment, production task allocation, and transportation mode selection. The reward value $R(s, a)$ for each state and action pair optimised through the Q-learning algorithm is a function of system performance, considering multiple objectives such as supply chain efficiency, cost, and response speed.

Regarding resource scheduling, Q-learning can dynamically optimise resource allocation based on real-time inventory, production capacity, and transportation capacity by learning and adjusting Q-values. After each schedule, the system is updated based on the new Q-value to adapt to changes in the supply chain and demand fluctuations.

In inventory management, Q-learning can adjust inventory levels through real-time feedback to respond to demand fluctuations or transportation delays in the supply chain. It is assumed that the inventory level is I_t , and the objective of inventory adjustment is to minimise the inventory cost $C(I_t)$ and the stockout cost $S(I_t)$. In this context, the reward function of Q-learning is:

$$r_t = -(C(I_t) + S(I_t)) \quad (7)$$

The cost weight and out-of-stock cost weight are based on the historical inventory cost data of the supply chain and the company's operating experience. The cost weight reflects the importance that the company attaches to inventory holding costs, including storage costs, capital occupation costs, etc., while the out-of-stock cost weight reflects the company's sensitivity to out-of-stock losses, including customer churn and emergency replenishment costs.

After each inventory adjustment, the system updates the Q-value based on real-time data and optimises inventory levels to avoid the risk of over-inventory or out-of-stock. Historical data and real-time information can be combined through intelligent algorithms, allowing inventory adjustment strategies to adapt to demand fluctuations in the supply chain dynamically.

The optimisation of transportation path selection also relies on the Q-learning algorithm. The state space represents each node's transportation demand and available transportation resources in the supply chain. The action space includes the selection of different transportation paths and methods. The objective is to minimise transportation costs and time. Q-learning optimises transportation path selection by iteratively updating Q-values so that each epoch of decision-making can minimise transportation costs and improve the overall responsiveness of the supply chain. Q-learning can quickly modify the transportation path when a problem occurs in a specific link to maintain the stability and responsiveness of the supply chain.

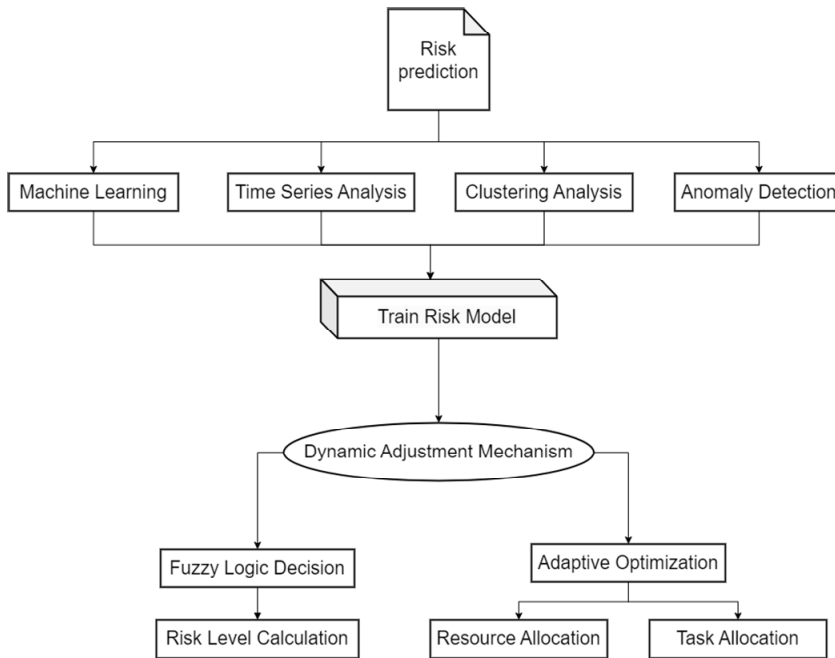
PSO is used for multi-objective optimisation problems, especially in optimising resource scheduling and path planning. In resource scheduling, the position vector of each particle is mapped to the resource allocation ratio and scheduling priority of each resource allocation node. For example, the dimension of the particle position vector corresponds to the resource allocation weights of different supplier, manufacturer and distributor nodes. The dynamic optimisation allocation of resources among different nodes is achieved through position update, and the optimal resource scheduling plan is gradually approached by combining the speed update rule. PSO comprehensively considers the resource cost, transportation efficiency, and inventory utilisation of the supply chain to help the system find the global optimal configuration and maximise the overall efficiency of the supply chain.

GA simulates the natural selection process to optimise resource scheduling and production task allocation in the supply chain. Each solution represents a resource allocation plan, and new solutions are generated through operations such as crossover and mutation. During the optimisation process, GA gradually improves the task scheduling efficiency and reduces resource waste through multiple generations of evolution. A new scheduling plan is generated after each crossover and mutation. The survival of the fittest is carried out according to the fitness function to ensure that the final solution has the optimal resource allocation and scheduling plan.

3.4 Risk prediction and dynamic adjustment mechanism

The supply chain's dynamic adjustment and risk prediction mechanisms can combine real-time information with previous data. The system dynamically responds to risks in the supply chain through a multi-level prediction and adjustment mechanism, ensuring that the system can recover quickly and maintain efficient operation when faced with uncertainty and emergencies. Figure 3 presents the framework for supply chain risk prediction and dynamic adjustment.

The risk prediction module is the core of the system. It mainly uses machine learning technology to train based on historical supply chain operation data to establish an efficient risk prediction model. Time series analysis is the primary method used to model the operating status of each link, especially the analysis of long-term and short-term trends, seasonal fluctuations, and cyclical fluctuations.

Figure 3 Framework for supply chain risk prediction and dynamic adjustment

In addition, cluster analysis is used to classify the behavioural patterns of various nodes in the supply chain, thereby identifying high-risk areas by classifying the nodes into different risk categories. The objective of cluster analysis is to assign each node in the supply chain to different risk categories according to its characteristics, such as transportation timeliness and inventory fluctuations. Anomaly detection is another important module that compares the data point with historical data to quickly identify data points that do not conform to regular fluctuations and discover possible failure modes early.

In this case, the system automatically triggers a dynamic adjustment mechanism after identifying potential risks and adjusts the decision using a fuzzy logic decision model. Fuzzy logic decision models apply uncertainty and ambiguity to decision making, so the system can dynamically adjust supply chain operation strategies based on real-time data, historical data, and risk patterns. Fuzzy logic control can fuzzify input data by comprehensively evaluating each node's status, risk level, historical performance, and current load in the supply chain. Then, the corresponding decision output is inferred through the preset fuzzy rule base. The current risk level is calculated with this fuzzy inference mechanism. Decisions are made through fuzzy rules at different risk levels and include the most appropriate strategy output. When each decision model is executed, it is dynamically adjusted according to the real-time status and risk level.

The implementation of dynamic adjustment mechanisms relies on multi-level feedback loops to monitor key indicators of the supply chain in real time. In the early stages of a supply chain disruption, the system uses an adaptive learning algorithm to dynamically update the parameters of the risk prediction model to optimise the identification and prediction accuracy of potential risks. The adaptive optimisation algorithm combines historical and real-time data to make predictions and automatically

adjust resource allocation and task allocation, allowing the supply chain to return to normal operation in the shortest time possible. The dynamic feedback mechanism continuously adjusts the prediction model and decision-making process based on real-time data updates to accurately identify and respond to risks and uncertainties in the supply chain.

When supply chain disruptions occur, the risk prediction and dynamic adjustment mechanism uses previously established risk models and fuzzy logic decision rules to optimise resource allocation and task scheduling. The system collects operational data from each node in the supply chain in real time to assess the current risk level and determine emergency response needs. Based on this real-time information, resource allocation is adjusted through adaptive optimisation algorithms; inventory management strategies are changed; transportation path selection is optimised; and production plans are adjusted. A weighted risk assessment function determines the risk level:

$$R = w_1 \cdot I + w_2 \cdot T + w_3 \cdot D \quad (8)$$

R is the overall risk level. I is the risk of insufficient inventory. T is the risk of transportation delay. D is the risk of demand fluctuation. w_1 , w_2 and w_3 are the weights of each risk factor. Based on the current risk level, the system selects an appropriate emergency strategy to ensure rapid recovery after an outage.

3.5 *Dynamic feedback and adaptive optimisation*

In achieving dynamic feedback and adaptive optimisation, the system continuously monitors various key performance indicators of the supply chain based on real-time data streams. The real-time operation data of each node is constantly transmitted through sensors, monitoring systems, or information systems to ensure the timeliness and accuracy of the data. In this way, the system can obtain the current status of the supply chain promptly, thereby providing reliable input for subsequent optimisation decisions.

The system uses a differential evolution algorithm (DE) for dynamic optimisation based on the combination of real-time data stream and historical data. DE has strong global search capabilities. It is suitable for high-dimensional and multi-objective optimisation problems. The algorithm generates new solutions and evaluates their fitness by perturbing and differencing existing solutions, gradually approaching the global optimal solution. Each candidate solution generated is assessed by the objective function, which considers constraints such as inventory fluctuations, transportation costs, and resource allocation to measure the quality of the solution.

In each iteration, the system fine-tunes resource allocation and optimisation strategies based on feedback from the objective function. Through real-time monitoring of status information, DE parameters are automatically adjusted. The algorithm generates new candidate solutions based on the differences between the current solution and the historical solutions. The quality of the solution is optimised through differential operations. The resource allocation plan is gradually improved after multiple iterations. During each iteration, the system adjusts the parameters of the differential evolution algorithm to respond to the real-time status of the supply chain. Assuming that the resource allocation and optimisation strategy of the system is represented by a solution vector $\mathbf{x} = [x_1, x_2, \dots, x_n]$, the dynamic adjustment of the system is described by formula (9):

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \Delta \mathbf{x}_t \quad (9)$$

$\mathbf{x}_t$ is the solution vector at the current moment, and $\Delta \mathbf{x}_t$ is the solution vector increment adjusted according to real-time data and feedback.

The system's optimisation objectives include inventory management, transportation path selection, and production plan adjustments. In inventory management, the differential evolution algorithm automatically adjusts the inventory level based on the feedback of the objective function. When market demand changes or supply chain nodes fail, the algorithm quickly responds to demand fluctuations or supply disruptions by adjusting inventory levels and replenishment strategies. In transportation path optimisation, the system analyses the status of the transportation network in real time, identifies bottlenecks, and optimises transportation paths with the help of the algorithm, reducing transportation delays and costs.

The application of the algorithm is not limited to static optimisation but also covers the dynamic adjustment of the system. When emergencies occur, such as sharp fluctuations in demand or supply chain disruptions, the differential evolution algorithm quickly adjusts supply chain operations through adaptive update strategies. The monitoring system identifies potential risks based on real-time data streams. The system immediately activates optimisation algorithms to minimise the negative impact of unexpected events by adjusting strategies such as inventory and transportation paths. The process is highly flexible. It can respond to short-term changes and consider long-term strategic adjustments.

To further improve the system's adaptive capabilities, the system combines historical data and real-time feedback to adjust the parameters of the differential evolution algorithm dynamically. For example, when demands fluctuate significantly, the system automatically adjusts the algorithm's search strategy through a feedback mechanism to improve resource allocation efficiency and reduce inventory level fluctuations. Each feedback is used as input to re-evaluate the objective function and adjust the optimisation process.

When the system identifies potential disruptions or transportation delays in the supply chain, the differential evolution algorithm regenerates solutions through perturbation operations. It reallocates resources to meet the challenges brought about by the emergency. For example, when a transportation delay occurs at a particular node, the system reduces the event's impact on the overall supply chain by optimising the transportation path or adjusting the resources of other nodes. Moreover, the adaptability of the algorithm enables the system to adjust its strategy in real time according to changes in the external environment, thereby enhancing its recovery capabilities.

In addition, in terms of inventory management, the differential evolution algorithm can quickly calculate and generate multiple alternative plans. It can select the optimal strategy for inventory adjustment based on the objective function. This process not only considers the current inventory status, but also predicts future inventory needs, and combines historical sales data to make optimisation decisions to ensure the stability of inventory levels and efficient use of resources. Regarding resource allocation, the system makes feedback adjustments based on real-time data streams, flexibly responds to changes in production capacity at each node, maximises resource utilisation, and reduces costs.

In the adaptive feedback mechanism, the system continuously updates the optimisation strategy based on real-time monitoring data. With this mechanism, the operating status of the supply chain is constantly monitored, and the algorithm adjusts its strategy based on feedback information to respond promptly to market changes, transportation delays, or supply disruptions. This process improves the system's responsiveness in the face of emergencies and automatically adjusts optimisation strategies in different supply chain scenarios, allowing the system to always maintain high adaptability and optimisation effects.

Combining a differential evolution algorithm and an adaptive feedback mechanism enables the system to adjust freely in a changing environment, ensuring the efficient operation of the supply chain. In practical applications, the system can automatically reconfigure resources and optimise decisions when changes occur at supply chain nodes, thereby improving the supply chain's resilience.

4 Evaluation of the effectiveness of the method

4.1 Experimental setup

To confirm the effectiveness of this method, this study uses a simulation environment to construct a typical heterogeneous supply chain network model containing multiple node types, covering different kinds of nodes, such as suppliers, manufacturers, and distributors, and reflecting the dependencies between each link through weighted connections. The model can simulate various risk events in a real supply chain and their mutual impact, providing a testing platform close to the actual environment. The experimental design simulates various supply chain disruptions and risk events, such as supplier failures, transportation delays, demand fluctuations, etc. These events are triggered at different time points. The experiment's primary purpose is to test the method's response speed, recovery ability, and adaptability when facing unexpected events.

To this end, comparative experiments between the method in this paper (method 1) and intelligent decision optimisation based on reinforcement learning (method 2) and multi-objective optimisation strategy based on PSO (method 3) are carried out. The experimental period is set to three months. Different risk events are simulated every month. Each experimental scenario is reproduced ten times, and relevant data are summarised and counted after each reproduction experiment.

4.2 Evaluation indicators

4.2.1 Recovery time

Recovery time measures the time it takes for a supply chain to return to normal operations after an unexpected event. The time interval from the moment the risk event occurs until the system returns to the preset normal operating state is calculated. This indicator reflects the supply chain's response speed and recovery ability to external shocks. A short recovery time indicates that the supply chain can quickly adapt and adjust its operating strategy.

Figure 4 Comparison of the recovery time of each method, (a) supplier failure (b) transportation delay (c) demand fluctuation (see online version for colours)

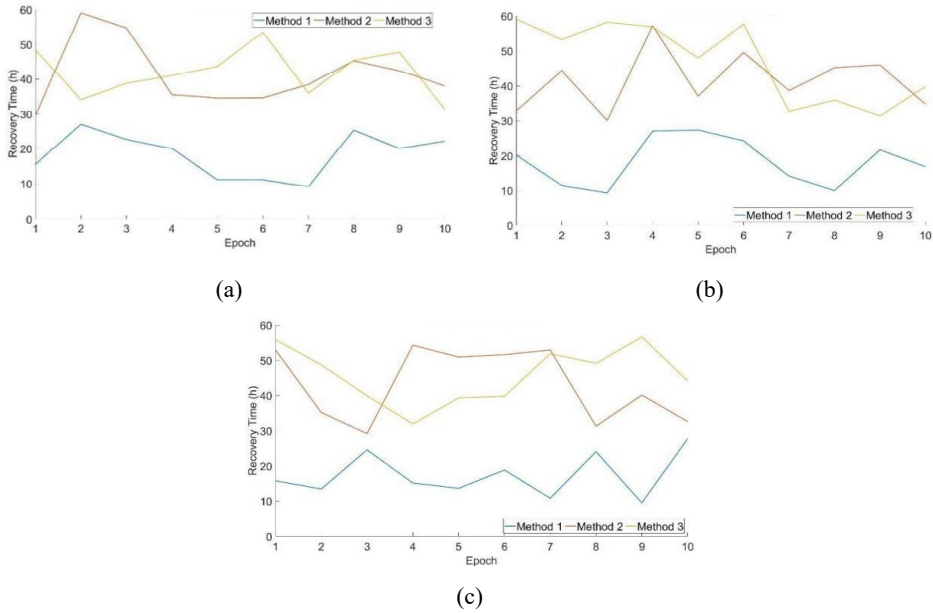


Figure 4 shows the recovery time for different types of risks. Method 1 has an apparent recovery advantage over methods 2 and 3 in supplier failure, transportation delay, and demand fluctuation. Method 1 has an average recovery time of 18.4 hours in the case of supplier failure, 18.19 hours in the case of transportation delay, and 17.35 hours in the case of demand fluctuation, which are all lower than those of other methods. This indicates that method 1 is more efficient in responding to supply chain risks, enabling it to resume normal operations more quickly.

4.2.2 Network connectivity

The supply chain network's average path length and connectivity indicator are used to assess network connectivity. This indicator is used to determine how the overall connectivity of the supply chain network changes after a disruption or risk event. The average path length is the average of the shortest path lengths required between two nodes, and connectivity quantifies the degree of connection between nodes in the network.

Table 1 shows that the network performance of the three methods varies in the influence of different risk events. In the case of supplier failure, the connectivity of method 1 is 0.92; the average path length is 3.1 nodes; the connectivity change is 0.03. Regarding transportation delay, the connectivity of method 1 is 0.91; the average path length reaches 2.9 nodes; the connectivity changes by 0.01. When demand fluctuates, the connectivity of method 1 is 0.9; the average path length is 3; the connectivity changes by 0.02. Method 1 is superior to the other two in all indicators. Overall, method 1 demonstrates stronger network connectivity in all risk events.

Table 1 Comparison of the network connectivity of each method

<i>Risk event</i>	<i>Method</i>	<i>Connectivity</i>	<i>Average path length</i>	<i>Network connectivity change</i>	<i>Connectivity after event recovery</i>
Supplier failure	Method 1	0.92	3.1	0.03	0.95
	Method 2	0.89	3.4	−0.05	0.84
	Method 3	0.87	3.5	−0.08	0.79
Transportation delay	Method 1	0.91	2.9	0.01	0.92
	Method 2	0.88	3.2	−0.03	0.85
	Method 3	0.85	3.6	−0.06	0.79
Demand fluctuation	Method 1	0.9	3	0.02	0.92
	Method 2	0.86	3.3	−0.06	0.8
	Method 3	0.83	3.7	−0.1	0.73

4.2.3 Response time

Response time is measured based on the period for the system to perform response activities after an event is detected. This indicator indicates how quickly the system responds to these documented incidents or emergencies. A short response time means the system can detect or identify problems quickly and effectively implement appropriate measures.

Figure 5 Comparison of the response time of each method, (a) supplier failure (b) transportation delay (c) demand fluctuation (see online version for colours)

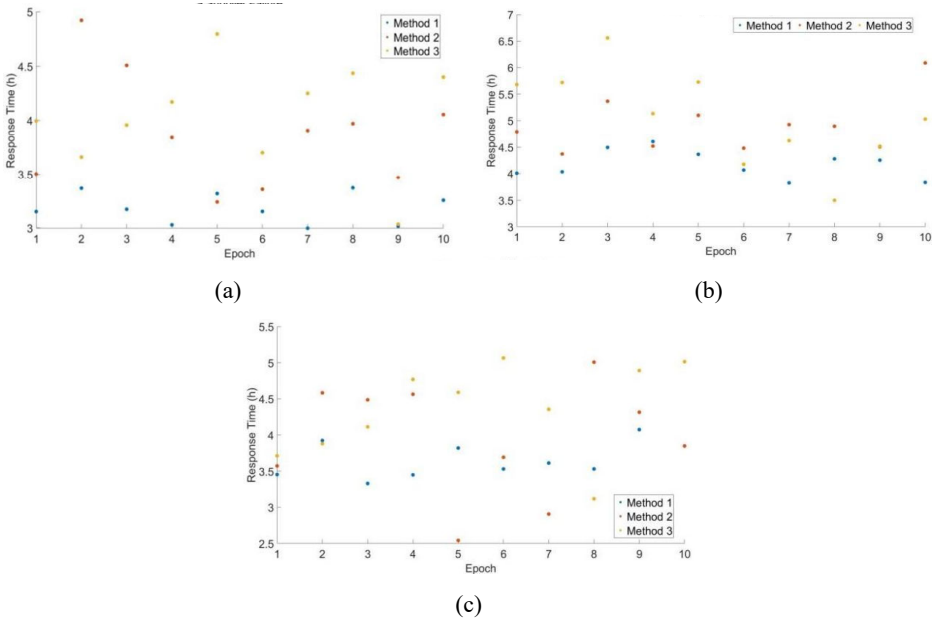


Figure 5 shows the response time of different approaches in the face of supplier failures, transportation delays, and demand fluctuations. The response time of method 1 is

generally short, ranging from 3 to 3.37 hours in the case of supplier failure, 3.83 to 4.61 hours in the case of transportation delay, and 3.33 to 4.07 hours in the case of demand fluctuation. In comparison, the response times of methods 2 and 3 are longer, and method 1 exhibits higher recovery speed and flexibility.

4.2.4 Resource utilisation

Resource utilisation is obtained by calculating the configuration and utilisation efficiency of resources at each node in the supply chain. The resource allocation optimisation algorithm is used to evaluate the balance of resource allocation. This indicator reflects whether the allocation of resources in the supply chain is reasonable and whether it can maximise support for system operations and improve overall efficiency. High resource utilisation indicates the system can achieve optimal configuration with limited resources.

Figure 6 Comparison of the resource utilisation of each method, (a) supplier failure (b) transportation delay (c) demand fluctuation (see online version for colours)

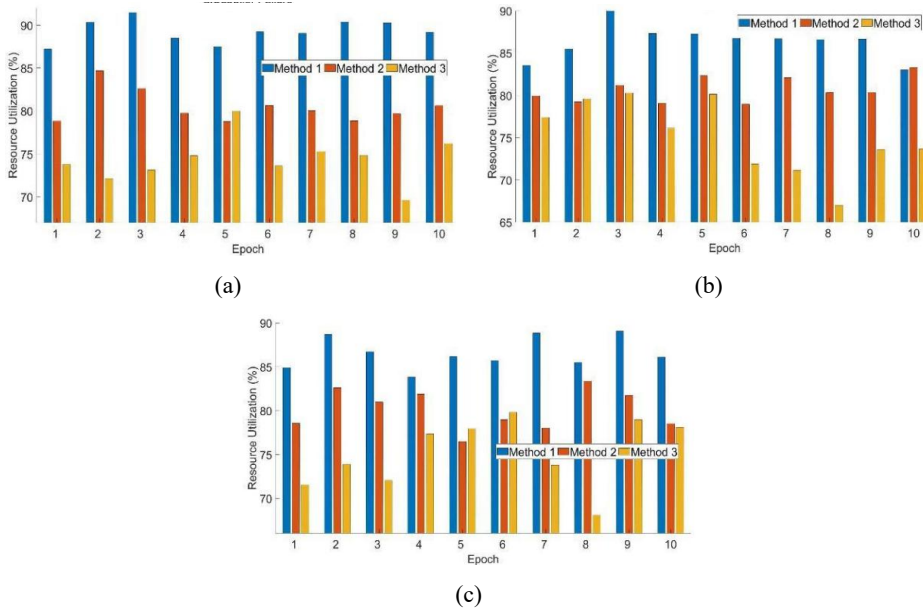


Figure 6 shows the resource utilisation of different methods in three risk events. In the scenario of supplier failure, the resource utilisation of method 1 fluctuates between 87.19% and 91.46%, which is always higher than that of methods 2 and 3. The utilisation rate of method 2 ranges from 78.78% to 84.69%, and method 3 has the lowest utilisation rate, ranging from 69.6% to 80%. In the case of transportation delay, the resource utilisation of method 1 is 83.03% to 90.72%, which is significantly better than that of methods 2 and 3. In the demand fluctuation scenario, the resource utilisation of method 1 ranges from 83.86% to 89.06%. In contrast, the utilisation rates of methods 2 and 3 range from 76.47% to 83.36% and from 68.09% to 79.82%, respectively. In general, the resource utilisation rate of method 1 in various risk events is higher than that of methods 2 and 3, demonstrating a strong resource allocation capability.

4.3 Discussion

In this study, the Monte Carlo simulation method is used to evaluate the vulnerability of the supply chain network. The number of simulations has a significant impact on the stability of the node importance ranking. When the number of simulations is small, the node importance ranking may fluctuate due to randomness, and the identification results of key nodes are not stable enough. However, as the number of simulations increases to a certain extent, the node importance ranking gradually becomes stable. Therefore, in subsequent studies, the reliability of node importance ranking can be improved by increasing the number of simulations.

The DE algorithm is used in this paper to dynamically optimise the supply chain resource allocation, but its convergence proof is relatively complicated. In theory, as the number of iterations increases, the solution vector of the DE algorithm will gradually approach the global optimal solution. However, due to the complexity and dynamics of supply chain problems, a strict mathematical convergence proof is difficult. This paper experimentally verifies that the DE algorithm can effectively optimise resource allocation within a certain number of iterations and restore the system to normal operation. In this study, although the DE algorithm shows good adaptability in dealing with supply chain optimisation problems, its computational efficiency and solution accuracy are affected to a certain extent when facing high-dimensional problems with more than 50 variables. Future research can further explore the convergence conditions of the DE algorithm in dynamic optimisation problems. And introduce dimensionality reduction technology or improved DE algorithm variants to improve its computational efficiency in high-dimensional optimisation problems.

The heterogeneous supply chain network model constructed in this paper does not fully consider the impact of node geographical distribution on transportation delay risk. In the actual supply chain, geographical factors have an important impact on transportation efficiency and delay risk. For example, the transportation time between nodes with longer distances is longer and may face more uncertain factors, such as weather and traffic conditions. Subsequent research can introduce geographic information system data, analyse the geographical distribution characteristics of nodes, and integrate them into transportation path optimisation and risk assessment models to more accurately simulate and predict transportation delay risks.

In the application of the Q learning algorithm, the exploration rate and discount factor have an important impact on the learning effect and strategy optimisation. The exploration rate determines the extent to which the agent explores new strategies during the learning process, while the discount factor reflects the discounted value of future rewards. This paper does not conduct an in-depth analysis of the sensitivity of these two parameters. Different parameter values may lead to different learning speeds and strategy convergence results. Future research can systematically adjust the exploration rate and discount factor, analyse their impact on Q learning in resource scheduling, inventory management, and transportation path selection, so as to determine a better parameter configuration.

The effectiveness of the dynamic adjustment mechanism proposed in this paper has been verified under a single risk event, but the attenuation effect under continuous shock events has not been fully evaluated. Continuous shocks may lead to system resource exhaustion or limited adjustment capabilities, thus affecting the continued effectiveness of the dynamic adjustment mechanism. Subsequent research can design experimental

scenarios containing continuous shock events, such as multiple supplier failures or demand fluctuations in a short period of time, observe the recovery ability and resource consumption of the dynamic adjustment mechanism, and analyse its performance attenuation law to further optimise the robustness of the dynamic adjustment mechanism.

When Q learning and PSO are used to collaboratively optimise supply chain problems, the existence of a Nash equilibrium is the key to ensuring the effect of collaborative optimisation. Nash equilibrium indicates that each agent cannot obtain higher returns by unilaterally changing its strategy when given the strategy of other agents. This paper does not theoretically prove the existence of a Nash equilibrium in the collaborative optimisation process. Although the experimental results show the effectiveness of collaborative optimisation, theoretically proving the existence of a Nash equilibrium helps to further enhance the credibility of the method. Future research can combine game theory and optimisation theory to analyse the Nash equilibrium conditions of Q learning and PSO collaborative optimisation, and provide a more solid theoretical basis for supply chain optimisation.

5 Conclusions

This paper constructs a comprehensive method framework based on complex network analysis and intelligent system collaborative optimisation to enhance the resilience of heterogeneous supply chain networks. By creating a multi-level heterogeneous supply chain network model and combining Q-learning, PSO, and a fuzzy logic dynamic adjustment mechanism, this paper realises the vulnerability identification, resource optimisation allocation, and dynamic risk response of the supply chain network. Experimental results indicate that this method has achieved significant optimisation effects regarding recovery time, network connectivity, response speed, and resource utilisation. It has effectively improved the proactive resilience of the supply chain and its ability to respond to emergencies.

However, this study still has some shortcomings. For example, model assumptions are based on existing data and typical scenarios, which may not fully cover all complex real supply chain environments. In addition, the real-time performance of the dynamic adjustment mechanism still needs to be further verified in high-frequency changing scenarios. Future research can focus on improving the model's applicability, utilising more real-time data sources to enhance dynamic response capabilities, and studying multi-objective optimisation techniques to improve the resilience and effectiveness of supply chain networks.

Declarations

This work was supported by the National Social Science Fund (No.: 23BJY229).

The author declares that he has no conflicts of interest.

References

- Abaku, E.A., Edunjobi, T.E. and Odimarha, A.C. (2024) 'Theoretical approaches to AI in supply chain optimization: pathways to efficiency and resilience', *International Journal of Science and Technology Research Archive*, Vol. 6, No. 1, pp.092–107.
- Agarwal, N., Seth, N. and Agarwal, A. (2022a) 'Evaluation of supply chain resilience index: a graph theory-based approach', *Benchmarking: An International Journal*, Vol. 29, No. 3, pp.735–766.
- Agarwal, U., Rishiwal, V., Tanwar, S. et al. (2022b) 'Blockchain technology for secure supply chain management: a comprehensive review', *IEEE Access*, Vol. 10, pp.85493–85517, DOI: 10.1109/ACCESS.2022.3194319.
- Ameh, B. (2024) 'Technology-integrated sustainable supply chains: balancing domestic policy goals, global stability, and economic growth', *Int. J. Sci. Res. Arch.*, Vol. 13, No. 2, pp.1811–1828.
- Baloch, N. and Rashid, A. (2022) 'Supply chain networks, complexity, and optimization in developing economies: a systematic literature review and meta-analysis', *South Asian Journal of Operations and Logistics*, Vol. 1, No. 1, pp.14–19.
- Calzada, P.E., Sami M S U.I., Azar, K.Z. et al. (2023) 'Heterogeneous integration supply chain integrity through blockchain and CHSM', *ACM Transactions on Design Automation of Electronic Systems*, Vol. 29, No. 1, pp.1–25.
- Chen, Y., Zhu, Q. and Sarkis, J. (2024) 'Heterogeneity in corporate green supply chain practice adoption: insights from institutional fields', *Business Strategy and the Environment*, Vol. 33, No. 2, pp.389–406.
- Chukwuka, O.J., Ren, J., Wang, J. et al. (2023) 'A comprehensive research on analyzing risk factors in emergency supply chains', *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 13, No. 3, pp.249–292.
- Cui, L., Gao, M., Dai, J. et al. (2022) 'Improving supply chain collaboration through operational excellence approaches: an IoT perspective', *Industrial Management & Data Systems*, Vol. 122, No. 3, pp.565–591.
- Ergun, O., Hopp, W.J. and Keskinocak, P. (2023) 'A structured overview of insights and opportunities for enhancing supply chain resilience', *IIE Transactions*, Vol. 55, No. 1, pp.57–74.
- Gao, J., Gao, Y., Guan, T. et al. (2024) 'Inhibitory influence of supply chain digital transformation on bullwhip effect feedback difference', *Business Process Management Journal*, Vol. 30, No. 1, pp.135–157.
- Hussain, G., Nazir, M.S., Rashid, M.A. et al. (2023) 'From supply chain resilience to supply chain disruption orientation: the moderating role of supply chain complexity', *Journal of Enterprise Information Management*, Vol. 36, No. 1, pp.70–90.
- Joel, O.S., Oyewole, A.T., Odunaiya, O.G. et al. (2024) 'Leveraging artificial intelligence for enhanced supply chain optimization: a comprehensive review of current practices and future potentials', *International Journal of Management & Entrepreneurship Research*, Vol. 6, No. 3, pp.707–721.
- Kamalahmadi, M., Shekarian, M. and Parast, M.M. (2022) 'The impact of flexibility and redundancy on improving supply chain resilience to disruptions', *International Journal of Production Research*, Vol. 60, No. 6, pp.1992–2020.
- Katsaliaki, K., Galetsi, P. and Kumar, S. (2022) 'Supply chain disruptions and resilience: a major review and future research agenda', *Annals of Operations Research*, Vol. 319, No. 1, pp.965–1002.
- Kazancoglu, I., Ozbiltekin-Pala, M., Mangla, S.K. et al. (2022) 'Role of flexibility, agility and responsiveness for sustainable supply chain resilience during COVID-19', *Journal of Cleaner Production*, Vol. 362, No. 2, pp.132431–132444.

- Liu, H., Han, Y. and Zhu, A. (2022) 'Modeling supply chain viability and adaptation against underload cascading failure during the COVID-19 pandemic', *Nonlinear Dynamics*, Vol. 110, No. 3, pp.2931–2947.
- Mamasoliev, S. (2024) 'Global supply chain resilience: implications for us trade policy and national security', *American Journal of Education and Learning*, Vol. 2, No. 4, pp.525–535.
- Moosavi, J., Fathollahi-Fard, A.M. and Dulebenets, M.A. (2022) 'Supply chain disruption during the COVID-19 pandemic: recognizing potential disruption management strategies', *International Journal of Disaster Risk Reduction*, Vol. 75, pp.102983–103002, DOI: 10.1016/j.ijdr.2022.102983.
- Namdar, J., Blackhurst, J., Zhao, K. et al. (2024) 'Cascading disruptions: impact of modularity and nexus supplier predictions', *Journal of Supply Chain Management*, Vol. 60, No. 3, pp.18–38.
- Nasereddin, A. (2024) 'A comprehensive survey of contemporary supply chain management practices in charting the digital age revolution', *Uncertain Supply Chain Management*, Vol. 12, No. 2, pp.1331–1352.
- Nwagwu, U., Niaz, M., Chukwu, M.U. et al. (2023) 'The influence of artificial intelligence to enhancing supply chain performance under the mediating significance of supply chain collaboration in manufacturing and logistics organizations in Pakistan', *Traditional Journal of Multidisciplinary Sciences*, Vol. 1, No. 2, pp.29–40.
- Pan, W., So, K.C. and Xiao, G. (2022) 'Benefits of backup sourcing for components in assembly systems under supply uncertainty', *European Journal of Operational Research*, Vol. 302, No. 1, pp.158–171.
- Pasupuleti, V., Thuraka, B., Kodete, C.S. et al. (2024) 'Enhancing supply chain agility and sustainability through machine learning: optimization techniques for logistics and inventory management', *Logistics*, Vol. 8, No. 3, pp.73–89.
- Rolf, B., Jackson, I., Müller, M. et al. (2023) 'A review on reinforcement learning algorithms and applications in supply chain management', *International Journal of Production Research*, Vol. 61, No. 20, pp.7151–7179.
- Song, M., Ma, X., Zhao, X. et al. (2022) 'How to enhance supply chain resilience: a logistics approach', *The International Journal of Logistics Management*, Vol. 33, No. 4, pp.1408–1436.
- Syed, Z.A., Dapaah, E., Mapfaza, G. et al. (2024) 'Enhancing supply chain resilience with cloud-based ERP systems', *IRE Journals*, Vol. 8, No. 2, pp.106–128.
- Tavana, M., Kian, H., Nasr, A.K. et al. (2022) 'A comprehensive framework for sustainable closed-loop supply chain network design', *Journal of Cleaner Production*, Vol. 332, pp.129777–129792, DOI: 10.1016/j.jclepro.2021.129777.
- Wang, J., Hu, Y., Qu, W. et al. (2022) 'Research on emergency supply chain collaboration based on tripartite evolutionary game', *Sustainability*, Vol. 14, No. 19, pp.11893–11918.
- Wang, J., Zhou, H., Sun, X. et al. (2023) 'A novel supply chain network evolving model under random and targeted disruptions', *Chaos, Solitons & Fractals*, Vol. 170, pp.113371–113394, <https://doi.org/10.1016/j.chaos.2023.113371>.
- Xu, X., Sethi, S.P., Chung, S.H. et al. (2023) 'Reforming global supply chain management under pandemics: the GREAT-3Rs framework', *Production and Operations Management*, Vol. 32, No. 2, pp.524–546.
- Yang, M., Lim, M.K., Qu, Y. et al. (2023) 'Supply chain risk management with machine learning technology: a literature review and future research directions', *Computers & Industrial Engineering*, Vol. 175, No. 3, pp.108859–108870.
- Yang, Y., Peng, C. and Qing-Kui, L. (2022) 'Modeling and analysis of supply chain with green product change', *Cyber-Physical Systems*, Vol. 10, No. 1, pp.84–103.
- Zhao, J., Cui, S. and Xu, Z. (2025) 'Research on the closed-loop supply chain of intelligent products considering government subsidies in the context of the internet of things', *Discov. Internet Things*, Vol. 5, No. 1, p.34.