Reliability Engineering and System Safety 265 (2026) 111606

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

A quantitative metric for assessing resilience in multistate supply chain network under disruptions

Kuan-Yu Lin [a], Yi-Kuei Lin [a,b,c,*]

[a] Department of Industrial Engineering and Management, National Yang Ming Chiao Tung University, Hsinchu 300, Taiwan
[b] Department of Industrial Engineering and Management, Chaoyang University of Technology, Taichung 413, Taiwan
[c] Department of Business Administration, Asia University, Taichung 413, Taiwan

ARTICLE INFO

Keywords:
Disruptions
Network reliability
Multistate supply chain network (MSCN)
Resilience index
Supplier addition

ABSTRACT

Recent occurrences of pandemics, geopolitical tensions, and regional conflicts have considerably heightened the risk of disruptions within global supply chains. In response to the growing need for resilience assessment, a quantitative metric is formulated to measure the susceptibility of supply chains to disruptions. A supply chain network is considered, where nodes represent suppliers, assemblers, or buyers, and edges denote transportation carriers from logistics companies. As suppliers and logistics companies serve multiple clients, production and transportation capacities are not guaranteed to be fully available. Given this context, the supply chain is modeled as a multistate supply chain network (MSCN). The network reliability defined as the probability of successful delivery of goods to a buyer by the MSCN, is subsequently adopted as a basis for resilience assessment. A resilience index is formulated by evaluating changes in network reliability before and after the addition of new suppliers, thereby quantifying the impact of supplier integration under disruption scenarios. Through this metric, supply chain resilience is assessed in a quantitative manner.

1. Introduction

The widespread globalization of supply chains has become a hallmark of contemporary business practices, enabling firms to scale their operations internationally. This trend promotes operational efficiency, cost reduction, and broader market access. Nonetheless, the increasing complexity and geographical dispersion of global supply networks have heightened their vulnerability to various forms of disruption, including natural disasters, geopolitical conflicts, and unexpected health crises such as the blockage of the Suez Canal, the Great East Japan Earthquake, the U.S.-China trade war, and the COVID-19 pandemic [1,2]. For instance, the COVID-19 pandemic illustrated how local production shutdowns can trigger widespread shortages that propagate through highly specialized, globally connected supply chains, ultimately disrupting entire systems and networks [3]. Similarly, the blockage of the Suez Canal by the Ever Given in March 2021 halted approximately 12 % of daily global trade for six days and resulted in an estimated economic loss of $6 to $10 billion, further illustrating the vulnerability of global supply chains [4]. The aforementioned scenarios have had a profound impact on global supply chains, leading to extensive disruptions, logistical bottlenecks, and significant economic repercussions worldwide [5]. The abrupt and widespread nature of such disruptions underscores the inherent vulnerability of supply chains and reinforces the urgent need for resilience in responding to unforeseen events. In light of increasing uncertainty and the growing frequency of disruptive events, there is a rising need for research focused on redesigning supply chain networks to enhance resilience [5,6]. Evaluating and quantifying supply chain resilience remains a critical challenge.

In the context of supply chain management, resilience refers to the capability of a supply chain to rapidly adapt to and recover from unexpected events or disruptions, thereby restoring normal operations with minimal delay [2,7]. It encompasses not only the flexibility to respond effectively to emergencies, but also the robustness and structural durability of the supply chain. A highly resilient supply chain is capable of swiftly adapting to dynamic environments and withstanding a wide range of challenges, including natural disasters, market volatility, political instability, and global crises [8]. Supply chain resilience has become a key concept to mitigate disruptions and ensure continuity of operations in the face of challenges such as pandemics and environmental disasters [2]. Given that resilience encompasses multiple stages (before, during, and after a disruption), a resilient supply chain must exhibit dynamic capabilities such as managing supplier production capacity and logistics transportation capacity across key phases, including

* Corresponding author.
E-mail address: yklin@nycu.edu.tw (Y.-K. Lin).

https://doi.org/10.1016/j.ress.2025.111606
Received 15 April 2025; Received in revised form 4 July 2025; Accepted 19 August 2025
Available online 21 August 2025

Nomenclature

ACRONYMS

SCN	Supply chain network
MSCN	Multistate supply chain network
MP	Minimal path
MICP	Minimal integrated capacity pattern
$RSDP^+$	Recursive Sum of Disjoint Product
TEU	Twenty-foot Equivalent Unit

NOTATIONS

z	number of suppliers
s_q	qth supplier, $q = 1, 2, \ldots, z$
u	number of buyers
b_v	vth buyer, $v = 1, 2, \ldots, u$
n	number of edges
e_j	jth edge, $j = 1, 2, \ldots, z + n$
$\mathbf{E}$	$\{e_j \mid j = 1, 2, \ldots, z + n\}$: set of edges
$m_{q,v}$	number of minimal paths from qth supplier to vth buyer
$\varphi_{q,v,i}$	ith MP linking s_q and b_v, $q = 1, 2, \ldots, z$, $v = 1, 2, \ldots, u$, $i = 1, 2, \ldots, m_{q,v}$
$f_{z,u,m_{z,u}}$	flow passing through MP $\varphi_{z,u,m_{z,u}}$
F	$(f_{1,1,1}, f_{1,1,2}, \ldots, f_{1,1,m_{1,1}}, f_{1,2,1}, f_{1,2,2}, \ldots, f_{1,2,m_{1,2}}, \ldots, f_{z,u,1}, f_{z,u,2}, \ldots, f_{z,u,m_{z,u}})$: flow pattern
d_v	vth demand from vth buyer, $v = 1, 2, \ldots, u$
D	$(d_1, d_2, \ldots, d_u)$: demand pattern
g_{z+n}	current capacity of g_j, $j = 1, 2, \ldots, z + n$
G	$(g_1, g_2, \ldots, g_n, g_{z+1}, g_{z+2}, \ldots, g_{z+n})$: integrated capacity pattern
γ	consumed transportation capacity per unit of production transfer
$\beta_{j\theta_j}$	maximal integrated capacity (production capacity and transportation capacity)
$\mathrm{Pr_D}$	probability of failing to sustain the same production capacity
$\mathrm{Pr}_0\{g_j\}$	probability of supplier production capacity before the disruption, $j = 1, 2, \ldots, z$
$\mathrm{Pr}_1\{g_j\}$	probability of supplier production capacity during the disruption, $j = 1, 2, \ldots, z$
$C_q^{supplier}$	unit production cost of qth supplier, $q = 1, 2, \ldots, z$
C_j^{tran}	unit cost of consumed logistics company transport capacity through edge e_j, $j = z + 1, 2, \ldots, z + n$
C	budget
$R_{D,C}$	network reliability
$R_{D,C}^{before}$	original network reliability (without new suppliers)
$R_{D,C}^{after}$	network reliability after the addition of the new suppliers
RI	resilience index
$\mathbf{\Psi}$	set of MICP candidates
$\mathbf{\Psi}_{\min}$	$\{G \mid G$ is a minimal pattern in $\mathbf{\Psi}\}$: set to store the minimal pattern in $\mathbf{\Psi}$

preparation, adjustment, response, and recovery [9,10]. The supplier production capacity is subject to uncertainty arising from factors such as material shortages, labor disruptions, and equipment failures. Similarly, logistics companies responsible for transportation operate under limited container capacity, which can be affected by external factors such as shared usage with other clients or the rapid spread of infectious diseases. Due to the inherent uncertainty in both production and transportation, these capacities are modeled as random variables within the proposed framework. To enhance the supply chain resilience, Wei, et al. [11] emphasized that supplier integration has a significant influence on enhancing supply chain resilience. Butt [12] further investigated the impact of competitive relationships among suppliers on supply chain performance. Wei, et al. [13] responded to supply chain network disruption risk through ternary closure motifs. A key challenge is posed in evaluating the extent to which a supply chain can fulfill market demand under uncertainties in supplier production and transportation capacities, as well as in determining whether resilience can be sustained through the integration of additional suppliers. To address this issue, a quantitative indicator is proposed in this study to assess the impact of supplier integration under disruption scenarios. Through this indicator, the supply chain's ability to maintain and restore service levels can be evaluated, enabling the mitigation of disruption impacts and the enhancement of overall resilience.

Recent studies have proposed various resilience indices and strategies to enhance supply chain performance under disruptions. For instance, Zhou, et al. [8] emphasized functional recovery across disruption phases. In addition, Wang, et al. [14] highlighted the importance of incorporating regional risk factors and mitigation strategies into the supplier selection process to improve resilience. Xu, et al. [15] proposed a dynamic optimization model to measure resilience in container logistics under adverse events. In addition, Abushaega, et al. [16] developed a fairness-based multi-objective distribution and restoration model to enhance supply chain transportation recovery. Tafakkori, et al. [17] proposed a decentralized robust-stochastic capacity planning framework to improve disruption tolerance on the supply side. Although these studies offer valuable insights, most do not incorporate multistate modeling of supplier production and transportation capacities, nor do they quantify resilience through changes in probabilistic network reliability. In contrast, the resilience index proposed in this study is built upon network reliability before and after the integration of new suppliers, providing a structured and quantitative evaluation of supply chain performance under disruptions. In contrast, the resilience index proposed in this study is based on changes in probabilistic network reliability before and after supplier integration, providing a more comprehensive and quantifiable evaluation of supply chain resilience under capacity uncertainty and budget constraints.

Under the uncertainty in both production and transportation capacities, network analysis is a practical and widely used approach for evaluating the performance of real-world systems [18–21]. In the context of supply chains, the entire transportation process can be modeled as a network to support decision-makers in understanding and managing the overall system. In this paper, the activity-on-arrow diagram is adopted to represent the supply chain network (SCN), where each node corresponds to a supplier, assembler, or buyer, and each edge represents a logistics connection. Then, the SCN is modeled as a multistate supply chain network (MSCN) to more accurately capture the uncertain characteristics of both suppliers and logistics companies. In supply chain management, network reliability represents the probability of successfully transmitting demand to the terminal and is often employed as a quantitative measure of network performance. Previous research has also considered the damage rate of goods [22], budget [23,24], sustainable level [25], carbon emission [18,19], or inventory [20,26]. To evaluate network reliability, several researchers [24,27,28] have evaluated in terms of the concept of minimal path (MP) which is defined as an order sequence of arcs from the source node to the sink node without cycle. Recognizing the critical role of network reliability, a network reliability-based quantitative metric is introduced to evaluate supply chain resilience. Network reliability is defined as the probability that the MSCN can successfully deliver sufficient goods while meeting both budget and demand constraints. In this study, supplier disruptions are quantified by modeling the probability of failing to sustain normal production capacity, and network reliability is evaluated before and after the integration of additional suppliers. Through this approach, a structured assessment of supply chain resilience is enabled. In addition, a quantitative indicator is proposed to assess the effects of different supplier integration strategies under anticipated disruption scenarios, providing a foundation for informed decision-making.

The remainder of this paper is organized as follows. The proposed MSCN model is presented in Section 2. The network reliability and resilience assessment framework, along with the corresponding algorithm, is introduced in Section 3. A numerical example based on the supply chain of a leading electric vehicle manufacturer is provided in Section 4 to demonstrate the applicability of the proposed algorithm. Finally, the conclusions are summarized in Section 5.

2. MSCN model formulation

An MSCN is composed of several nodes and edges, containing z suppliers, several assemblers, and u buyers. Let $\boldsymbol{E} = \{e_j \mid 1 \le j \le z + n\}$ represents a set of $z + n$ edges. The notation s_q is denoted as the qth supplier, $q = 1, 2, \ldots, z$, and b_v is denoted as the vth buyer, $v = 1, 2, \ldots, u$. Along each edge, a supplier is responsible for providing goods and a contracted logistics company is responsible for transportation. Regardless of each supplier's available production capacity or each logistics company's available transportation capacity, it may be in one of the following states: $0 = \beta_{j1} < \beta_{j2} < \cdots < \beta_{j\theta_j}$ for $j = 1, 2, \ldots, z + 1, z + 2, \ldots, z + n$, in which θ_j shows the number of states for edge e_j and β_{jr} is the rth available production capacities or transportation capacity with $r \in \{1, 2, \ldots, \theta_j\}$. For a pair of supplier s_q and buyer b_v, there exists $m_{q,v}$ MPs connecting them, where $q \in \{1, 2, \ldots, z\}$ and $v \in \{1, 2, \ldots, u\}$. Let $\varphi_{q,v,i}$ be the ith MP linking s_q and b_v for $q = 1, 2, \ldots, z$, $v = 1, 2, \ldots, u$, $i = 1, 2, \ldots, m_{q,v}$. To evaluate the network reliability of MSCN, this research adheres further to the following assumptions:

I. The flow in the MSCN is an integer value.
II. The transportation (production) capacities of different logistics companies (suppliers) in the MSCN both before and during disruptions are statistically independent.
III. The flow in the MSCN must satisfy the flow-conservation law [29].
IV. All existing and newly integrated suppliers in the MSCN are presumed to be readily available to engage in supply chain operations without delay.

2.1. Relationship between flow pattern and capacity pattern

The flow pattern is denoted as $F = (f_{1,1,1}, f_{1,1,2}, \ldots, f_{1,1,m_{1,1}}, f_{1,2,1}, f_{1,2,2}, \ldots, f_{1,2,m_{1,2}}, \ldots, f_{z,u,1}, f_{z,u,2}, \ldots, f_{z,u,m_{z,u}})$ with $f_{z,u,m_{z,u}}$ being the flow passing through MP $\varphi_{z,u,m_{z,u}}$. Any flow pattern is said to fulfill the demand pattern $D = (d_1, d_2, \ldots, d_u)$ if it satisfies Eq. (1)

$$\sum_{q=1}^{z} \left\{ \sum_{i=1}^{m_{q,v}} f_{q,v,i} | m_{q,v} \neq 0 \right\} = d_v, \ \ v = 1, 2, \ldots, u. \tag{1}$$

The condition '$m_{q,v} \neq 0$' means at least one MP connecting s_q and b_v. $\sum_{q=1}^{z} \left\{ \sum_{i=1}^{m_{q,v}} f_{q,v,i} | m_{q,v} \neq 0 \right\}$ signifies the total flow entering the buyer b_v.

Additionally, let $G = (g_1, g_2, \ldots, g_n, g_{z+1}, g_{z+2}, \ldots, g_{z+n})$ be the integrated capacity pattern which is composed of the production capacity and the transportation capacity. The elements of the integrated capacity pattern G from g_1 to g_z are represented the current production capacity of supplier and g_{z+1} to g_{z+n} are represented current transportation capacity of edge. Any flow pattern F is said to be feasible under the integrated capacity pattern G if it meets the following constraints:

$$\sum_{v: s_q \in \varphi_{q,v,i}} \sum_{i=1}^{m_{q,v}} f_{q,v,i} \le g_j, j = 1, 2, \ldots, z, \tag{2}$$

$$\left[\gamma \sum_{q=1}^{z} \sum_{v=1}^{u} \sum_{i: e_j \in \varphi_{q,v,i}} f_{q,v,i} \right] \le g_j, j = z + 1, z + 2, \ldots, z + n. \tag{3}$$

Constraint (2) signifies the required production capacity of supplier by the flow passing through MP $\varphi_{q,v,i}$ should not exceed the current production capacity. The symbol γ is the consumed transportation capacity per unit for product transporting. Constraint (3) means the required transportation capacity should not exceed the current transportation capacity. To easily display all F feasible under G, any F is said to be feasible under the maximal integrated capacity (production capacity and transportation capacity),

$$\sum_{v: s_q \in \varphi_{q,v,i}} \sum_{i=1}^{m_{q,v}} f_{q,v,i} \le \beta_{j\theta_j}, j = 1, 2, \ldots, z, \tag{4}$$

$$\left[\gamma \sum_{q=1}^{z} \sum_{v=1}^{u} \sum_{i: e_j \in \varphi_{q,v,i}} f_{q,v,i} \right] \le \beta_{j\theta_j} j = z + 1, z + 2, \ldots, z + n. \tag{5}$$

Constraint (4) represents that the consumed production capacity of the supplier s_q should not exceed its maximal production capacity and constraint (4) shows that the consumed transportation capacity by the logistics company above edge e_j should not exceed its maximal transportation capacity.

2.2. Establishment of supplier production probability table

Due to the rapid spread of diseases like covid-19, monkeypox, and malaria, as well as natural disasters such as floods and earthquakes pandemic, suppliers were unable to obtain raw materials as expected, resulting in disruptions and a reduced probability of each production capacity. To measure the severity of the disruption, the variable $\mathrm{Pr_D}$ is defined as the probability that a supplier fails to maintain its original production capacity. In contrast, the probability of sustaining the same production level during the disruption is given by $(1 - \mathrm{Pr_D})$. The value of $\mathrm{Pr_D}$ may differ among suppliers depending on their geographic locations or the degree to which they are impacted by unexpected events. In conclusion, disruption is defined in this study as a situation where the supply chain is unable to steadily satisfy demand due to a sudden pandemic affecting suppliers.

In an MSCN, the production capacity during disruption can be calculated by multiplying the probability of being able to produce normally during the disruption, $\mathrm{Pr_D}$, directly by the production capacity probability table generated from historical data. Since there are two situations: maintaining the same production capacity and being unable to produce during the disruption, different calculations apply to each situation. If there is production capacity g_j during the disruption, then $g_j = 0, 1, 2, \ldots, \beta_{j\theta_j}$, $j = 1, 2, \ldots, z$. Let $\mathrm{Pr}_0\{g_j\}$ and $\mathrm{Pr}_1\{g_j\}$ represent the probability of the production capacity g_j before and during the disruption respectively. The supplier production capacity probability under the disruption can be constructed eventually as the following equation.

$$\mathrm{Pr}_1\left\{g_j\right\} = \begin{cases} (1 - \mathrm{Pr_D}) \times \mathrm{Pr}_0\left\{g_j\right\}, \text{when} g_j = 1, 2, \ldots, \beta_{j\theta} \\ 1 - \sum_{g_j=1}^{\beta_{j\theta}} \left[(1 - \mathrm{Pr_D}) \times \mathrm{Pr}_0\left\{g_j\right\} \right], \text{when} g_j = 0 \end{cases}, j = 1, 2, \ldots, z. \tag{6}$$

An example of a supplier production capacity probability table is shown in Table 1 to illustrate Eq. (6). For instance, when there is 50 % ($\mathrm{Pr_D} = 0.5$) that the supplier cannot maintain the same production capacity, the probability that the supplier can supply 3 units of goods during disruption would be revised as $(1 - 0.5) \times 0.7 = 0.35$. The probability of being unable to supply during the disruption is $1 - [0.5 \times 0.7 + 0.5 \times 0.15 + 0.5 \times 0.1] = 0.525$. Comparing the probability that the supplier can supply 3 units of goods before and during the

Table 1
The production capacity probability table.

Supplier	Probability	
Production capacity	Before disruption	During disruption
3	0.7	0.35
2	0.15	0.075
1	0.1	0.05
0	0.05	0.525

disruption, the probability decreased from 70 % to 35 %. This indicates the impact of the disruption on the supplier's supply.

2.3. Budget constraint

It should be noted that the unit production cost of qth supplier is denoted by $C_q^{supplier}$, $q = 1, 2, \ldots, z$ and the per unit cost of consumed capacity through edge e_j for transportation is denoted by C_j^{tran}, $j = 1, 2, \ldots, n$. The volume of capacity utilized affects the cost of production for a supplier, and the total supplier production cost for any flow pattern is calculated by adding up the supplier production costs among all suppliers. The logistics company transport cost for a route is affected by the volume of capacity utilized, and the total logistics company transportation cost for any flow pattern is computed by adding up the logistics company transportation costs along all edges. The total cost consists of the total supplier production cost and the total logistics company transportation cost. Thus, any flow pattern F is within the budget C if and only if it satisfies

$$\sum_{q=1}^{z}\left(C_q^{supplier}\sum_{v:s_q\in\varphi_{q,v,i}}\sum_{i=1}^{m_{q,v}}f_{q,v,i}\right)+\sum_{j=z+1}^{z+n}C_j^{tran}\left[\gamma\sum_{q=1}^{z}\sum_{v=1}^{u}\sum_{i:e_j\in\varphi_{q,v,i}}f_{q,v,i}\right]\leq C, \qquad (7)$$

where $\sum_{q=1}^{z}\left(C_q^{supplier}\sum_{v:s_q\in\varphi_{q,v,i}}\sum_{i=1}^{m_{q,v}}f_{q,v,i}\right)$ represents the supplier production cost that qth supplier provides $\sum_{v:s_q\in\varphi_{q,v,i}}\sum_{i=1}^{m_{q,v}}f_{q,v,i}$ goods and $\sum_{j=z+1}^{z+n}C_j^{tran}\left[\gamma\sum_{q=1}^{z}\sum_{v=1}^{u}\sum_{i:e_j\in\varphi_{q,v,i}}f_{q,v,i}\right]$ denotes the logistics company transportation costs through edge e_j. Constraint (7) requires that the total cost cannot exceed budget C.

3. Network reliability and resilience evaluation

In this section, network reliability is first defined for an MSCN, and the minimal integrated capacity pattern is introduced to efficiently determine network reliability. Next, a quantitative metric for assessing resilience is developed. Finally, an algorithm is developed for evaluating network reliability and resilience.

3.1. Definition of network reliability and minimal integrated capacity pattern

The network reliability $R_{D,C}$ is the probability that the MSCN meets the demand D and budget C. Let $\boldsymbol{\rho} \equiv \{G|G$ satisfies all requirements of the demand D, budget C $\}$. The network reliability $R_{D,C}$ can be represented as

$$R_{D,C} = \sum_{G\in\rho}\Pr\{G\}. \qquad (8)$$

By the assumption 2, Pr $\{G\}$ can be calculated as $\Pr\{g_1\} \times \Pr\{g_2\} \times \ldots \times \Pr\{g_z\} \times \Pr\{g_{z+1}\} \times \Pr\{g_{z+2}\} \times \ldots \times \Pr\{g_{z+n}\}$. However, when the network is of considerable magnitude, it becomes impractical to search for all feasible G and aggregate their corresponding probabilities to determine $R_{D,C}$. In order to efficiently determine $R_{D,C}$, the minimal integrated capacity pattern (MICP) is defined as if $V \in \boldsymbol{\rho}$ and any integrated capacity vector U with $U < V$ such that $U \notin \boldsymbol{\rho}$, then V is called a MICP. That is, a MICP is the minimal one from $\boldsymbol{\rho}$. Additionally, the relationships between any two integrated capacity vectors V and U are further defined as follows,

- $V \leq U$: $(v_1, v_2, \ldots, v_n, v_{n+1}, v_{n+2}, \ldots, v_{n+z}) \leq (u_1, u_2, \ldots, u_n, u_{n+1}, u_{n+2}, \ldots, u_{n+z})$ if and only if $v_i \leq u_i$ for each i.
- $V < U$: if and only if $V \leq U$ and $v_i < u_i$ for at least one i.

To clarify the situation, let $\boldsymbol{\Psi}$ be the set of MICP candidates and $\boldsymbol{\Psi}_{\min} = \{V|V$ is minimal in $\boldsymbol{\Psi}\}$. For finding all MICPs, Procedure is applied as follows.

Procedure: The comparison procedure for generating all MICPs.
Input: $\boldsymbol{\Psi} = \{G_1, G_2, \ldots, G_w\}$ // w is the number of MICP candidates
Set $\boldsymbol{\Psi}_{\min} \leftarrow \varnothing$, $I \leftarrow \varnothing$.
FOR $j \leftarrow 1$ to $w - 1$ and $j \notin I$
FOR $k \leftarrow k + 1$ to w and $k \notin I$
IF $G_j > G_k$ //G_j does not belong to $\boldsymbol{\Psi}_{\min}$.
$I \leftarrow I \cup \{j\}$.
BREAK //Next j
ELSE IF $G_j \leq G_k$ //G_k does not belong $\boldsymbol{\Psi}_{\min}$.
$I \leftarrow I \cup\{k\}$.
END IF
END FOR
$\boldsymbol{\Psi}_{\min} \leftarrow \boldsymbol{\Psi}_{\min} \cup G_j$
END FOR
Output: $\boldsymbol{\Psi}_{\min}$ // all MICPs that we find.

After executing the Procedure 1, suppose it is found w MICPs: $G_1, G_2, \ldots, G_w$. The network reliability can be can be rewritten to $\Pr\{\bigcup_{k=1}^{w} G|G \geq G_k\}$, and Recursive Sum of Disjoint Product (RSDP^{+}) [30] is one of an efficient method to efficiently calculate such the probability.

3.2. Development of a quantitative metric for assessing resilience

Network reliability refers to the probability that the supply chain network can fulfill the required demand under given disruption scenarios. It reflects the system's operational success based on the availability of supplier production and transportation capacities. In contrast, resilience captures the supply chain's ability to adapt to and recover from disruptions. While network reliability is a static, scenario-specific performance measure, resilience emphasizes the comparative improvement or sustainability of performance before and after a disruption response strategy is implemented. When a supply chain disruption occurs, suppliers would be unable to sustain the same production capacity. To mitigate the impact of supply chain disruptions, finding new suppliers has become a critical strategy. In the event of a disruption, let $R_{D,C}^{before}$ be the original network reliability (without new suppliers) and $R_{D,C}^{after}$ be the network reliability after the addition of the new suppliers. Then, the resilience index denoted as RI, a quantitative metric for assessing resilience, is developed based on these two network reliabilities and is expressed as follows:

$$RI = R_{D,C}^{after} - R_{D,C}^{before}. \qquad (11)$$

The resilience index RI is defined as a quantitative indicator ranging from 0 to 1, reflecting the supply chain's capability to sustain operations and recover under disruption. This metric quantifies the impact of integrating new suppliers on the ability of the current supply chain to meet demand. Additionally, it serves as a reference for supplier selection, ultimately contributing to the achievement of the supply chain resilience objectives established by management.

3.3. Algorithm for assessing network reliability and resilience under disruptions

The flow chart of the proposed algorithm is shown in Fig. 1. For all

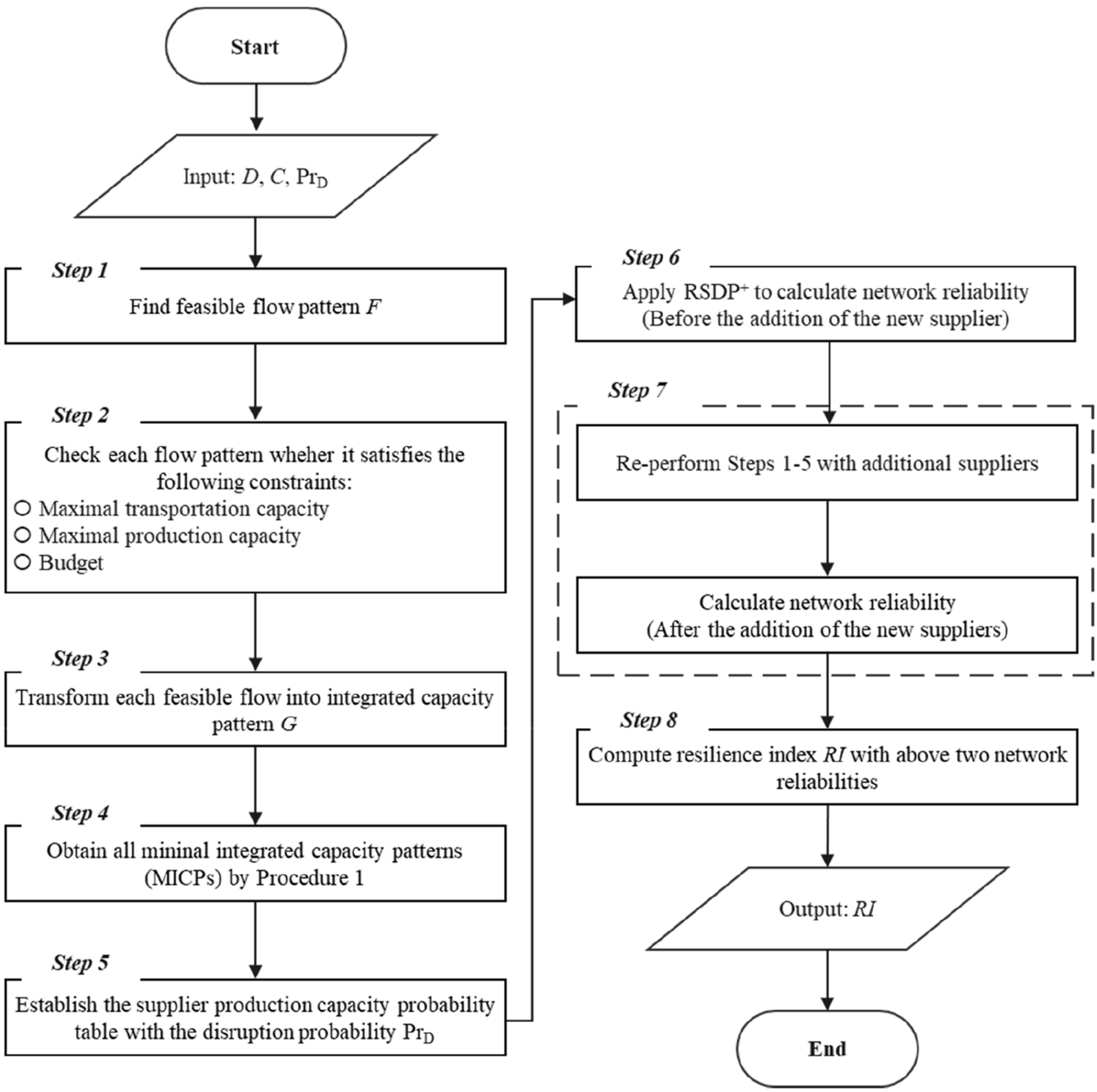

Fig. 1. The flow chart of the proposed algorithm.

MPs, carrier transport cost, and supplier production cost are known in advance in an MSCN. Given demand pattern D from all buyer, budget C, and the probability $\mathrm{Pr_D}$ of failing to sustain the production capacity, an algorithm is developed to evaluate network reliability and resilience for an MSCN as follows.

Network reliability and resilience algorithm//Evaluate network reliability and resilience for an MSCN.

Input: D, C, $\mathrm{Pr_D}$

Step 1. Find all flow pattern $F = (f_{1,1,1}, f_{1,1,2}, \ldots, f_{1,1,m_{1,1}}, f_{1,2,1}, f_{1,2,2}, \ldots, f_{1,2,m_{1,2}}, \ldots, f_{z,u,1}, f_{z,u,2}, \ldots, f_{z,u,m_{z,u}})$ that meet the demand pattern $D = (d_1, d_2, \ldots, d_u)$

$$\sum_{q=1}^{z}\left\{\sum_{i=1}^{m_{q,v}} f_{q,v,i} \middle| m_{q,v} \neq 0\right\} = d_v, v = 1, 2, \ldots, u. \tag{12}$$

Step 2. Check each flow pattern F which is obtained in step 1 whether it satisfies the following constraints.

2.1. *The maximal transportation capacity of the logistics company*

$$\left[\gamma \sum_{q=1}^{z}\sum_{v=1}^{u}\sum_{i:e_j\in\varphi_{q,v,i}} f_{q,v,i}\right] \leq \beta_{j\theta_j}, j = z+1, z+2, \ldots, z+n. \tag{13}$$

2.2. *The maximal production capacity of the supplier*

$$\sum_{v:s_q\in\varphi_{q,v,i}}\sum_{i=1}^{m_{q,v}} f_{q,v,i} \leq \beta_{j\theta_j}, j = 1, 2, \ldots, n. \tag{14}$$

2.3. Budget

$$\sum_{q=1}^{z}\left(C_q^{supplier}\sum_{v:s_q\in\varphi_{q,v,i}}\sum_{i=1}^{m_{q,v}}f_{q,v,i}\right)+\sum_{j=z+1}^{z+n}C_j^{tran}\left[\gamma\sum_{q=1}^{z}\sum_{v=1}^{u}\sum_{i:e_j\in\varphi_{q,v,i}}f_{q,v,i}\right]\leq C. \tag{15}$$

Delete the flow pattern F as long as one of the constraints is not met.

Step 3. Transform each feasible flow pattern F from step 2 into the integrated capacity pattern $G = (g_1, g_2, \ldots, g_n, g_{z+1}, g_{z+2}, \ldots, g_{z+n})$ via

$$g_j = \beta_{jr}\text{where}\,\beta_{j(r-1)} < \sum_{v:s_q\in\varphi_{q,v,i}}\sum_{i=1}^{m_{q,v}}f_{q,v,i}\leq\beta_{jr}, j=1,2,\ldots,z, \tag{16}$$

$$g_j = \beta_{jr}\text{where}\beta_{j(r-1)} < \left[\gamma\sum_{q=1}^{z}\sum_{v=1}^{u}\sum_{i:e_j\in\varphi_{q,v,i}}f_{q,v,i}\right]\leq\beta_{jr}, j = z+1, z+2, \ldots, z+n. \tag{17}$$

Step 4. Each G is an MICP candidate, and check each G whether it is a MICP by Procedure 1.

Step 5. Establish the supplier production probability table with the disruption probability $\mathrm{Pr_D}$.

$$\mathrm{Pr}_1\{g_j\}=\begin{cases}(1-\mathrm{Pr_D})\times\mathrm{Pr}_0\{g_j\}, \text{when} g_j=1,2,\ldots,\beta_{j\theta} \\ 1-\sum_{g_j=1}^{\beta_{j\theta}}\left[(1-\mathrm{Pr_D})\times\mathrm{Pr}_0\{g_j\}\right], \text{when} g_j=0\end{cases} j=1,2,\ldots,z. \tag{18}$$

Step 6. Suppose there are a MICPs: $G_1, G_2, \ldots, G_a$ obtained from step 4 and according to the supplier production probability table obtained from step 5, use RSDP$^+$ to derive the network reliability $R_{D,C}^{before} = \Pr\{\bigcup_{k=1}^{a} G|G\geq G_k\}$ before the addition of the new supplier.

Step 7. *Re*-perform steps 1 through 5 based on the newly added supplier, obtain h MICPs, and use RSDP$^+$ to calculate the network reliability $R_{D,C}^{after} = \Pr\{\bigcup_{k=1}^{h} G|G\geq G_k\}$ after the addition of the new supplier.

Step 8. Compute the resilience index via

$$RI = R_{D,C}^{after} - R_{D,C}^{before}. \tag{19}$$

Output: *RI*

From Step 1 to Step 2, all feasible flow patterns are generated, satisfying demand, budget, and maximum transportation (or production) capacity constraints. Based on these feasible flow patterns, integrated capacity patterns are derived from Step 3, and the minimal integrated capacity patterns are obtained through Procedure 1 in Step 4. In Step 5, the supply volume probabilities of each supplier under disruption scenarios are adjusted accordingly. The RSDP$^+$ is employed in Step 6 to calculate network reliability $R_{D,C}^{before}$ in the absence of new suppliers. With the inclusion of new suppliers in Step 7, the Steps 1 through 5 are executed to evaluate network reliability $R_{D,C}^{after}$. Finally, the difference between the two network reliability values as a resilience metric is computed in Step 8, providing decision-makers with guidance in identifying suitable new suppliers while maintaining supply chain resilience under disruption conditions.

4. Numerical example

In this section, the impact of disruptions on newly sought suppliers is examined, considering factors such as geographical location, supply chain dependencies, and external conditions like geopolitical issues, natural disasters, or global crises. Events such as the COVID-19 pandemic, trade wars, or geopolitical tensions can severely disrupt supply chains by causing border closures, export restrictions, labor shortages, and transportation bottlenecks. In practice, the new supplier may also be affected if they operate within the disrupted region or rely on impacted logistics, raw materials, or regulatory environments. As a result, they may face similar constraints as existing suppliers, leading to continued shortages, production delays, and an unreliable supply chain. Conversely, if the new supplier is located outside the disruption zone, has diversified supply sources, or operates in a stable economic and regulatory environment, they can at least maintain the original supply stability, helping to mitigate risks and enhance supply chain resilience. Analyzing these two scenarios allows for a better assessment of seeking new suppliers during disruptions and their impact on overall supply chain stability.

4.1. Scenario 1: the added suppliers are affected by the disruptions

In 2022 and 2023, a leading electric vehicle manufacturer faced significant challenges in securing lithium, a critical material for EV batteries. The company initially relied on lithium sourced from suppliers in South America and Australia. However, global logistics disruptions caused by the COVID-19 pandemic, combined with geopolitical tensions and export restrictions, created severe bottlenecks in the supply chain. To address the issue, the company shifted its focus to U.S.-based suppliers in an effort to reduce dependency on international sources and mitigate risks. Despite this adjustment, the U.S. suppliers encountered their own constraints, including limited production capacity and shortages of upstream materials, which resulted in further delays. Consequently, the company struggled to meet production schedules, faced rising costs for battery materials, and experienced difficulties in fulfilling growing market demand.

The supply chains before and after the addition of suppliers are shown in Figs. 2a and 2b, respectively. In this case, based on the monthly demand for electric vehicles in North America and Europe, the critical material for EV batteries required for the month are approximately 300 tons and 200 tons, respectively. Every unit is counted in terms of 100, and the orders are thus three and two units (i.e., $D = (3, 2)$). This critical material for EV batteries delivered through the ocean and land shipping is filled into Twenty-foot Equivalent Unit (TEU) containers. Each TEU (container) contains 20 tons. In other words, one unit of critical material for EV batteries consumes approximately 5 TEU. In addition, each supplier and contracted logistics company has several available capacities with probability distributions determined through long-term observations. The data on production and transportation capacity, as well as production and transportation costs before the disruption, without the newly added supplier and with the newly added supplier, are listed in Tables 2 and 3, respectively.

The proposed algorithm is implemented in Python and run on a personal computer with Intel Core Ultra 9 185H and 16GB RAM. Under the demand $D = (3, 2)$, budget $C = 5650$, and the disruption probability PrD for all suppliers is equal to 0.2, the result of the network reliabilities $R_{(3,2),5650}^{before}$, $R_{(3,2),5650}^{after}$ and the quantitative metric for assessing resilience *RI* are computed by the following steps.

Input: $D = (3, 2)$, $C = 5650$, $\mathrm{Pr_D} = 0.2$

Step 1. Find all flow pattern $F = (f_{1,1,1}, f_{1,2,1}, f_{2,1,2}, f_{2,2,2})$ that meet the demand pattern $D = (3, 2)$ as follows

$$f_{1,1,1} + f_{2,1,2} = 3,$$
$$f_{1,2,1} + f_{2,2,2} = 2.$$

Then, a total of eight feasible flow patterns are found and listed in Table 4.

Step 2. According to the feasible flow patterns found in Step 1, check whether each flow pattern satisfies the following three constraints.

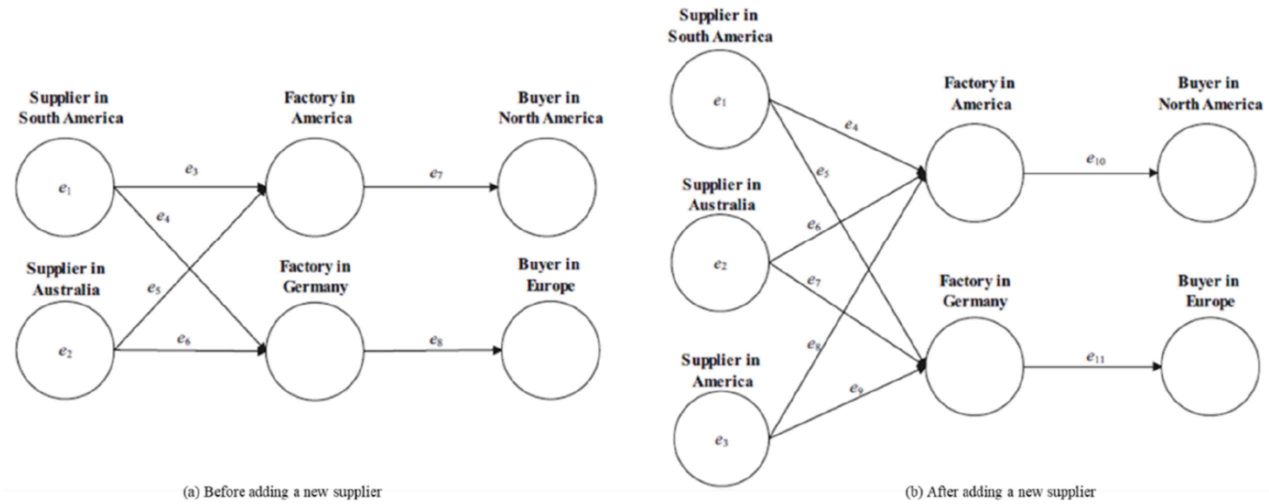

Fig. 2. The supply chain of electric vehicle manufacturer.

Table 2
The data on capacity and cost before disruption without newly added supplier.

Supplier		Cost* (Unit: USD)	Available capacity's probability** Pr(0)	Pr(1)	Pr(2)	Pr(3)	Pr(4)
South America	e_1	150	0.01	0.04	0.1	0.15	0.7
Australia	e_2	175	0.01	0.14	0.1	0.75	
Edge	e_3	480	0.01	0.01	0.01	0.1	0.87
	e_4	450	0.01	0.05	0.07	0.87	
	e_5	650	0.01	0.02	0.07	0.1	0.8
	e_6	550	0.01	0.03	0.06	0.9	
	e_7	500	0.01	0.02	0.05	0.1	0.82
	e_8	520	0.01	0.05	0.09	0.85	

* Cost is counted in terms of unit of order.
** Available capacity is counted in terms of unit of five TEU.

Table 3
The data on capacity and cost before disruption with newly added supplier.

Supplier		Cost* (Unit: USD)	Available capacity's probability** Pr(0)	Pr(1)	Pr(2)	Pr(3)	Pr(4)
South America	e_1	150	0.01	0.04	0.1	0.15	0.7
Australia	e_2	175	0.01	0.14	0.1	0.75	
America	e_3	170	0.01	0.14	0.14	0.71	
Edge	e_4	480	0.01	0.01	0.01	0.1	0.87
	e_5	450	0.01	0.05	0.07	0.87	
	e_6	650	0.01	0.02	0.07	0.1	0.8
	e_7	550	0.01	0.03	0.06	0.9	
	e_8	400	0.01	0.07	0.04	0.88	
	e_9	420	0.01	0.05	0.09	0.85	
	e_{10}	500	0.01	0.02	0.05	0.1	0.82
	e_{11}	520	0.01	0.05	0.09	0.85	

* Cost is counted in terms of unit of order.
** Available capacity is counted in terms of unit of five TEU.

Table 4
The feasible flow patterns.

Flow pattern $F = (f_{1,1,1}, f_{1,2,1}, f_{2,1,2}, f_{2,2,2})$
(0, 2,3,0)
(1, 1, 2, 1)
(1, 2, 2, 0)
(2, 0, 1, 2)
(2, 1, 1, 1)
(2, 2, 1, 0)
(3, 0, 0, 2)
(3, 1, 0, 1)

2.1. The maximal transportation capacity of the logistics company constraint

$$\lceil 1 \times f_{1,1,1} \rceil \le 4, \lceil 1 \times f_{1,2,1} \rceil \le 3,$$
$$\lceil 1 \times f_{2,1,2} \rceil \le 4, \lceil 1 \times f_{2,2,2} \rceil \le 3,$$
$$\lceil 1 \times f_{1,1,1} + 1 \times f_{2,1,2} \rceil \le 4,$$
$$\lceil 1 \times f_{1,2,1} + 1 \times f_{2,2,2} \rceil \le 3.$$

2.2. The maximal production capacity of the supplier constraint

$$f_{1,1,1} + f_{1,2,2} \le 4,$$
$$f_{2,1,2} + f_{2,2,2} \le 3.$$

2.3. Budget constraint

$$150 \times (f_{1,1,1} + f_{1,2,2}) + 175 \times (f_{2,1,2} + f_{2,2,2}) +$$
$$480 \times \lceil 1 \times f_{1,1,1} \rceil + 450 \times \lceil 1 \times f_{1,2,1} \rceil +$$
$$650 \times \lceil 1 \times f_{2,1,2} \rceil + 550 \times \lceil 1 \times f_{2,2,2} \rceil +$$
$$500 \times \lceil 1 \times f_{1,1,1} + 1 \times f_{2,1,2} \rceil +$$
$$520 \times \lceil 1 \times f_{1,2,1} + 1 \times f_{2,2,2} \rceil \le 5650.$$

After checking, a total of five feasible flow patterns are obtained and listed in Table 5.

Step 3. Each feasible F from step 2 is transformed into $G = (g_1, g_2, \ldots, g_8)$ via,

$$\begin{cases} g_1 = \beta_{1r}, \text{if} \beta_{1(r-1)} < f_{1,1,1} + f_{1,2,2} \le \beta_{1r} \\ g_1 = 0, \text{otherwise} \end{cases},$$

$$\begin{cases} g_2 = \beta_{2r}, \text{if} \beta_{2(r-1)} < f_{2,1,1} + f_{2,2,2} \le \beta_{2r} \\ g_2 = 0, \text{otherwise} \end{cases},$$

$$\begin{cases} g_3 = \beta_{3r}, \text{if} \beta_{3(r-1)} < \lceil 1 \times f_{1,1,1} \rceil \le \beta_{3r} \\ g_3 = 0, \text{otherwise} \end{cases},$$

$\vdots$

$$\begin{cases} g_8 = \beta_{8r}, \text{if} \beta_{8(r-1)} < \lceil 1 \times f_{1,2,1} + 1 \times f_{2,2,2} \rceil \le \beta_{8r} \\ g_8 = 0, \text{otherwise} \end{cases}.$$

Table 5
The results of checking three constraints.

Flow pattern $F = (f_{1,1,1}, f_{1,2,1}, f_{2,1,2}, f_{2,2,2})$	Maximal transportation capacity	Maximal production capacity	Budget
(0, 2,3,0)	✓	✓	5740 (X)
(1, 1, 2, 1)	✓	✓	5645
(1, 2, 2, 0)	✓	✓	5720 (X)
(2, 0, 1, 2)	✓	✓	5550
(2, 1, 1, 1)	✓	✓	5625
(2, 2, 1, 0)	✓	✓	5700 (X)
(3, 0, 0, 2)	✓	✓	5530
(3, 1, 0, 1)	✓	✓	5605

Then, a total of five MICP candidates are shown in Table 6.

Step 4. Executing the comparison process and removing the non-minimal ones from those G of step 3 to obtain all MICPs. After executing, a total of five MICPs are obtained.

Step 5. Eighty percent of suppliers maintain the same production capacity, while 20 % are unable to produce. For instance, if the South American supplier provides 4 units, the probability of supplying 4 units during the disruption is calculated as follows:

$$\Pr_1\{g_1 = 4\} = (1 - \Pr_D) \times \Pr_0\{g_1 = 4\} = (1 - 0.2) \times 0.7 = 0.56.$$

The probability of being unable to provide products during the disruption is:

$$\Pr_1\{g_1 = 0\} = 1 - (1 - 0.2) \times [0.7 + 0.15 + 0.1 + 0.04] = 0.208.$$

Finally, the adjustments in production capacity probabilities during disruption for the two suppliers are listed in Table 7.

Step 6. Based on the five MICPs from Step 4 and the adjusted probability table from Step 5, the network reliability $R^{before}_{(3,2),5650} = \Pr\{\bigcup_{k=1}^{5} G | G \geq G_k\} = 0.4829$ before adding new supplier is calculated by using the RSDP$^+$.

Step 7. *Re*-perform Steps 1–5 based on the newly added supplier. The adjusted production capacity probability for the new supplier though Step 5 is shown in Table 8, and the network reliability $R^{after}_{(3,2),5650} = 0.732$ after the addition of the new supplier is calculated by RSDP$^+$.

Step 8. The resilience index (RI), a quantitative metric for assessing resilience, is computed as $RI = R^{after}_{(3,2),5650} - R^{before}_{(3,2),5650} = 0.732 - 0.4829 = 0.2491$.

4.2. Scenario 2: the added suppliers are not affected by the disruptions

As the U.S.-China trade war escalated and global geopolitical risks increased, the company not only implemented measures to secure its lithium supply chain but also strengthened collaborations with battery suppliers in other parts of Asia. This strategy aimed to diversify battery production and mitigate potential risks associated with trade restrictions and tariffs. Under this scenario, the newly added supplier remained unaffected by disruptions, ensuring a stable flow of critical materials and production continuity.

The network diagram (Fig. 2) and probability tables (Tables 2 and 3) introduced in Section 4.1 are used for a simple demonstration to compute the network reliability $R^{after}_{(3,2),5650}$ and the resilience index RI under the scenario where the added supplier is not affected by the disruptions. The flow chart of the proposed algorithm under Scenario 2 is shown in Fig. 3.

Table 6
The transformation results into MICP candidates.

$F = (f_{1,1,1}, f_{1,2,1}, f_{2,1,2}, f_{2,2,2})$	$G = (g_1, g_2, \ldots, g_8)$
(1, 1, 2, 1)	(2, 3, 1, 1, 2, 1, 3,2)
(2, 0, 1, 2)	(2, 3, 2, 0, 1, 2, 3, 2)
(2, 1, 1, 1)	(3, 2, 2, 1, 1, 1, 3, 2)
(3, 0, 0, 2)	(3, 2, 3, 0, 0, 2, 3, 2)
(3, 1, 0, 1)	(4, 1, 3, 1, 0, 1, 3, 2)

Table 7
The adjusted production capacity probabilities during disruption.

	Supplier in South America (e_1)		Supplier in Australia (e_2)	
	Probability			
Production capacity	Before disruption	During disruption	Before disruption	During disruption
4	0.7	0.56	0	0
3	0.15	0.12	0.75	0.6
2	0.1	0.08	0.1	0.08
1	0.04	0.032	0.14	0.112
0	0.01	0.208	0.01	0.208

Table 8
The adjusted production capacity probabilities of the newly added supplier during the disruption.

Supplier in America (e_3)		
	Probability	
Production capacity	Before disruption	During disruption
3	0.71	0.568
2	0.14	0.112
1	0.14	0.112
0	0.01	0.208

Regarding the algorithm presented in this paper, the probability of production capacity for the newly added suppliers does not require adjustment in Step 7, as their operations remain stable. The remaining steps are identical to those in Scenario 1. As a result, the network reliability $R^{after}_{(3,2),5650} = 0.7863$ after the addition of the new supplier is calculated using RSDP$^+$. Instead, the resilience index is derived by calculating the network reliability before and after the inclusion of new supplier during the disruption period and then measuring the difference: $RI = 0.7863 - 0.4829 = 0.3034$.

5. Discussion

Compared to the first scenario, the resilience index in scenario 2 has been increased by nearly 5 %, indicating a significant improvement in the supply chain's ability to withstand disruptions. This increase indicates that the addition of a new supplier, unaffected by the disruption, enhances network reliability and overall supply chain resilience. The resilience index highlights the importance level of strategic supplier selection in mitigating risks and ensuring supply chain stability, providing a quantitative assessment of the supply chain's adaptability to external shocks for a more comprehensive evaluation of its resilience.

We further evaluate the impact of disruption probability $\Pr_D$ representing the likelihood of failing to sustain production capacity on the network reliability. The impact of varying $\Pr_D$ from 0 to 0.9 in increments of 0.1 on network reliability and resilience index are presented in Table 9. As $\Pr_D$ increases, a sharp decline in network reliability is observed, revealing the network's vulnerability to disruptions. When $\Pr_D = 0$, a 10 % increase in network reliability is achieved through the addition of a new supplier. Improvements in network reliability are observed under both Scenario 1 and Scenario 2, with Scenario 2 consistently demonstrating greater resilience across all levels of $\Pr_D$. At $\Pr_D = 0.5$, resilience is improved by up to 38 % in Scenario 2, compared to 20 % in Scenario 1.

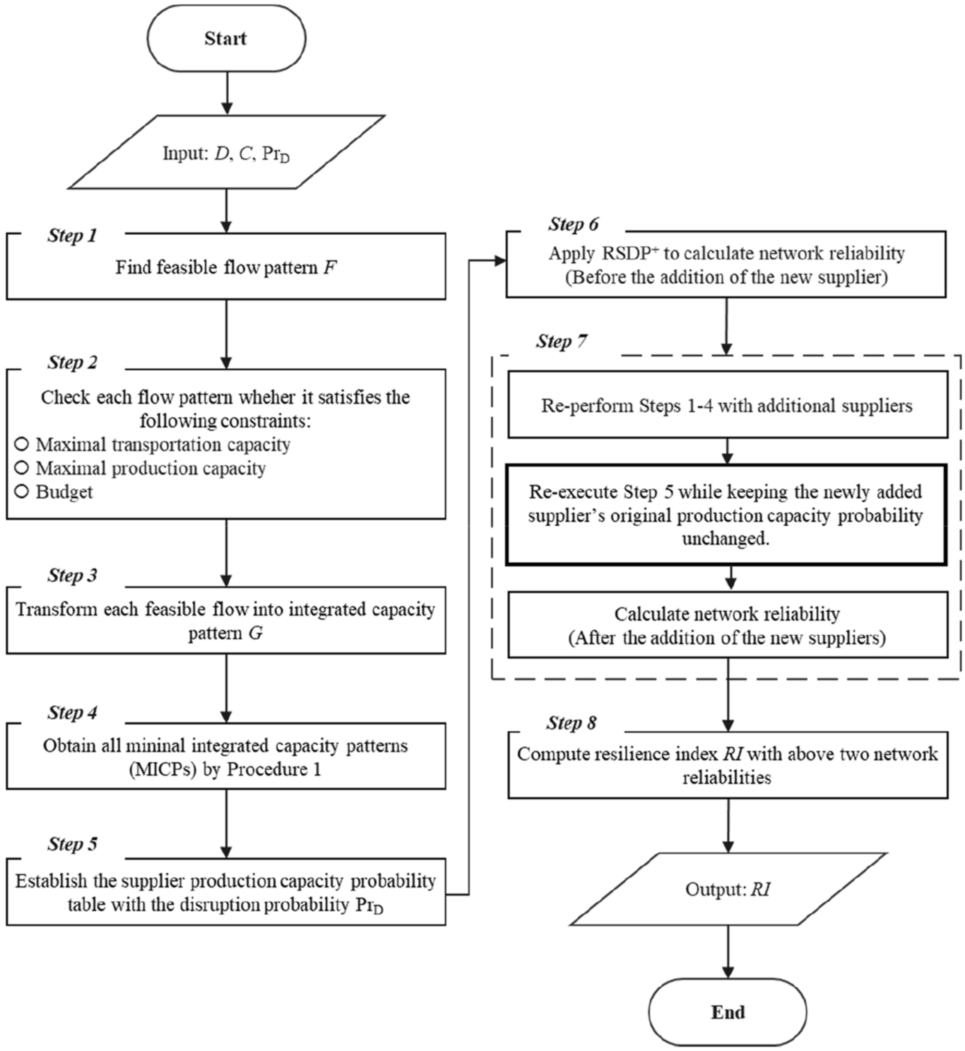

Fig. 3. The flow chart of the proposed algorithm under scenario 2.

6. Conclusions

A quantitative metric based on network reliability was proposed to evaluate the resilience of a supply chain network under disruption scenarios. By modeling both supplier production capacity and logistics transportation capacity as multistate variables, the supply chain network was analyzed through a multistate supply chain network incorporating minimal integrated capacity patterns and the Recursive Sum of Disjoint Product method. To measure the improvement in performance following disruption mitigation strategies, a resilience index (RI) was developed based on changes in network reliability before and after the addition of new suppliers. Two disruption scenarios were analyzed to demonstrate the applicability of the proposed algorithm. In Scenario 1, newly added suppliers were themselves affected by the disruption, while in Scenario 2, the new suppliers remained unaffected. The results reveal that network reliability decreases significantly with increasing disruption probability. Nevertheless, introducing new suppliers improves resilience in both cases, with Scenario 2 consistently yielding higher RI values. Notably, the RI reached up to 38 % in Scenario 2, compared to 20 % in Scenario 1, illustrating the critical role of supplier selection in enhancing supply chain stability. In this study, network reliability is used as the foundational performance indicator, and resilience is evaluated by comparing reliability values before and after the integration of additional suppliers. This approach enables a quantitative assessment of the effectiveness of disruption response strategies in maintaining or restoring supply chain performance. These findings

Table 9
The network reliabilities and resilience indexes under different $\mathrm{Pr_D}$.

$\mathrm{Pr_D}$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$R^{before}_{(3,2),5650}$	0.7546	0.6112	0.4829	0.3697	0.2717	0.1886	0.1207	0.0679	0.0302	0.0075
Scenario 1										
$R^{after}_{(3,2),5650}$	0.8559	0.8176	0.732	0.6263	0.5085	0.3867	0.269	0.1634	0.078	0.0208
RI	10 %	21 %	25 %	26 %	24 %	20 %	15 %	10 %	5 %	1 %
Scenario 2										
$R^{after}_{(3,2),5650}$	0.8559	0.836	0.7863	0.7257	0.6544	0.5722	0.4794	0.3757	0.2612	0.136
RI	10 %	22 %	30 %	36 %	38 %	38 %	36 %	31 %	23 %	13 %

provide supply chain decision-makers with a practical and quantitative tool for assessing and improving supply chain resilience.

While the current framework is designed for a static disruption period and focuses on assessing supply chain capability and resilience during disruptions, many real-world disruptions extend over multiple time periods. Extending the model to accommodate dynamic or multi-period scenarios would enhance its practical relevance. Extending the model to accommodate dynamic or multi-period scenarios would enhance its practical relevance. Future research is encouraged to investigate this direction and further expand the model to capture the evolving nature of supply chain disruptions over time.

CRediT authorship contribution statement

Kuan-Yu Lin: Writing – original draft, Methodology, Formal analysis, Data curation. **Yi-Kuei Lin:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research was supported in part by the National Science and Technology Council, Taiwan under grants NSTC112–2221-E-A49–110-MY3.

Data availability

Data will be made available on request.

References

[1] Meier M, Pinto E. Covid-19 supply chain disruptions. Eur Econ Rev 2024;162: 104674.
[2] Bruckler M, Wietschel L, Messmann L, Thorenz A, Tuma A. Review of metrics to assess resilience capacities and actions for supply chain resilience. Comput Ind Eng 2024;192:110176.
[3] Xu Z, Elomri A, Kerbache L, El Omri A. Impacts of COVID-19 on global supply chains: facts and perspectives. IEEE Eng Manag Rev 2020;48:153–66.
[4] Russon M-A. The cost of the Suez Canal blockage. BBC News 2021;29.
[5] Raj A, Mukherjee AA, de Sousa Jabbour ABL, Srivastava SK. Supply chain management during and post-COVID-19 pandemic: mitigation strategies and practical lessons learned. J Bus Res 2022;142:1125–39.
[6] Choi T-M. Risk analysis in logistics systems: a research agenda during and after the COVID-19 pandemic. Transport Res E-log 2021;145:102190.
[7] Yang B, Zhang L, Zhang B, Wang W, Zhang M. Resilience metric of equipment system: theory, measurement and sensitivity analysis. Reliab Eng Syst Saf 2021; 215:107889.
[8] Zhou C, Song W, Wang H, Wang L. Resilience assessment of supply chain networks considering continuously varying sates of firms in ripple effect: a comprehensive and dynamic operational-structural analysis. Omega-Int J Manage Sci 2025: 103322.
[9] Chowdhury MMH, Quaddus M. Supply chain resilience: conceptualization and scale development using dynamic capability theory. Int J Prod Econ 2017;188: 185–204.
[10] Song H, Chang R, Cheng H, Liu P, Yan D. The impact of manufacturing digital supply chain on supply chain disruption risks under uncertain environment—Based on dynamic capability perspective. Adv Eng Inform 2024;60:102385.
[11] Wei S, Liu H, Chen X, Ke W. How does supplier integration influence supply chain robustness and resilience? The moderating roles of information technology agility and managerial ties. Inf Manage 2024;61:104028.
[12] Butt AS. Coopetition in supply chains: a case study of Australian construction industry in supplier market. J Bus Res 2025;189:115111.
[13] Wei X, Cai X, Tian Y, Guo L. Response to supply chain network disruption risk through link addition: resilience enhancement strategies based on ternary closure motifs. Reliab Eng Syst Saf. 2025:111381.
[14] Wang Y, Long Y, Wang J. Does the innovation-driven digital economy improve the resilience of industrial and supply chains? J Innov Knowl 2025;10:100733.
[15] Xu B, Liu W, Li J, Yang Y, Wen F, Song H. Resilience measurement and dynamic optimization of container logistics supply chain under adverse events. Comput Ind Eng 2023;180:109202.
[16] Abushaega MM, González AD. Moshebah OY. A fairness-based multi-objective distribution and restoration model for enhanced resilience of supply chain transportation networks. Reliab Eng Syst Saf 2024;251:110314.
[17] Tafakkori K, Jolai F, Tavakkoli-Moghaddam R. Disruption-resilient supply chain entities with decentralized robust-stochastic capacity planning. Reliab Eng Syst Saf 2023;238:109447.
[18] Huang D-H. Evaluation and management of sustainable supply chain systems with carbon emissions and transport damage based on multi-state system reliability assessment. Reliab Eng Syst Saf 2025;257:110821.
[19] Niu Y-F, Zhao X, Xu X-Z, Zhang S-Y. Reliability assessment of a stochastic-flow distribution network with carbon emission constraint. Reliab Eng Syst Saf 2023; 230:108952.
[20] Huang C-F. System reliability for a multi-state distribution network with multiple terminals under stocks. Ann Oper Res 2022;311:117–30.
[21] Huang C-H, Lin Y-K. Rescue and safety system development and performance evaluation by network reliability. Reliab Eng Syst Saf 2024;241:109669.
[22] Lin Y-K, Huang C-F, Liao Y-C. Reliability of a stochastic intermodal logistics network under spoilage and time considerations. Ann Oper Res 2019;277:95–118.
[23] Niu Y-F, He C, Fu D-Q. Reliability assessment of a multi-state distribution network under cost and spoilage considerations. Ann Oper Res 2022:1–20.
[24] Xu X-Z, Niu Y-F, Song Y-F. Computing the reliability of a stochastic distribution network subject to budget constraint. Reliab Eng Syst Saf 2021;216:107947.
[25] Lin K-Y, Lin Y-K. Sustainable supply chain evaluation with supplier sustainability in terms of reliability. Ann Oper Res 2024:1–17.
[26] Huang C-F. Evaluation of system reliability for a stochastic delivery-flow distribution network with inventory. Ann Oper Res 2019;277:33–45.
[27] Huang C-F, Huang D-H, Lin Y-K. Network reliability evaluation for multi-state computing networks considering demand as the non-integer type. Reliab Eng Syst Saf 2022;219:108226.
[28] Lin K-Y, Lin Y-K. Network reliability evaluation of a supply chain under supplier sustainability. Comput Ind Eng 2024;190:110023.
[29] Ford L.R., Fulkerson D.R. Flows in networks. 2015.
[30] Bai G, Zuo MJ, Tian Z. Ordering heuristics for reliability evaluation of multistate networks. IEEE Trans Reliab 2015;64:1015–23.