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IMPACT OF RESOURCE RECONFIGURATION ON THE DAIRY SUPPLY CHAIN RESILIENCE

Marzieh Keshavarz, Hasan Hosseini-Nasab*, Mohammad bagher Fakhrzad and Hasan Khademi Zare

Abstract. Investment in food supply chain resilience, as a critical infrastructure, has become necessary for all governments. Disruption of food supply chains can lead to significant economic challenges. Building a resilient supply chain requires resources; however, it is difficult for firms to allocate resources to various resilience strategies. This study allocates the budget to resilient capacity, that is, absorptive, adaptive, and restorative capacity, to minimize supply chain costs and maximize service levels. We developed a novel multi-objective mixed-integer nonlinear programming method for problem formulation. The developed model was converted into an equivalent linear model. We used the Monte Carlo approach to generate the scenarios and the average sample approximation to determine the required scenarios. Finally, the Lexicographic max-min approach solves the model using actual data from a dairy supply chain. The analysis revealed that allocating 50% of the budget to restorative capacity and the remaining to adaptive and absorptive capacity optimizes supply chain performance. This study provides insights for managers to make better decisions with a knowledge-based background, allocate resources to various resilient strategies, and build a more resilient and efficient supply chain.

Mathematics Subject Classification. 91B32, 90C05, 34E13.

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1. Introduction

Supply chains worldwide are facing disruptions. Among all supply chains, the food supply chains are highly vulnerable [19]. Disruptions have more consequences in the food supply chain than in other industries because of the perishability of processed materials [7, 19, 42]. Establishing a resilient supply chain system and recovery strategy is crucial for combating increased disruption and uncertainty in indoor and outdoor environments [12]. The Institute for Supply Management reports that 75% of companies have disrupted their supply chains during coronavirus outbreaks, and 44% have no plans to recover from these disruptions [14].

Recently, the United States Agency for International Development (USAID) and the United Nations Environment Programme (UNEP) reported that investment in supply chain resilience is necessary to support vulnerable areas worldwide [31]. It is also noteworthy that building a resilient supply chain requires resources and costs to invest, and it is difficult for a firm to monetize payback [33, 46]. The head of the Supply Chain Center of Excellence argues that most companies must allocate more funds to supply chain resilience [51]. Supply chain

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Department of Industrial Engineering, Yazd University, Yazd, Iran.
*Corresponding author: hhn@yazd.ac.ir

resource reconfiguration can help firms develop supply chain disruptions [31, 44]. Food supply chains require temperature control to ensure safety and prevent the growth of microorganisms. Disruption of the food supply chain can cause economic challenges [42]. Therefore, the following questions arise in allocating the budget to various resilience strategies: How can we analyze budget allocation? What is the most economical, operational, and strategic option for a portfolio of budgets allocated to various resilience strategies? Based on the above discussion, the central stimulus of the present study was to discover the impact of budget allocation on supply chain performance resilience. Therefore, this study investigates how budget allocation affects supply chain performance resilience.

There are two ways to build a resilient supply chain: proactive strategies before disruption, and reactive strategies after disruption in the operational phase. In proactive strategies, the absorption capacity must be built. Reactive strategies include the ability to adapt and recover, which play a role during and after a disturbance [11]. The literature shows that most research has focused on individual resilient capacity in the supply chain or on integrating a couple of resilient capacities in supply chain management, such as adaptive and absorptive capacity [15, 16, 41], absorptive, and restorative [29]. However, the simultaneous integration of restorative, adaptive, and absorptive capacities in a supply chain may help supply chains become more resilient and efficient. No research has been conducted on budget allocation among absorptive, adaptive, and restorative strategies. The budget tradeoffs between absorptive, adaptive, and restorative capacities are actual issues that may help supply chains become more efficient and resilient.

To the best of our knowledge, no study has allocated a resilient budget for resilience strategies. The primary contributions of this study that distinguish it from other related studies are as follows.

– Develop a novel multi-objective model for budget allocation to resilient capacities.
– Evaluate the effect of budget allocation on supply chain costs and service levels using the developed model and the results of various sensitivity analyses.
– The recovery rate depends on the disruption severity, required recovery budget, and resilience budget.

The rest of the article in Section 2 discusses the literature on resilient supply chain supply. Section 3 presents the problem definition, mathematical model, and linearization of the mathematical model. Section 4 presents a case study. The solution approach, computational results, and analysis results are discussed in Section 5. We present a sensitivity analysis and managerial insights in Section 6. Section 7 presents conclusions and suggestions for future research.

2. Literature review

This section examines the background of the research on resilient supply chain networks. Hosseini *et al.* [10] introduced resilient capacity into absorptive, adaptive, and restorative capacity. Each category represents the temporal characteristics before, during, and after disruption. This categorization is illustrated in Figure 1. Based on previous research, it is possible to classify the research into three distinct groups.

2.1. Resilient supply chain with absorptive strategies

Absorptive capacity is the first line of defense against disruptions. According to Hosseini *et al.* [11], absorptive capacity is the capability of a system to absorb or withstand the impact of system disruptions and minimize the negative consequences of disruption with low effort. Multiple sourcing strategies, transportation channels, supplier segregation, and inventory are typical resilience strategies at this level [11].

Many studies have used absorptive strategies to create resilient supply chain. Sabouhi *et al.* [36] designed a supply chain network model for the petrochemical industry. The primary purpose of this study was to investigate the relationship between resilience and sustainability. They used actual data from an Iranian petrochemical business to evaluate their model. They found that considering the geographical distribution of facilities in regions with varying degrees of steady performance and risky circumstances is vital for the development of a supply chain. They found that any resilient strategy effectively reduces costs and strengthens the supply chain

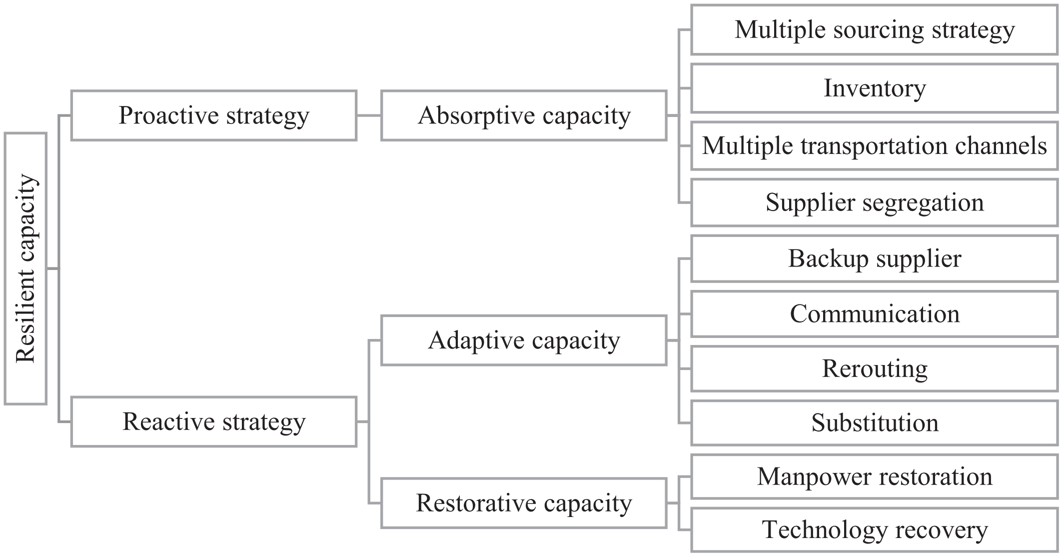

FIGURE 1. Resilient capacity of supply chain.

against disruptions. They did not examine restorative and adaptive capacities to boost the resilience of the petrochemical industry.

Jabbarzadeh *et al.* [17] considered the possibility of disruption for suppliers and manufacturers. They use multiple sourcing strategies, contracting backup suppliers, and capacity expansion to overcome disruptions. Their research revealed that the simultaneous application of these three strategies could reduce the costs. However, they do not consider the effects of budget allocation on supply chain costs. Rezapour *et al.* [35] investigated the impact of disruption on supply chain competition. They used emergency inventory, multiple sourcing, and backup supplier strategies to reduce disruption risk and used a nonlinear mixed-integer model to find the most profitable design networks. Their findings showed that applying risk reduction measures not only maintains and improves market share but also helps customers because of the stability of retailer prices in the market. However, they did not address the effects of restorative strategies on retailer prices. Bottani *et al.* [2] developed a two-objective mixed-integer programming model for the food supply chain network. They considered multiple sourcing to address operational and disruption risks in the supply chain. They used two objective functions to maximize the total profit and minimize the supply chain procurement time. Their results showed that the proposed model can aid in designing a resilient supply chain. They did not consider the effects of restorative and adaptive capacities on procurement time.

2.2. Resilient supply chain with adaptive and absorptive strategies

The second line of defense, when absorptive capacity does not harm disruption, is adaptive capacity [11]. Adaptive capacity is the degree to which a system can adapt and overcome disruptions without recovery [1]. Backup suppliers, Communication, Rerouting, and Substitution are common adaptive capacity strategies. Many researchers have focused on adaptive and absorptive methods to create resilient supply chain. For example, Sazvar *et al.* [40] designed a resilient supply chain network. The primary purpose of their investigation was to identify the variables that influence decisions regarding facility capacity. According to their findings, supply chain networks are more vulnerable to higher demand. They discovered that the capacity of manufacturing facilities and warehouses expanded as demand increased. They considered resilience as a function of vulnerability, while neglecting recoverability.

Torabi *et al.* [43] developed a mixed-integer stochastic programming model for selecting a resilient supplier and resource allocation under operational and disruption risks. They considered several strategies, such as suppliers' business continuity plans, fortification of suppliers, and contracting with backup suppliers, to enhance the resilience of supplier selection. The computational results showed that the occurrence of disruption risks could have a significant effect on supplier selection. Another important factor in supplier selection is the supply chain's restorative capacity. Zare-Mehrjerdi and Shafiee [27] developed a mixed-integer programming model for the closed-loop supply chain network. They used the fuzzy TOPSIS method to select resilient strategies. Multiple sourcing, contracting with backup suppliers, and sharing information create a resilient supply chain network. The results show that the need for backup suppliers increases with increasing demand. In addition, multiple sourcing and contracting backup suppliers had a synergistic effect, and the amount of information sharing aligned with visibility. However, they did not investigate the simultaneous development of these three resilient capacities.

Gholami-Zanjani *et al.* [7] presented a two-stage stochastic mathematical model for the resilient design of a food supply chain. In the proposed model, demand and disruptions are uncertain. The suggested model includes strategies of reinforcement resilience, backup, multiple resources, and capacity expansion to mitigate the consequences of disruptions. Their study suggested that reinforcement and backup strategies would provide more resilient solutions than multiple resourcing and capacity expansion. Yavari and Zaker [48] explored the effects of using resilience in a green closed supply chain network. They proposed integrating two supply chains and electric power networks as a resilience strategy. They use a case study of the dairy industry to validate their model. They found that this strategy was the most effective in mitigating disruptions. Restorative capacity is essential in the food supply chain but is not the only factor to consider. Margolis *et al.* [26] proposed a multi-objective mathematical model to design a resilient supply chain network. The primary motivation for their research was to investigate the interactions between minimizing supply chain network costs and maximizing connectivity between members of the supply chain network. They ignored the uncertainty in their proposed mathematical model. According to their study, improving the connectivity between members of the supply chain network will increase supply chain costs but make it more resilient.

2.3. Resilient supply chain with restorative and absorptive strategies

The third line of defense against disruptions occurs when the system's absorptive and adaptive capacities cannot preserve an acceptable level of performance [11]. Restorative capacity is the ability of a system to be restored quickly and efficiently [1]. Workforce restoration and technological recovery are two strategies for restorative capacity [11]. Few researchers have used restorative strategies alone or in combination with absorptive strategies. Hosseini *et al.* [13] proposed a two-objective stochastic mixed-integer programming model for supplier selection and resource allocation. They used the capacity expansion of suppliers, backup suppliers, and invested resources for a faster recovery. The suggested model may assist manufacturers in evaluating the performance of suppliers based on cost and resilience criteria. However, they considered recovery to be a constant. In addition, they ignored the budget required for recovery. Ni *et al.* [29] designed a two-stage stochastic programming model to measure supply chain resilience with disruption risks. They examined backup supplier strategy, excess inventory, and idle capacity to boost supplier resilience and evaluate customer behavior during recovery. They found a difference between the maximum and average recovery costs. Decision-makers with a risk-averse attitude prefer to lose customers in high-intensity, low-probability disruptions, rather than investing more in proactive strategies. Enriching the study stream, they considered the amount of recovery as a constant parameter. In their model, multiple disruptions were not possible. In addition, they should pay more attention to the budget required to recover from disruptions.

Khamseh *et al.* [22] developed a mathematical model based on finite optimal control for supply chain recovery with minimum operating costs and solved it with Pontryagin's maximum principle. They demonstrated the application of the proposed model in a poultry supply chain. The results of the dynamic recovery model revealed that the proposed model could help supply chain managers cope with disruptions by comparing alternative recovery options based on two essential criteria: the time and cost of supply chain recovery. This study examined

TABLE 1. Summary of resilient supply chain networks literatures.

Authors (year)	Network stages	Multi period	Disruption origin		Disruption type		Vulnerable element			Resilient capacity			Budget allocation	Modeling framework	Type of uncertainty	Objective number	Solution method	Case study
			Supply chain	Infrastructure	Single disruption	Multiple disruption	Supplier	Manufacturer	Distributer	Absorptive capacity	Adaptive capacity	Restorative capacity						
Torabi *et al.* [40]			✓		✓		✓			✓				MIP	Stochastic	MO	Exact	General
Sawik [36]	1	✓	✓		✓			✓		✓		✓		NLP	Stochastic	SO	Exact	General
Rezapour *et al.* [32]	4		✓		✓				✓	✓				MINLP	Stochastic	SO	Exact	Gear
Ni *et al.* [26]	3	✓	✓		✓		✓			✓		✓		MIP	Stochastic	MO	Exact	General
Jabbarzadeh *et al.* [16]	3		✓		✓		✓	✓			✓			MIP	Stochastic	MO	Heuristic	Plastic pipe
Yavari and Zaker [45]	3	✓		✓	✓			✓		✓	✓			MIP	Stochastic	MO	Exact	Food
Hosseini *et al.* [13]	2	✓	✓		✓		✓			✓		✓		MIP	Stochastic	MO	Exact	General
Bottani *et al.* [2]	3	✓	✓		✓		✓			✓				MIP	–	MO	Metaheuristic	Food
Zare-Mehrjerdi and Shafiee [24]	4		✓		✓		✓				✓			MIP	Stochastic	MO	Exact	Tire
Khamseh *et al.* [19]	2	✓	✓		✓			✓		✓		✓		NLP	Dynamic Programming	SO	Exact	Poultry
Goldbeck *et al.* [7]	1	✓		✓	✓			✓		✓		✓		LP	Stochastic	SO	Exact	General
Sabouhi *et al.* [33]	4	✓	✓		✓		✓	✓	✓	✓	✓			MIP	Stochastic	MO	Exact	Petrochemical
Sazvar *et al.* [37]	4	✓	✓		✓			✓			✓			MIP	Fuzzy Robust	MO	Exact	Influenza vaccine
Gholami-Zanjani *et al.* [6]	3	✓	✓		✓	✓	✓	✓		✓	✓			MIP	Stochastic	SO	Exact	Food
This research	3	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	MINLP	Stochastic	MO	Exact	Food

the characteristics of a dynamic supply chain and recommended attention to the efficacy and efficiency of recovery strategies. However, they considered recovery to be a constant. They assumed that there would be no further disruption during the recovery period. Sawik [39] developed an integer programming model to select primary and backup suppliers and allocate order quantities at disruption risk. Based on the findings of the study, resource recovery was the sole viable option in the event of disruption to all primary suppliers. To avoid all potential disruption scenarios, an integrated decision-making approach would involve choosing more diverse suppliers. The hierarchical approach selects the cheapest supplier as the primary supplier, or only one reliable supplier. Sawik [39] considered recovery as a parameter. In comparison, we considered recovery as a function of various factors, such as the severity of the disruption, budget, and the required budget for recovery.

Goldbeck *et al.* [8] offered a multi-stage stochastic linear model to optimize pre-disruption investment decisions, dynamic post-disruption supply chain operations settings, and repair resource allocation. They concluded that, to deal with the increased risk of disruption and unpredictability in both internal and external environments, a firm must create a resilient supply chain system and a recovery plan. Supply chain managers may use this model for resource recovery and operational capacity planning for new and current supply networks. As in earlier publications, they saw the quantity of recovery as a constant parameter. However, the recovery rate depends on the disruption severity, existing budget, and the required budget for recovery.

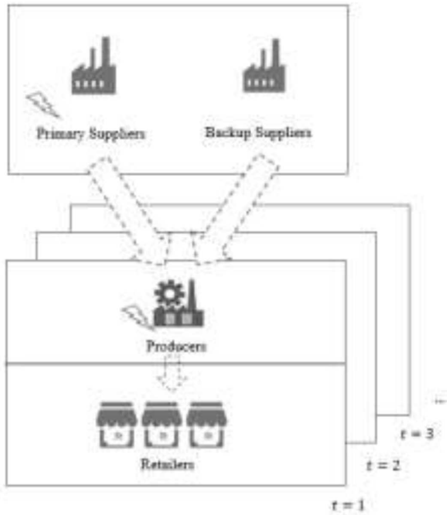

FIGURE 2. Dairy supply chain network.

2.4. Research gap

Our study makes three contributions: (1) investigating the simultaneous integration of restorative, adaptive, and absorptive capacity in supply chain resilience; (2) studying budget allocation and its effects on supply chain performance; and (3) considering recoverability as a function of the severity of disruptions and the required budget for recovery. These findings will inform future research and decision-making in this area.

In this study, we first developed mixed-integer nonlinear programming. In addition, we allocated the budget to resilient capacity (*i.e.*, absorptive, adaptive, and restorative capacity) to minimize supply chain costs and maximize service levels. For this purpose, we converted the model into a linear model. To solve this problem, in the first step, the stochastic parameters, including demand, severity of the disruptions, and required budget for recovery, were generated using the Monte Carlo method. In the second step, the number of scenarios required to solve the stochastic problem was estimated, and finally, the model was solved using the Lexicographic Max-Min method. We implemented this model in a real case study in Shiraz. This company seeks to allocate budgets to resilience strategies in the best way to develop its market share because of the positive impact of resilience on the market [24, 47, 49] and to prevent economic loss. Thus, this study is helpful for other industries that want to build a resilient supply chain and to know how to allocate budgets among resilient strategies. In this way, the supply chain gains the long-term benefits of resilience outcomes from budget allocation and the prevention of economic loss.

3. Problem definition

This study presents a real-world dairy supply chain network comprising primary suppliers, backup suppliers, producers, and retailers. The supply chain network is illustrated in Figure 2. The fundamental features and assumptions of the dairy supply chain are outlined below.

- Milk is the primary raw material used in dairy production. Milk is transported daily from farms to factories. Disruptions can occur in the primary suppliers. The Severity of supplier disruptions is known and stochastic. If a disruption occurs in the primary supplier, the factory's production is disrupted and the backup supplier plan is activated. We consider that backup suppliers are always able to supply the required raw materials.

- Food supply chains need time and temperature control to maintain safety and prevent the growth of microorganisms and the production of toxins. Disruption of heating and cooling systems or production technology can lead to spoilage of processed materials and significant economic losses for producers. We assume that the severity of disruptions in producers is known and stochastic. Investing in technology recovery to recover from disruptions is essential. Therefore, we used a technology recovery strategy.
- In the dairy supply chain, producers transport their products directly to retailers, who in turn sell them to consumers. Because demand can vary unpredictably, retailers have implemented a holding inventory strategy that considers the stochastic nature of demand and their constant production capacity. We regard unmet demand as lost and penalize each unfulfilled demand unit within the objective function.
- Products have a specific expiration date. The products should be refrigerated to prevent spoilage. If the expiry date of the items at the manufacturer or retailer's warehouse has passed, they should be disposed.
- We considered the disruption severity in producers to be known and stochastic. Thus, the budget required for technology recovery is stochastic.

The issue is to boost resiliency by improving absorptive, adaptive, and restorative capacity within the budget. The major decisions of the model include primary supplier selection before the occurrence of the disruption, backup supplier selection in the event of a disruption, decisions related to the material flow in the suppliers and products in the producer, and production capacity in each period according to disruption severity, the rate of capacity recovery in each period, and the total vulnerability in each period. Because of the cost of resilient strategies and the limited budget for supply chains, budget allocation to resilient capacities can improve the performance of supply chains. Thus, a resilient budget was allocated to the holding inventory, backup supplier, and technology recovery strategies to boost absorptive, adaptive, and restorative capacity. We consulted experts and managers of the Saba Salem factory to identify resilience strategies that align with the historical disruption records. After thorough consideration and approval, we selected three effective implementation strategies.

- Producer inventory strategy: In this factory, maintaining inventory can be a suitable resilience strategy to overcome unexpected increases in demand caused by seasonal changes or random modifications. Product inventory can serve as a backup plan when the primary supplier cannot provide milk as the primary raw material for dairy product production. Inventory strategy is a component of absorptive capacity. We employed an inventory strategy during temporary disruptions in the supply chain network. The level of manufacturers' resilience relies not only on their initial capacity but also on their inventory. Thus, the manufacturer uses an inventory strategy to increase supply chain resilience. Additionally, the producer uses an inventory strategy that considers the unpredictable nature of demand. The inventory amount is determined by the resilient budget.
- Backup supplier strategy: Milk is the main ingredient in dairy products. Primary suppliers deliver milk to producers daily. If there is a disruption in primary supply, backup suppliers provide a solution. We use backup suppliers when disruption occurs in the primary supplier. The amount of raw material that can be purchased from backup suppliers was determined based on the resilient budget.
- Budget for technology recovery: Historical records show that a failure in temperature control can spoil materials or lower product quality, leading to rejection by the factory's quality control department. Investing in such breakdowns can prevent economic loss. Restorative capacity is the third and last line of defense for building a resilient supply chain after absorptive and adaptive capacities. Restorative capacity plays a role after disruption and is a function of the response actions performed by the supply chain. Hosseini and Barker [10] have noted supplier recovery budget and technical resource recovery as two arms of recovery capacity. Thus, budget allocation to restore technological resources expedites the recovery of technologies from producers. In this study, the required budget for recovery, resilient budget, and disruption severity govern the recovery rate in each period.

The purpose of the model is to minimize the expected costs of the supply chain in a multi-period planning horizon and maximize the supply chain's service level because of a resilient budget. We used an integer nonlinear programming approach for the modeling. The model uses stochastic programming to account for probabilistic uncertainty in the problem data. In stochastic uncertainty, reliable historical data are available for the accurate or approximate estimation of the probability distribution of uncertain parameters of supply chain models [9]. The indices, parameters, and variables are as follows:

Indices:

I	Set of primary suppliers indexed by $i\,(i \in I)$
B	Set of backup suppliers indexed by $b(b \in B)$
J	Set of producers indexed by $j\,(j \in J)$
T	Set of time period (based on weekly scale) indexed by $t\&r \quad (t\&r \in T)$
K	Set of retailers indexed by $k\,(k \in K)$
P	Set of products indexed by $p\,(p \in P)$
S	Set of scenarios indexed by $s \quad (s \in S)$

Parameters:

Cap_i	Maximum capacity of primary supplier i
Cap_b	Maximum capacity of backup supplier b
CAP_{jpt}	The current production capacity of product p in producer j in period t
Max^I_{jpt}	Maximum storage capacity of product p in producer j in period t
Max^{Iraw}_{jt}	Maximum storage capacity of milk in producer j in period t
Max^I_{kpt}	Maximum storage capacity of product p in the retailer in the period t
V^s_{jpt}	Disruption severity for the production technology of product p in producer j in period t and under scenario s
V^s_{it}	Disruption severity for supplier i in period t and under scenario s
P^s	Probability of s^{th} scenario occurrence
HR^s_{jpt}	Percentage of the required budget to recover the production technology of product p in producer j in period t and under scenario s
CH_{jt}	Cost of raw material holding in producer j in period t
CH_{jpt}	Product holding cost p in producer j in period t
CH_{kpt}	Product holding cost p in retailer k in period t
CL_{kpt}	Lost sales cost of product p in retailer k in period t
CM_{jpt}	The production cost of product p in producer j in period t
CT_{jkpt}	Unit transportation cost of product p from producer j to retailer k in period t
CC_i	Fixed cost of the contract with primary supplier i
CC_b	Fixed cost of the contract with backup supplier b
D^s_{kpt}	Product demand p in retailer k in period t and scenario s
SL_p	Shelf life of product p
CE_{jpt}	Expiration cost of product p in producer j in period t
CE_{kpt}	Expiration cost of product p in producer j in period t
CT_{ijt}	Transportation cost of raw materials from primary supplier i to producer j in period t
CT_{bjt}	Transportation cost of raw materials from backup supplier b to producer j in period t
α_p	Amount of required raw materials to produce a unit of product p
Prc_{it}	Purchase price of raw materials from primary supplier i in period t
Prc_{kt}	Purchase price of raw materials from backup supplier b in period t
TB_{jt}	Available budget for resilient strategy in producer j in period t
CAP_{it}	The current capacity of primary supplier i in period t
CAP_{bt}	The current capacity of backup supplier b in period t
Dis_{ij}	Distance from primary supplier i to producer j
Dis_{bj}	Distance from backup supplier b to producer j
Dis_{jk}	Distance from producer j to retailer k

First stage decision variables:

S_i	Equals 1 if primary supplier i is selected, otherwise 0
S_b	Equals 1 if backup supplier b is selected, otherwise 0

Second stage decision variables:

Q^s_{jpt}	Amount of produced product p in producer j in period t and scenario s
Q^s_{jkprt}	Amount of produced product p in period r in producer j and sent to retailer k in period t and scenario s
Q^s_{kprt}	Amount of product p received by the customer from retailer k in period t, which is received by the retailer in period r and under scenario s
I^s_{jprt}	Amount of produced product p in period r remaining in producer j until period t under scenario s
I^s_{kprt}	Amount of produced product p in period r remaining in retailer k until period t under scenario s
L^s_{kpt}	Lost sales of product p in retailer k in period t and under scenario s
E^s_{jpt}	Amount of expired product p in producer j in period t and under scenario s
E^s_{kpt}	Amount of expired product p in retailer k in period t and under scenario s
Cap^s_{jpt}	Production capacity of product p in producer j in period t and scenario s
Cap^R_{jpts}	Amount of recovered capacity of product p in producer j in period t and scenario s
R^s_{jpt}	Rate of recovered capacity to produce product p at producer j in period t and scenario s
BR^s_{jpt}	Amount of budget allocated to recovering production technology of product p in producer j in period t and scenario s
Q^s_{ijt}	Amount of raw materials sent by primary supplier i to producer j in period t and scenario s
Q^s_{bjt}	Amount of transported raw materials by backup supplier b to producer j in period t and scenario s
I^s_{jt}	Amount of raw materials inventory in producer j in period t and scenario s
TV^s_{jpt}	Total vulnerability of production technology of product p in producer j in period t and scenario s

Mathematical formulation:

Objective function (1) minimizes total supply chain costs. The supply chain cost includes two parts: 1) the fixed cost of the contract with primary and backup suppliers. 2) Variable costs include inventory cost of products in producers($CH_{jt}I^s_{jt}$), inventory cost of milk maintenance($CH_{jpt}I^s_{jprt}$), inventory cost of products in retailers($CH_{kpt}I^s_{kprt}$), lost sales cost of products in retailers($CL_{kpt}L^s_{kprt}$), expiration cost of products in producers($CE_{jpt}E^s_{jpt}$) and retailers($CE_{kpt}E^s_{kpt}$), production cost of producers($CM_{jpt}Q^s_{jpt}$), transportation cost of products from producers to retailers($CT_{jkpt}Q^s_{jkprt}Dis_{jk}$), transportation cost of milk from primary suppliers to producers($CT_{ijt}Q^s_{ijt}Dis_{ij}$), transportation cost of raw materials from backup suppliers to producers($CT_{bjt}Q^s_{bjt}Dis_{bj}$), purchase cost of raw materials from primary suppliers($Prc_{it}Q^s_{ijt}$), purchase cost of milk from backup suppliers($Prc_{bt}Q^s_{bjt}$), and cost of recovered capacity in producers($R^s_{jpt}TB_{jts}$).

Objective function (2) maximizes the service level of the supply chain. Each retailer calculates the service level provided to the end-customer. The service level was quantified as a percentage. Percentage of customer demand fulfilled by the retailer at different times and in different scenarios. To calculate the supply chain service level, we take the average service level of products from various retailers across different scenarios and periods.

$$
\begin{aligned}
\text{Min } Z_1 = {} & \sum_i CC_i S_i + \sum_b CC_b S_b \\
& + \sum_s P^s \Bigg(\sum_j \sum_t CH_{jt} I^s_{jt} + \sum_j \sum_p \sum_{t|r\le t} \sum_r CH_{jpt} I^s_{jprt} + \sum_k \sum_p \sum_{t|r\le t} CH_{kpt} I^s_{kprt} \\
& + \sum_k \sum_p \sum_t \sum_r CL_{kpt} L^s_{kprt} + \sum_j \sum_p \sum_t CE_{jpt} E^s_{jpt} + \sum_k \sum_p \sum_t CE_{kpt} E^s_{kpt}
\end{aligned}
$$

$$+\sum_j\sum_p\sum_t CM_{jpt}Q^s_{jpt}+\sum_j\sum_k\sum_p\sum_{t|r\le t} CT_{jkpt}Q^s_{jkprt}Dis_{jk}+\sum_i\sum_j\sum_t CT_{ijt}Q^s_{ijt}Dis_{ij}$$
$$+\sum_b\sum_j\sum_t CT_{bjt}Q^s_{bjt}Dis_{bj}+\sum_i\sum_j\sum_t Prc_{it}Q^s_{ijt}+\sum_b\sum_j\sum_t Prc_{bt}Q^s_{bjt}$$
$$\left.+\sum_j\sum_p\sum_t\sum_s R^s_{jpt}TB_{jts}\right) \tag{1}$$

$$\text{Max}\ \ Z_2=\sum_k\sum_p\sum_t\sum_s 1-((L^s_{kpt}+E^s_{kprt})/D^s_{kpt})/KPTS. \tag{2}$$

Constraints:

Constraint (3) demonstrates theat the total amount of raw materials transferred from the backup suppliers and primary suppliers to each producer is equal to the product produced by that producer. Constraint (4) shows the maximum milk tank capacity for each producer. The amount of milk stored should be less than the maximum capacity of the milk storage tank. The capacities of the primary and backup suppliers are determined by Constraints (5) and (6). The amount of milk sent from primary and backup suppliers is less than the supplier's capacity.

$$\sum_i Q^s_{ijt}\left(1-V^s_{it}\right)+\sum_b Q^s_{bjt}=\sum_p \alpha_p Q^s_{jpt}+I^s_{jt} \qquad \forall j\in J,t\in T,s\in S \tag{3}$$
$$I^s_{jt}\le \text{Max}^{\text{Iraw}}_{jt} \qquad \forall j\in J,t\in T,s\in S \tag{4}$$
$$\sum_j Q^s_{ijt}\le Cap_i S_i \qquad \forall i\in I,t\in T,s\in S \tag{5}$$
$$\sum_j Q^s_{bjt}\le Cap_b S_b \qquad \forall b\in B,t\in T,s\in S. \tag{6}$$

Constraints (7) and (8) show the balance of the producer for each period. The amount of product produced each time equals the amount of product sent to the retailer and the amount of inventory in the producer. Constraint (9) specifies the maximum amount of inventory for the producer in terms of the limited capacity of the refrigerator. Constraint (10) expresses the producer's number of expired products.

$$Q^s_{jpt}=\sum_K Q^s_{jkprt}+I^s_{jprt} \qquad \forall j\in J,p\in P,s\in S,t\&r\in T|0\le t-r\le SL_p \tag{7}$$
$$I^s_{jprt}=I^s_{jpr(t-1)}-\sum_K Q^s_{jkprt} \qquad \forall j\in J,p\in P,t\&r\in T,s\in S \tag{8}$$
$$\sum_{r\in T|0<r\le t} I^s_{jprt}\le \text{Max}^I_{jpt} \qquad \forall j\in J,p\in P,t\in T,s\in S \tag{9}$$
$$\sum_{r\in T|t-r=SL_p} I^s_{jprt}=E^s_{jpt} \qquad \forall k\in K,p\in P,s\in S,t\&r\in T|r=t. \tag{10}$$

Constraints (11) and (12) reveal the inventory balance of each retailer in each period. The amount of product received each time equals the sum of the product sold by the retailer and the retailer's inventory.

$$\sum_j Q^s_{jkprt}=I^s_{kprt}+Q^s_{kprt} \qquad \forall\, k\in K,\ p\in P,s\in S,\ t\&r\in T\,|0\le t-r\le SL_p \tag{11}$$
$$I^s_{kprt}=I^s_{kpr(t-1)}+\sum_j Q^s_{jkprt}-Q^s_{kprt} \qquad \forall\, k\in K,\ p\in P,s\in S,t\&r\in T. \tag{12}$$

Constraint (13) specifies the maximum inventory of retailers. The amount of inventory in retailers can be, at most, a certain amount because of the refrigerators' capacity. Constraint (14) shows the number of expired products for each retailer in each period:

$$\sum_{r\in T|0<r\le t} I^s_{kprt} \le \text{Max}^I_{kpt} \qquad \forall\, k\in K,\, p\in P, s\in S, t\in T \tag{13}$$

$$\sum_{r\in T|t-r=SL_p} I^s_{kprt} = E^s_{kpt} \qquad \forall\, k\in K,\, p\in P, s\in S, t\in T. \tag{14}$$

Constraint (15) expresses demand balance. The demand for each product is equal to the total lost sales and products delivered to the customers.

$$\sum_{r\in T|0\le t-r\le SL_p} Q^s_{kprt} + L^s_{kprt} = D^s_{kpt} \qquad \forall\; k\in K, p\in P, s\in S,\; t\&r\in T. \tag{15}$$

Constraint (16) shows that the amount of product produced by each producer in each period and scenario is less than the producer's production capacity. Constraints (17) and (18) show the production capacity in each period according to the total severity of disruptions.

$$Q^s_{jpt} \le Cap^s_{jpt} \qquad \forall\, j\in J,\, p\in P, s\in S,\; t\in T|\; t=1 \tag{16}$$

$$Cap^s_{jpt} = CAP_{jpt}\left(1 - TV^s_{jpt}\right) \qquad \forall\, j\in J,\, p\in P, s\in S,\; t\in T|\; t=1 \tag{17}$$

$$Cap^s_{jpt} = Cap^s_{jp(t-1)}\left(1 - TV^s_{jpt}\right) \qquad \forall\, j\in J,\, p\in P, s\in S,\; t\in T|\; t>1. \tag{18}$$

Constraints (19) and (20) reveal the total severity of disruptions in each period and for each producer. These constraints indicated the possibility of multiple disruptions in the model.

$$TV^s_{jpt} = V^s_{jpt} - R^s_{jpt} \qquad \forall\, j\in J,\, p\in P, s\in S,\; t\in T|\; t=1 \tag{19}$$

$$TV^s_{jpt} = V^s_{jpt} - R^s_{jpt} + TV^s_{jp(t-1)} \qquad \forall\, j\in J,\, p\in P, s\in S,\; t\in T|\; t>1. \tag{20}$$

Constraint (21) shows that all disruptions in the supply chain must recover by the end of the period.

$$\sum_t TV^s_{jpt} = \sum_t R^s_{jpt} \qquad \forall\, j\in J,\, p\in P, s\in S. \tag{21}$$

Constraint (22) specifies the maximum recovery in each period, according to the budget. Constraint (23) allocates the required budget to recover from the producer's disruption in each period.

$$R^s_{jpt} \le \tfrac{BR^s_{jpt}}{HR^s_{jpt}TB_{jts}} \qquad \forall\, j\in J,\, p\in P, s\in S, t\in T \tag{22}$$

$$BR^s_{jpt} \le HR^s_{jpt}TB_{jts} \qquad \forall\, j\in J,\, p\in P, s\in S, t\in T. \tag{23}$$

The cost of resilient strategies should be less than the budget (TB_{jts}), according to Constraint (24). The model's resilience strategies include inventory maintenance, backup suppliers, and technology recovery, belonging to the absorptive, adaptive, and recovery capacity categories.

$$\sum_p BR^s_{jpt} + \sum_b (Prc_b - Prc_i)Q^s_{bjt} + \sum_p I^s_{jprt}CH_{jpt} \le TB_{jts} \qquad \forall\, j\in J, s\in S,\; t\&r\in T. \tag{24}$$

Finally, constraints (25) and (26) impose binary and nonnegative restrictions on the decision variables.

$$Q^s_{ijt}, Q^s_{bjt}, Q^s_{jpt}, Q^s_{jkprt}, Q^s_{kprt}, Cap^s_{jpt}, L^s_{kprt}, I^s_{jt}, I^s_{jprt}, I^s_{kprt},\, E^s_{jpt}, E^s_{kpt}, R^s_{jpt}, BR^s_{jp}, TV^s_{jpt} \ge 0$$

$$\forall i\in I, b\in B, j\in J, t\&r\in T, k\in K, p\in P, s\in S \tag{25}$$

$$S_i, S_b \epsilon \left\{0,1\right\}. \tag{26}$$

3.1. Linearization of mathematical models

The proposed model uses mixed-integer nonlinear programming (MINLP). McCormick's envelope [4] was used to create an equivalent linear model. McCormick's inequality is a relaxation method used for nonlinear models with multiplication of two continuous decision variables. The complexity of solving nonlinear models is high; thus, by converting the nonlinear problem into an equivalent linear one, we achieved a more accurate answer in a more appropriate time. The expression in constraint (20) is nonlinear and the variables are continuous and negative. The upper bound and lower bound of $TV^s_{jpt}$and $Cap^s_{jp(t-1)}$ are:

$$LR^s_{jpt} \le TV^s_{jpt} \le UR^s_{jpt} \tag{27}$$

$$LCap^s_{jp(t-1)} \le Cap^s_{jp(t-1)} \le UCap^s_{jp(t-1)}. \tag{28}$$

We replaced the variable $CapR^s_{jp(t-1)}$with the expression $Cap^s_{jp(t-1)}\left(TV^s_{jpt}\right)$ and added the following linear constraints to the problem:

$$CapR^s_{jp(t-1)} \ge -UR^s_{jpt}UCap^s_{jp(t-1)} + UCap^s_{jp(t-1)}TV^s_{jpt} + UR^s_{jpt}Cap^s_{jp(t-1)} \tag{29}$$

$$CapR^s_{jp(t-1)} \ge -LR^s_{jpt}LCap^s_{jp(t-1)} + LCap^s_{jp(t-1)}TV^s_{jpt} + LR^s_{jpt}Cap^s_{jp(t-1)} \tag{30}$$

$$CapR^s_{jp(t-1)} \le -UR^s_{jpt}LCap^s_{jp(t-1)} + LCap^s_{jp(t-1)}R^s_{jpt} + UR^s_{jpt}Cap^s_{jp(t-1)} \tag{31}$$

$$CapR^s_{jp(t-1)} \le -LR^s_{jpt}UCap^s_{jp(t-1)} + UCap^s_{jp(t-1)}R^s_{jpt} + LR^s_{jpt}Cap^s_{jp(t-1)}. \tag{32}$$

4. Case study

Global milk production increased from 522 million tons in 1986 to 798 million tons in 2016 [19]. The United Nations Food and Agriculture Organization (FAO) has estimated that six billion people in developing countries use milk and milk products [19]. The dairy industry has recently received increasing attention because of its increased milk production. However, increased awareness has raised concerns, including the vulnerability of the dairy supply chain. Disruptions in the dairy supply chains lead to dairy being wasted the most because milk goods are highly perishable and time-sensitive distribution networks [28]. Thus, disruptions in dairy supply chains can lead to economic losses [3, 34]. Therefore, building a resilient supply chain in the dairy industry is more significant. Therefore, we chose the dairy industry in Iran for this research, as it has 400 dairy factories, 1600 raw milk collection centers, and exports over 40 products, making it crucial to build a resilient supply chain.

The case study relates to the dairy industry and is based on the Saba Salem Trading Company information. Saba Salem Trading Company with Golestan Domish brand has produced and distributed all dairy products, yogurt, buttermilk, cream, Etc., in Fars province in Iran since 2003. The company's manufacturing hub is Shiraz Industrial City. We select one product from each group using the same technology and production process. The chosen products were as follows.

1. Traditional high-fat yogurt (700 grams)
2. High fat pasteurized yogurt (800 grams)
3. Low fat pasteurized yogurt (400 grams)
4. Flavored buttermilk without gas (0.8 ml)
5. Fermented carbonated buttermilk (2 liters)
6. Pasteurized top milk

Saba Salem plans to increase its resilience to gain market share. Thus, increasing resilience requires investment. Therefore, according to the organization's budget, the company is attempting to allocate the budget to resilience capacities to increase resilience. Table 2 lists the parameters of the case study. To estimate the parameters of the mathematical model, specialists and management were consulted through discussions. Figure 3 displays the producer, primary suppliers, backup suppliers, and retailers' geographical areas in Shiraz.

TABLE 2. Values of case study parameters.

Parameter	Value	Unit	Parameter	Value	Unit
i	2	Number	t, r	12	Number
b	4	Number	s	50	Number
p	6	Number	k	11	Number
Max^{I}_{jpt}	U(500,2000)	Number	dis_{jk}	U(18,43)	Kilometer
dis_{bj}	U(9,12)	Kilometer	Sl_p	U(3,9)	Week
CAP_{krt}	U(10000,25000)	Number	dis_{ij}	U(4,6)	Kilometer
CAP_{jpt}	U(15000,20000)	Number	α_p	U(0.5,1)	Number
CAP_{irt}	U(10000,25000)	Littre	V^{s}_{jpt}	U(0,1)	
HR^{s}_{jpt}	U(0,1)		V^{s}_{it}	U(0,1)	

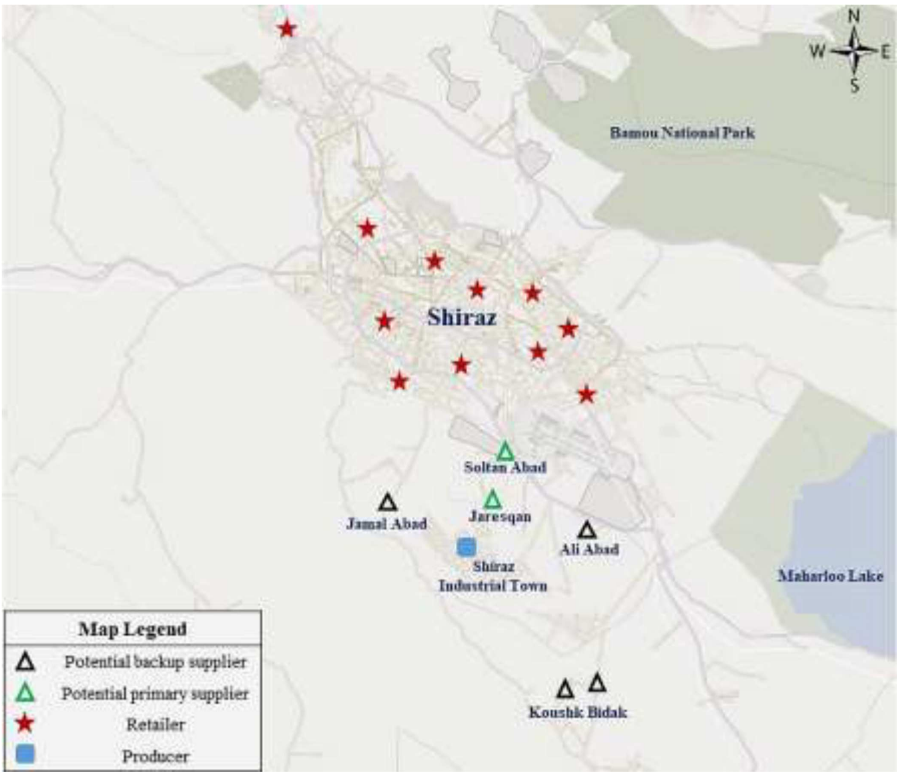

FIGURE 3. Geographical locations of the producer, primary suppliers, backup suppliers, and retailers.

5. SOLUTION METHOD

The stochastic parameter generation is explained in Subsection 5.1, the number of necessary scenarios is determined in Subsection 5.2, and the Lexicographic Max-Min method is presented in Subsection 3.5. Algorithm 2 in Subsection 5.2 was solved using the CPLEX solver in GAMS 24.1.2, whereas Algorithm 1 in Subsection 5.1 was coded in MATLAB R2020b. Algorithms 1 and 2 were executed on a PC with an Intel Core i7-10750H CPU (2.6 GHz) and 8.00 GB of RAM.

5.1. Scenario generation

In scenario-based stochastic programming, generating probabilistic scenarios is vital for addressing uncertainty. However, owing to the many scenarios, limiting the scenarios to achieve a specific problem scope is necessary. This section proposes a scenario generation approach based on the Monte Carlo approach [6] for stochastic parameters. V^s_{jpt}, HR^s_{jpt}, and V^s_{it} are generated based on the inverse of the Poisson Distribution [18,48], and demand (D^s_{kpt}) is generated based on the inverse of the uniform distribution [5] in MATLAB. The proposed Monte Carlo method to generate stochastic parameters is given in Algorithm 1 for generating, V^s_{jpt}, HR^s_{jpt}, V^s_{it}, and D^s_{kpt}, respectively.

Algorithm 1. Monte Carlo Scenario generation procedure for stochastic parameters ($\boldsymbol{V^s_{jpt}}$, $\boldsymbol{HR^s_{jpt}}$, $\boldsymbol{V^s_{it}}$, and $\boldsymbol{D^s_{kpt}}$).

For all s $\in$ S do

Generate $\boldsymbol{V^s_{jpt}}$, and $\boldsymbol{HR^s_{jpt}}$:

For all j $\in$ J, p $\in$ P and t $\in$ T do
$\eta = 0$
While $\eta \leq$ T/
Generate $\alpha^{\mathrm{s}}_{\lambda}$ and compute the next disruption arrival time in manufacturer: $\eta = \eta + \mathrm{F}^{-1}(\alpha^{\mathrm{s}}_{\lambda})$.
Add $\lceil \eta \rceil$ to the chronological list.
End while
Generate disruption intensity $\mathrm{U1^s_{jpt}}$ on the interval $[0, 1]$.
Generate percentage of required budget $\mathrm{U2^s_{jpt}}$ for dealing with various disruption scenarios on the interval $[0, 1]$.
Compute $\mathrm{V^s_{jpt}}$=$\mathrm{F}^{-1}(\mathrm{U1^s_{jpt}})$
Compute $\mathrm{HR^s_{jpt}}$=$\mathrm{F}^{-1}(\mathrm{U2^s_{jpt}})$
End for

Generate $\boldsymbol{V^s_{it}}$:

For all i $\in$ I and t $\in$ T do
$\eta = 0$
While $\eta \leq$ T
Generate $\beta^{\mathrm{s}}_{\lambda}$ and compute the next disruption arrival time in manufacturer: $\eta = \eta + \mathrm{F}^{-1}(\beta^{\mathrm{s}}_{\lambda})$.
Add $\lceil \eta \rceil$ to the chronological list.
End while
Generate disruption intensity $\mathrm{U3^s_{it}}$ on the interval $[0, 1]$.
Compute $\mathrm{V^s_{it}}$=$\mathrm{F}^{-1}(\mathrm{U3^s_{it}})$
End for

Generate $\boldsymbol{D^s_{kpt}}$

For all k $\in$ K and t $\in$ T do
Generate uniformly random numbers $\mathrm{U4^s_{kpt}}$ on the interval $[0, 1]$
Compute demand value $\mathrm{D^s_{kpt}}$=$\underline{\mathrm{D}}^{\mathrm{s}}_{\mathrm{kpt}}$+($\overline{\mathrm{D}}^{\mathrm{s}}_{\mathrm{kpt}}$−$\underline{\mathrm{D}}^{\mathrm{s}}_{\mathrm{kpt}}$)$\mathrm{U4^s_{kpt}}$
End for

End For

5.2. Scenario reduction

There are unlimited scenarios for the stochastic parameters. Unlimited scenarios in stochastic programming problems may increase the complexity of the solutions. The sample average approximation (SAA) method approximates the required scenarios. Selecting an appropriate sample is essential to balance the quality of

TABLE 3. Gap value, upper bound and lower bound.

M	V_N^m	$\hat{f}_N^m$
1	1997946935.63	1972398551.74
2	2026743250.67	1972398551.74
3	2013306839.82	1972398551.74
4	2017906992.08	1968187093.69
5	2033559486.33	1972398551.74
6	2030142944.56	1972398551.74
7	2032645017.20	1972398551.74
8	2023281066.92	1968187093.69
9	2022846543.23	1972398551.74
10	2037116992.48	1972398551.74
11	2024063393.74	1972398551.74
12	2042824824.64	1972398551.74
13	2006410027.28	1972398551.74
14	2030441752.21	1972398551.74
15	2016320573.61	1972398551.74
	$\bar{V}_N^m = \bar{V}_{50}^{15} = 2023703776.03$	$\hat{f}_N^m = \hat{f}_{100}^{15} = 1968187093.69$
	gap = 0.02	

the solutions and computational time. SAA is a statistical approach that uses sampling to solve stochastic programming problems. Algorithm 2 explains the sample average approximation method [25, 30, 38]. Table 3 shows the initial sample sizes, lower and upper bound values for the 15 sample problems, and statistical gap. The value of the gap is 0.02. Thus, 50 scenarios are appropriate for this problem.

5.3. Lexicographic max–min method

We solved the problem using GAMS software and the CPLEX solver. We solved the model using the Lexicographic max–min method. The Lexicographic max-min method chooses the most efficient solution with the smallest distance from the ideal. The lexicographic max-min method minimizes the deviation of objective functions from their optimal values. The lexicographic max-min model is as follows (see [32]):

$$\begin{aligned} &\text{Max}\left\{\min\left(\frac{f_1}{f_1^*}, \frac{f_2}{f_2^*}, \dots, \frac{f_k}{f_k^*}\right)\right\} \\ &\text{s.t.}: \quad x \in X. \end{aligned} \tag{33}$$

The model included k objective functions and constraints ($x \in X$). We solved it with one objective function each time to obtain the individual optimal values for each model. f_k^* is the ideal value of objective function k. The Lexicographic max–min method has been applied to multi-period resource allocation [23], fair bandwidth allocation in computer networks [37], and water resource allocation [45]. This method is used by conservative decision makers. The decision-maker optimizes the worst result. The company seeks to increase its service level and maintain its current sales during disruptions. Thus, the Lexicographic max–min method, a conservative method, was used.

According to the results, the earliest time for technology recovery was one unit of time, and the maximum technology recovery time was seven. The average disruption recovery time was 1.4 units of time. Only one backup supplier was used to optimize the objective functions of the individual optimization method. All four backup suppliers were employed in the max-min method. The technology recovery strategy allocates nearly 50% of the budget to increase supply chain resilience and the remaining 50% to back up supplier and inventory strategies. This allocation shows the importance of the technology recovery strategy over the backup supplier

Algorithm 2. SAA Method.

1: Setting the initial sample sizes N, $\acute{N}$, and M.
2: Estimating the lower bound: solve the stochastic Problem with N scenarios for M sample problems and calculate the following values.

$$\bar{V}_{N\cdot M} = \frac{1}{M}\sum_{m=1}^{M} V_N^m$$

$$\sigma^2_{\bar{V}_{N\cdot M}} = \frac{1}{M(M-1)}\sum_{m=1}^{M}\left(V_N^m - \bar{V}_{N,M}\right)^2.$$

3: Estimating the upper bound: select a feasible solution and estimate the objective function value of the original problem with sample of size $\acute{N}$.
4: Calculate the gap between the upper and lower bounds using the equations below and evaluate the quality of the solution.

$$gap = \frac{\hat{f}_{\acute{N}} - \bar{V}_{N,M}}{\hat{f}_{\acute{N}}}$$

$$\sigma^2_{gap} = \sigma^2_{\bar{V}_{N,M}} + \sigma^2_{\acute{N}}.$$

5: **If** Gap is acceptable
6: Return gap and the initial sample sizes N, $\acute{N}$, and M
7: **Else**
8: Repeat step1-4 using larger N and/or M
9: **End** if

Table 4. Obtained result from solving solution methods.

Solution Methods	Supply chain cost	Service level
Individual Programming	2014462254.73	0.76
Lexicographic Max-Min	7165656439.82	0.53
Sum of deviation of the objective functions from their optimal values	0.70	

strategy and holding of inventory. Producer inventory is greater than retailer inventory. The number of products sent to each of the 11 retailer areas was almost equal, with products being distributed evenly.

6. Sensitivity analysis

The following sensitivity analysis was performed to investigate the model behavior and answer the research questions:

1. Demonstrating the impact of producer holding inventory strategy (absorptive capacity), backup supplier strategy (adaptive capacity), and technology recovery strategy (restorative capacity) on total cost and service level.
2. Effect of disruption severity on results.
3. Uncovering the best allocation to resilient capacities.

– **Analysis of the impact of resilient strategies on objective functions**

In this section, we examine the impact of omitting producer inventory, backup, and technology recovery strategies on supply chain performance. Thus, we have the following three modes.

TABLE 5. Results of omitting the resilient strategies.

	Omitting producer inventory strategy	Omitting backup supplier strategy	Omitting technology recovery strategy
Supply chain cost (in Iranian toman)	776208640.01	2010990065.66	1727384145.57
Service level	0.70	0.62	0.55

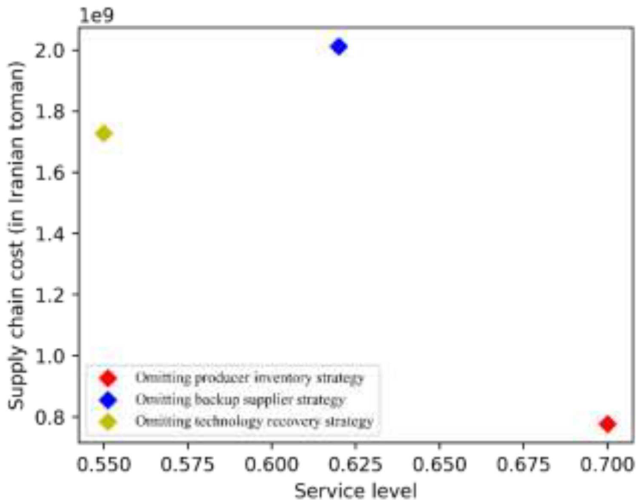

FIGURE 4. Results of omitting the resilient strategies.

1. Omitting producer inventory strategy (OPI).
2. Omitting backup supplier strategy (OBS).
3. Omitting technology recovery strategy (OTR): The recovery rate was considered constant.

A detailed formulation for each case is provided in Appendix A. The objective function values after eliminating each strategy are presented in Table 5 and Figuer 4.

1. The elimination of the holding inventory strategy reduced the service level to 0.70 and the total cost of the supply chain to 776208640.01. The service level and supply chain cost experienced a percentage change of 0.14 and 0.61, respectively.
2. Removing the backup supplier strategy reduced the service level and supply chain cost to 0.62 and 2010990065.66, respectively, resulting in a percentage reduction of 0.27 and 0.001.
3. Eliminating the technology recovery strategy reduced the service level to 0.55 and 1727384145.57, resulting in a 0.17% and 0.14% decrease in the service level and supply chain cost, respectively.

Our analysis determined that the inventory strategy is the most expensive, followed by technology recovery, and the backup supplier plan has the lowest incurred cost. Our analysis also shows that the technology recovery strategy significantly affects the supply chain service level, with backup suppliers being the second most crucial strategy. Inventory strategy has a comparatively minimal effect on the overall service level.

This sensitivity analysis concludes that the inventory strategy is the most expensive and has a negligible effect on the service level compared with the backup supplier and technology recovery. The technology recovery

Table 6. Effect of disruption severity on outcomes.

	Level 1: [0–.25]	Level 2: [0.25–0.5]	Level 3: [0.5–0.75]	Level 4: [0.75–1]
Supply chain cost	1809241312.61	1971339484.60	2103350829.41	2133839484.60
Service level	0.61	0.62	0.42	0.65

strategy had the most significant impact on elevating the supply chain service level, and after the inventory strategy, it had the most significant cost increase in the supply chain. The backup supplier plan had the lowest cost. Following the technology recovery strategy, the backup supplier strategy had the most significant impact on elevating the supply chain service level, and after the inventory strategy, it had the most significant cost increase in the supply chain. Thus, the following results were obtained.

1. The strategy of the producer's inventory has had a minimal effect on reducing the service level but has significantly increased costs. The retailer's inventory is the primary reason for the inability to reduce service levels.
2. The backup supplier strategy significantly reduces the service level. The producer can then produce the raw material. The removal of this strategy has also increased supply chain costs. Much of this cost is related to lost sales because of the reduced service level.
3. Omitting the technology recovery strategy: Even when omitting the technology recovery cost increase costs, the service level decreased. The reason for the reduction in service level is that the producer cannot produce.

– **Sensitivity analysis of the effect of disruption severity on results**

To determine the impact of disruption severity on budget configuration, we consider disruption severity at the following levels:

– Level 1: Disruption severity between [0-.25]
– Level 2: Disruption severity between [0.25-0.5]
– Level 3: Disruption severity between [0.5-0.75]
– Level 4: Disruption severity between [0.75-1]

The Monte Carlo simulation generated disruption severity at each level. We then ran the model with each level of disruption severity. Table 6 shows the results of disruption severity on the outcomes.

In Table 6, the supply chain cost and service level are shown based on the disruption severity at the four levels. At level one, the supply chain cost is 1809241312.61, and the service level is 0.61. In level two, costs and service levels are equal to 1971339484.60 and 0.62, respectively. In the third level, the costs and service level of the chain are equal to 2103350829.41 and 0.42, respectively. Finally, in the fourth case, the cost and service level are equal to 2133839484.60 and 0.65, respectively.

Table 6 shows that supply chain costs increase with a higher disruption severity. This increase seems to be reasonable. Recovery and resilience costs also increase. It is currently unclear whether disruption severity significantly affects the supply chain's overall service level. Further research and analysis are necessary to better understand the relationship between these factors. In the third case, the supply chain failed to provide satisfactory services despite increased costs. At levels one, two, and four, as disruption severity and costs increase, the supply chain performs well and service levels increase.

– **Sensitivity analysis of the allocated budget to each resilient strategy**

A sensitivity analysis was performed on the budget allocation percentages to determine the optimal distribution of resilience strategies.

TABLE 7. The analysis results of the allocated budget to each strategy.

	First mode	Second mode	Third mode	Fourth mode
Supply chain cost	2203914247.17	2014462254.73	2014462254.73	2014462254.73
Service level	0.47	0.58	0.58	0.56
	Fifth mode	Sixth mode	Seventh mode	Eighth mode
Supply chain cost	2014462254.73	2014462254.73	2014462254.73	2014462254.73
Service level	0.58	0.91	0.47	0.53

1. Allocate 100% of the resilience budget to the technology recovery strategy (FA1).
2. Allocate 90% of the resilience budget for technology recovery and the remaining 10% to the inventory and backup supplier strategies (FA2).
3. Allocate 80% of the resilience budget to the technology recovery strategy and the remaining 20% to the backup supplier and inventory strategy (FA3).
4. Allocate 70% of the resilience budget to the technology recovery strategy and the remaining 30% to the backup supplier and inventory strategies (FA4).
5. Allocate 60% of the resilience budget to the technology recovery strategy and the remaining 40% to the backup supplier and inventory strategies (FA5).
6. Allocate 50% of the resilience budget to the technology recovery strategy, and the remaining 50% to the backup supplier and inventory strategies (FA6).
7. Allocate 50% of the resilience budget to the backup supplier strategy and the remaining 50% to the technology recovery and inventory strategies (FA7).
8. Allocate 50% of the resilience budget to the inventory strategy and the remaining 50% to the technology recovery and backup supplier strategies (FA8).

A detailed formulation for each case is provided in Appendix A. The supply chain costs and service levels for each case are presented in Table 7. In the first mode, the supply chain cost was 2203914247.17, and the service level was 0.47. In the second mode, the cost and service levels were 2014462254.73916 and 0.58, respectively. In the third mode, the supply chain cost was 2014462254.73, and the service level was 0.58. In the fourth mode, the cost and service level are 2014462254.73 and 0.56, respectively. In the fifth mode, the supply chain cost was 2014462254.73, and the service level was 0.58. In the sixth mode, the cost and service level of the supply chain are 2014462254.73 and 0.91, respectively. In the seventh mode, the costs and service level of the supply chain are 2014462254.73 and 0.47, respectively. Finally, in the eighth case, the cost and service levels were 2014462254.73 and 0.53, respectively.

Allocating 50% of the resilient budget to the technology recovery strategy leads to the exact cost and higher service level compared to other strategies, whereas allocating 50% of the resilient budget to the backup supplier or inventory strategy does not increase the cost but reduces the service level. In addition, allocating more than 50% of the budget to the recovery strategy causes the supply chain's service level to decrease considerably.

6.1. Managerial insights

Supply chain networks play a critical role in local and global economies. Because of its elevated nutritional value, we considered dairy supply chain networks to be an influential part of the food supply chain. According to evidence, global milk production has experienced a 53% growth over the previous 30 years. Specifically, milk production on a worldwide scale increased from 522 million tons in 1986 to 798 million tons in 2016 [16]. More attention should be paid to the dairy supply chain networks. This study investigates the effects of budget assignment on different resilience strategies on dairy supply chain performance. Hence, the findings of the present study can help managers of dairy supply chain networks decide with a knowledge-based background.

Based on the results of the sensitivity analyses, we derived the following managerial insights for managers and supply chain planners.

- In the first sensitivity analysis, we studied the effect of eliminating each resilience strategy on the supply chain performance. The strategy of the producer's inventory has had a minimal effect on reducing the service level but has increased costs significantly. Such a finding may stem from keeping dairy products in inventory, which incurs product holding costs. In addition, dairy products are highly perishable, which results in unwanted expiration costs. As an absorptive strategy, the producer inventory strategy does not have an influential role on the service level compared with other resilience strategies. Retailer inventory is the primary reason for the minimal effect of reducing the service level. Hence, managers and dairy supply chain planners should know that absorptive strategies are less influential in coping with disruptions in dairy supply chain networks. The results also revealed that a backup supplier, as an adaptive resilience strategy, is more critical than a producer inventory strategy, given that omitting a backup supplier leads to a higher supply chain cost and lower service level. As a restorative resilience scheme, the technology recovery strategy is the most effective strategy for optimizing the service level. A conceivable explanation for this result may be that the manufacturer's technology breakdown stops production.
- Based on claims from international agencies (*e.g.*, USAID and UNEP), investment in supply chain resilience has become necessary to protect vulnerable areas worldwide [30]. According to Professor Walid Klibi, the head of the Supply Chain Center of Excellence, most companies must invest sufficiently in supply chain resilience [51]. In this study, we analyze how budget allocation affects supply chain resilience and determine the optimal investment in each strategy for the overall portfolio. Using such a scheme helps managers and supply chain planners to maximize service levels and avoid unnecessary supply chain costs. The results of the sensitivity analysis suggest that the dairy supply chain performs poorly when the entire budget is invested in the technology recovery strategy. By contrast, the dairy supply chain performs better in terms of efficiency and service level by investing in absorptive, adaptive, and restorative capacities.
- According to the study's findings, the most effective strategy for achieving optimal supply chain performance involves allocating 50% of the budget towards restorative capacity, with the other 50% devoted to absorptive and adaptive capacity. This approach has proven to be highly successful in enhancing supply chain resilience and adaptability, which are essential for maintaining a competitive edge in the business world.

7. Conclusion

Resilient capacity in the food supply chain is critical because of its unique production, storage, and transportation conditions. Resilient capacity includes absorptive, adaptive, and restorative capacity. In this study, we allocated a budget to resilience capacities to build a resilient supply chain and considered a limited resilience budget. Therefore, we developed a two-objective stochastic model under disruption conditions to increase the resiliency of the food supply chain. Effective strategies have been implemented to bolster the resilience of food supply chains. These strategies include inventory management, backup supplier engagement, and technology recovery. These strategies aim to improve the supply chain's ability to adapt and recover when faced with unforeseen disruptions. The developed stochastic model with dual objectives aims to minimize supply chain costs during disruptive events, while maximizing service levels. The model employs a mixed-integer nonlinear programming (MINLP) approach, which is linearized and optimized at an appropriate time. The Monte Carlo approach was used to generate stochastic problem parameters, and the sample-average approximation method was employed to estimate the number of required problem scenarios.

Subsequently, we solved the model by using individual programming to determine the optimal value of the objective functions. Finally, we used the Lexicographic max–min method to solve the model. Enhancing supply chain resilience and adaptability has been a highly successful approach to remain competitive in the business world. The results of the sensitivity analysis show that the supply chain has better cost- and service-level performance when simultaneously using absorptive, adaptive, and restorative capacities. We recommend allocating the most significant portion of the resilience budget to the technology recovery strategy, which is more significant than the backup supplier or inventory strategy. Reactive strategies have a more significant effect on enhancing the resilience capacity of the supply chain than proactive strategies. In addition, the optimal budget allocation was 50% of the resilient budget for the technology recovery strategy, and the remaining budget for the backup supplier plus inventory strategies. This allocation reflects the overall positive impact of the technology recovery strategy on the supply chain cost and service levels. The analysis showed that the technology recovery strategy had the most significant impact on increasing the supply chain service levels. The inventory maintenance strategy significantly increased the supply chain cost and had the most negligible impact on increasing service level. We recognize the significance of developing strategies for budget allocation because of sensitivity analysis.

1. Technology recovery strategy
2. Backup supplier strategy
3. Inventory strategy

Cost and time are two factors for evaluating recovery strategies. Thus, calculating and minimizing recovery time are crucial and applicable topics in food supply networks that require further research. Future studies will also investigate the recovery potential of fundamental infrastructure, such as water, power, and blood supply networks. This study provides an excellent resource for tackling recovery tactics in various fields.

Appendix A.

This section shows how we get each model in the sensitivity analysis. We presented each model and the abbreviation of each model below. Also, the Equations of each model are presented in Table A.1.

– **Analysis of the impact of resilient strategies on objective functions**
1. Omitting producer inventory strategy (OPI)
2. Omitting backup supplier strategy (OBS)
3. Omitting technology recovery strategy (OTR)

– **Sensitivity analysis of the allocated budget to each resilient strategy**
- Allocate 100% of the resilience budget to the technology recovery strategy (FA1)
- Allocate 90% of the resilience budget to technology recovery and the remaining 10% to inventory and backup supplier strategies (FA2).
- Allocate 80% of the resilience budget to the technology recovery strategy and the remaining 20% to the backup supplier and inventory strategies (FA3).
- Allocate 70% of the resilience budget to the technology recovery strategy and the remaining 30% to the backup supplier and inventory strategies (FA4).
- Allocate 60% of the resilience budget to the technology recovery strategy and the remaining 40% to the backup supplier and inventory strategies (FA5).
- Allocate 50% of the resilience budget to the technology recovery strategy and the remaining 50% to the backup supplier and inventory strategies (FA6).
- Allocate 50% of the resilience budget to the backup supplier strategy and the remaining 50% to the technology recovery and inventory strategies (FA7).
- Allocate 50% of the resilience budget to inventory strategy and the remaining 50% to technology recovery and backup supplier strategies (FA8).

A.1. Appendix

In this section, we presented equations related to the OPI model (omitting the producer inventory strategy):

$$\begin{aligned}
\text{Min } Z_1 = {} & \sum_i CC_i S_i + \sum_b CC_b S_b \\
& + \sum_s P^s \Bigg(\sum_j \sum_t CH_{jt} I^s_{jt} + \sum_k \sum_p \sum_{t|r\leq t} CH_{kpt} I^s_{kprt} + \sum_k \sum_p \sum_t \sum_r CL_{kpt} L^s_{kprt} \\
& + \sum_j \sum_p \sum_t CE_{jpt} E^s_{jpt} + \sum_k \sum_p \sum_t CE_{kpt} E^s_{kpt} + \sum_j \sum_p \sum_t CM_{jpt} Q^s_{jpt} \\
& + \sum_j \sum_k \sum_p \sum_{t|r\leq t} CT_{jkpt} Q^s_{jkprt} Dis_{jk} + \sum_i \sum_j \sum_t CT_{ijt} Q^s_{ijt} Dis_{ij} \\
& + \sum_b \sum_j \sum_t CT_{bjt} Q^s_{bjt} Dis_{bj} + \sum_b \sum_j \sum_t CC_b S^s_{bt} + \sum_i \sum_j \sum_t Prc_{it} Q^s_{ijt} \\
& + \sum_b \sum_j \sum_t Prc_{bt} Q^s_{bjt} + \sum_j \sum_p \sum_t \sum_s R^s_{jpt} TB_{jts} \Bigg)
\end{aligned} \tag{A.1}$$

$$Q^s_{jpt} = \sum_K Q^s_{jkprt} \qquad \forall j \in J, p \in P, s \in S, t\&r \in T\,|0 \leq t - r \leq SL_p \tag{A.2}$$

$$\sum_{k|t-r=SL_p} Q^s_{jkprt} = E^s_{jpt} \qquad \forall k \in K, p \in P, s \in S, t\&r \in T\,|r = t \tag{A.3}$$

$$\sum_p BR^s_{jpt} + \sum_b (Prc_b - Prc_i) Q^s_{bjt} \leq TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.4}$$

A.2. Appendix

In this section, equations related to the OBS model (omitting backup supplier strategy) are presented:

$$\begin{aligned}
MinZ_1 = {} & \sum_i CC_i S_i \\
& + \sum_s P^s \Bigg(\sum_j \sum_t CH_{jt} I^s_{jt} + \sum_j \sum_p \sum_{t|r\leq t} \sum_r CH_{jpt} I^s_{jprt} + \sum_k \sum_p \sum_{t|r\leq t} CH_{kpt} I^s_{kprt} \\
& + \sum_k \sum_p \sum_t \sum_r CL_{kpt} L^s_{kprt} + \sum_j \sum_p \sum_t CE_{jpt} E^s_{jpt} + \sum_k \sum_p \sum_t CE_{kpt} E^s_{kpt} \\
& + \sum_j \sum_p \sum_t CM_{jpt} Q^s_{jpt} + \sum_j \sum_k \sum_p \sum_{t|r\leq t} CT_{jkpt} Q^s_{jkprt} Dis_{jk} + \sum_i \sum_j \sum_t CT_{ijt} Q^s_{ijt} Dis_{ij} \\
& + \sum_b \sum_j \sum_t CT_{bjt} Q^s_{bjt} Dis_{bj} + \sum_i \sum_j \sum_t Prc_{it} Q^s_{ijt} + \sum_j \sum_p \sum_t \sum_s R^s_{jpt} TB_{jts} \Bigg)
\end{aligned} \tag{A.5}$$

$$\sum_i Q^s_{ijt} \left(1 - V^s_{it}\right) = \sum_p \alpha_p Q^s_{jpt} + I^s_{jt} \qquad \forall j \in J, t \in T, s \in S \tag{A.6}$$

$$\sum_p BR^s_{jpt} + \sum_p I^s_{jprt} CH_{jpt} \leq TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.7}$$

TABLE A.1. Equations of each model.

Number	Abbreviation	Equations of each model: Objective functions	Equations of each model: Constraints	Appendix
1	OPI	Equations (A.1) and (2)	Equations (3)–(6) and Equations (A.2)–(A.4) and Equations (11)–(23) and Equations (25)–(26)	Appendix A.1
2	OBS	Equations (A.5) and (2)	Equations (4) and (5) and Equations (7)–(23) and Equations (A.6–A.7) and Equations (25)–(26)	Appendix A.2
3	OTR	Equations (A.8) and (2)	Equations (3)–(21) and Equation (A.9) and Equations (25)–(26)	Appendix A.3
4	FA1	Equations (1)–(2)	Equations (3)–(23) and Equations (A.10)–(A.11) and Equations (25)–(26)	Appendix A.4
5	FA2	Equations (1)–(2)	Equations (3)–(23) and Equations (A.12)–(A.13) and Equations (25)–(26)	Appendix A.5
6	FA3	Equations (1)–(2)	Equations (3)–(23) and Equations (A.14)–(A.15) and Equations (25)–(26)	Appendix A.6
7	FA4	Equations (1)–(2)	Equations (3)–(23) and Equations (A.16)–(A.17) and Equations (25)–(26)	Appendix A.7
8	FA5	Equations (1)–(2)	Equations (3)–(23) and Equations (A.18)–(A.19) and Equations (25)–(26)	Appendix A.8
9	FA6	Equations (1)–(2)	Equations (3)–(23) and Equations (A.20)–(A.21) and Equations (25)–(26)	Appendix A.9
10	FA7	Equations (1)–(2)	Equations (3)–(23) and Equations (A.22)–(A.23) and Equations (25)–(26)	Appendix A.10
11	FA8	Equations (1)–(2)	Equations (3)–(23) and Equations (A.24)–(A.25) and Equations (25)–(26)	Appendix A.11

A.3. Appendix

In this section, we presented equations related to the OTR model (omitting technology recovery strategy):

$$MinZ_1 = \sum_i CC_i S_i + \sum_b CC_b S_b$$

$$+ \sum_s P^s \left(\sum_j \sum_t CH_{jt} I^s_{jt} + \sum_j \sum_p \sum_{t|r\leq t} \sum_r CH_{jpt} I^s_{jprt} + \sum_k \sum_p \sum_{t|r\leq t} CH_{kpt} I^s_{kprt} \right.$$

$$
\begin{aligned}
&+\sum_{k}\sum_{p}\sum_{t}\sum_{r} CL_{kpt}L^{s}_{kprt} + \sum_{j}\sum_{p}\sum_{t} CE_{jpt}E^{s}_{jpt} + \sum_{k}\sum_{p}\sum_{t} CE_{kpt}E^{s}_{kpt}\\
&+\sum_{j}\sum_{p}\sum_{t} CM_{jpt}Q^{s}_{jpt} + \sum_{j}\sum_{k}\sum_{p}\sum_{t|r\leq t} CT_{jkpt}Q^{s}_{jkprt}Dis_{jk} + \sum_{i}\sum_{j}\sum_{t} CT_{ijt}Q^{s}_{ijt}Dis_{ij}\\
&+\sum_{b}\sum_{j}\sum_{t} CT_{bjt}Q^{s}_{bjt}Dis_{bj} + \sum_{b}\sum_{j}\sum_{t} CC_{b}S^{s}_{bt} + \sum_{i}\sum_{j}\sum_{t} Prc_{it}Q^{s}_{ijt}\\
&+\left.\sum_{b}\sum_{j}\sum_{t} Prc_{bt}Q^{s}_{bjt}\right)
\end{aligned}
\tag{A.8}
$$

$$
\sum_{b}(Prc_b - Prc_i)Q^{s}_{bjt} + \sum_{p} I^{s}_{jprt}CH_{jpt} \leq TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.9}
$$

A.4. Appendix

In this section, we presented equations related to the FA1 model (Allocating 100% of the available budget to the technology recovery strategy):

$$
\sum_{p} BR^{s}_{jpt} \leq TB_{jts} \qquad \forall j \in J, t \in T, s \in S \tag{A.10}
$$

$$
\sum_{b}(Prc_b - Prc_i)Q^{s}_{bjt} + \sum_{p} I^{s}_{jprt}CH_{jpt} \leq \qquad \forall j \in J, t \in T, s \in S. \tag{A.11}
$$

A.5. Appendix

In this section, equations related to the FA2 model (Allocating 90% of the available budget to the technology recovery strategy, 10% to the backup supplier strategies, and inventory) are presented:

$$
\sum_{p} BR^{s}_{jpt} \leq 0.9 * TB_{jts} \qquad \forall j \in J,\ t \in T, s \in S \tag{A.12}
$$

$$
\sum_{b}(Prc_b - Prc_i)Q^{s}_{bjt} + \sum_{p} I^{s}_{jprt}CH_{jpt} \leq 0.1 * TB_{jts} \qquad \forall j \in J,\ t \in T, s \in S. \tag{A.13}
$$

A.6. Appendix

In this section, equations related to the FA2 model (Allocating 80% of the available budget to the technology recovery strategy, 20% to the backup supplier strategies, and inventory) are presented:

$$
\sum_{p} BR^{s}_{jpt} \leq 0.8 * TB_{jts} \qquad \forall j \in J,\ t \in T, s \in S \tag{A.14}
$$

$$
\sum_{b}(Prc_b - Prc_i)Q^{s}_{bjt} + \sum_{p} I^{s}_{jprt}CH_{jpt} \leq 0.2 * TB_{jts} \qquad \forall j \in J,\ t \in T, s \in S. \tag{A.15}
$$

A.7. Appendix

In this section, equations related to the FA2 model (Allocating 70% of the available budget to the technology recovery strategy, 30% to the backup supplier strategies, and inventory) are presented:

$$
\sum_{p} BR^{s}_{jpt} \leq 0.70 * TB_{jts} \qquad \forall j \in J,\ t \in T, s \in S \tag{A.16}
$$

$$
\sum_{b}(Prc_b - Prc_i)Q^{s}_{bjt} + \sum_{p} I^{s}_{jprt}CH_{jpt} \leq 0.30 * TB_{jts} \qquad \forall j \in J,\ t \in T, s \in S. \tag{A.17}
$$

A.8. Appendix

In this section, equations related to the FA2 model (Allocating 60% of the available budget to the technology recovery strategy, 40% to the backup supplier strategies, and inventory) are presented:

$$\sum_p BR^s_{jpt} \leq 0.60 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S \tag{A.18}$$

$$\sum_b (Prc_b - Prc_i)Q^s_{bjt} + \sum_p I^s_{jprt}CH_{jpt} \leq 0.40 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.19}$$

A.9. Appendix

In this section, equations related to the FA3 model (Allocating 50% of the available budget to the technology recovery strategy, 50% of the backup supplier strategies, and inventory) are presented:

$$\sum_p BR^s_{jpt} \leq 0.5 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S \tag{A.20}$$

$$\sum_b (Prc_b - Prc_i)Q^s_{bjt} + \sum_p I^s_{jprt}CH_{jpt} \leq 0.5 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.21}$$

A.10. Appendix

In this section, equations related to the FA4 model (Allocating 50% of the resilient budget to the backup supplier strategy, 50% to the technology recovery strategy, and the inventory strategy) are presented:

$$\sum_b (Prc_b - Prc_i)Q^s_{bjt} \leq 0.5 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S \tag{A.22}$$

$$\sum_p BR^s_{jpt} + \sum_p I^s_{jprt}CH_{jpt} \leq 0.5 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.23}$$

A.11. Appendix

In this section, equations related to the FA5 model (Allocating 50% of the resilient budget to inventory strategy, 50% to the technology recovery strategy, and backup supplier) are presented:

$$\sum_p I^s_{jprt}CH_{jpt} \leq 0.5 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S \tag{A.24}$$

$$\sum_p BR^s_{jpt} + \sum_b (Prc_b - Prc_i)Q^s_{bjt} \leq 0.5 * TB_{jts} \qquad \forall j \in J, t \in T, s \in S. \tag{A.25}$$

Data Availability Statements

The research data associated with this article are available in Zenodo repository: https://zenodo.org/records/10796024 [20]. The code used in this paper is available online in Github repository: https://github.com/marziehKeshavarz/Monte-Carlo [21].

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.

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