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Fuzzy Optimization with Resilience Metrics for Sustainable Supply Chain Planning under Uncertain and Disruption Environments

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Abstract

In the evolving landscape of modern supply chains, achieving sustainability while ensuring resilience presents a significant challenge. This study introduces a novel fuzzy optimization technique designed to develop sustainable supply chain plans under uncertain environments. The proposed framework integrates the principles of Chance-Constrained Programming (CCP) with Intuitionistic Fuzzy Linear Programming (IFLP), enabling decision-makers to manage the risk of constraint violations while simultaneously addressing levels of satisfaction and non-satisfaction. By incorporating resilience metrics, the model evaluates its capacity to respond effectively to disruptions and uncertainties, ensuring robust operational performance characterized by flexibility, redundancy, and recovery capabilities. The methodology aims to optimize sustainable supply chain planning by minimizing total costs and maximizing social and environmental performance scores, while accounting for imprecise costs and customer demands. A case study demonstrates the practical application of the model, emphasizing its efficacy in addressing sustainability and resilience challenges in real-world scenarios. The findings highlight the potential of fuzzy optimization to enhance decision-making processes in sustainable supply chain management.

Keywords: Supply Chain Planning; Sustainability; Resilience Indexes; Uncertainty; Disruption; Fuzzy Optimization

1. Introduction

Sustainable Supply Chain Planning (SSCP) is essential in modern operations, integrating economic, environmental, and social factors [1]. With rising environmental and social concerns, businesses must optimize resources while minimizing their ecological impact. SSCP strategically aligns production, procurement, and logistics with sustainability, balancing costs and corporate responsibilities. As global supply chains grow more complex amid

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market uncertainty and resource scarcity, SSCP becomes crucial, shifting the focus from short-term cost efficiency to long-term environmental and social outcomes.

Moreover, uncertainty is a key challenge in SSCP, requiring advanced modeling to manage fluctuating demand, disruptions, and regulatory shifts. This study integrates Chance-Constrained Programming (CCP) with Intuitionistic Fuzzy Linear Programming (IFLP) to balance constraint risk, satisfaction, and non-satisfaction. CCP enhances robustness by incorporating confidence levels (γ) to quantify the probability of constraint satisfaction, ensuring feasible flexible decisions [2]. IFLP complements CCP by optimizing trade-offs in multi-objective fuzzy models, maximizing satisfaction while minimizing non-satisfaction [3]. Together, they offer a comprehensive framework for strengthening SCAPP in uncertain environments.

Resilience is vital in supply chain planning, ensuring adaptability to disruptions in a volatile global environment. It enables supply chains to prepare for, respond to, and recover from crises while maintaining stability [4]. Rising risks from natural disasters, geopolitical tensions, and market shifts highlight its importance. Unlike efficiency-driven models, resilience requires flexibility to adapt, redundancy for backup options, and recovery capability to restore operations. These strategies collectively strengthen supply chains against uncertainty, safeguarding competitiveness and stability.

Advancements in analytical tools enhance resilience in supply chain planning through scenario analysis and optimization. By integrating resilience metrics, organizations can assess preparedness and identify improvements. This study evaluates resilience across flexibility, redundancy, and recovery capability by simulating disruptions. Scenario testing quantifies the model's stability, demonstrating its effectiveness in managing uncertainties. The findings validate its robustness, ensuring operational continuity and reinforcing its value in dynamic supply chain environments.

The primary contributions of this study are as follows:

- This paper proposes a fuzzy optimization framework combining CCP and IFLP to manage constraint risks while balancing satisfaction and non-satisfaction levels. Integrating resilience metrics; flexibility, redundancy, and recovery, it strengthens supply chain resilience under uncertainty.
- A case study demonstrates the model's effectiveness in tackling real-world sustainability and resilience challenges. By minimizing costs and maximizing social and environmental performance, while handling imprecise data, the study validates the framework's potential to enhance decision-making in sustainable supply chain management.

2. Related Work

Sustainable supply chain production planning is a strategic approach that integrates environmental, social, and economic considerations into the production planning processes of supply chains [5]. It aims to optimize resource allocation and production activities while minimizing environmental impacts such as carbon emissions and waste. This approach also emphasizes social responsibility, including ethical labor practices and community welfare, alongside economic goals like cost-efficiency and profitability. By adopting principles such as the circular economy and leveraging advanced optimization techniques, sustainable supply chain production planning seeks to create resilient systems that align operational efficiency with sustainability objectives, ensuring long-term value creation for all stakeholders [6].

Uncertainty and disruption in sustainable supply chain production planning refer to unpredictable events or conditions that impact the efficiency, reliability, and sustainability of supply chain operations [7]. These include demand variability, supply shortages, natural disasters, geopolitical issues, and other unforeseen challenges. Managing these uncertainties is crucial to ensuring that production plans align with sustainability objectives, such as reducing environmental impact and maintaining social responsibility. Advanced approaches like fuzzy optimization and resilience strategies are employed to address these challenges, enabling supply chains to adapt and maintain performance under uncertain and disruptive conditions [8].

Fuzzy optimization is a mathematical approach used to address uncertainty in decision-making problems, particularly when exact data is unavailable. It leverages fuzzy sets to model ambiguous parameters, enabling more flexible and realistic solutions. Chance-constrained programming and intuitionistic fuzzy linear programming are specialized methods within fuzzy optimization. CCP integrates probabilistic constraints into the fuzzy framework, ensuring that constraints are satisfied with a certain probability level, making it ideal for managing risk and variability in uncertain environments. On the other hand, IFLP uses membership and non-membership functions to represent uncertainty. Together, these approaches enhance the applicability of fuzzy optimization in complex and uncertain systems [9].

Resilience metrics in sustainable supply chain production planning evaluate a supply chain's capacity to anticipate, respond to, recover from, and adapt to disruptions while maintaining sustainability objectives. These metrics include measures such as time to recover, system robustness, flexibility, redundancy, and cost-effectiveness during disruption response [10]. They also assess the environmental and social impacts of recovery efforts to ensure alignment with sustainability goals. By quantifying these factors, resilience metrics help organizations design strategies that enhance operational continuity and long-term sustainability under uncertain and disruptive conditions.

This study aims to propose a fuzzy optimization approach with resilience metrics for SSCP, which will allow decision-makers to optimize sustainable supply chain production planning effectively, offering actionable insights for real-world applications.

3. Methodology

This section introduces a fuzzy optimization methodology integrated with resilience metrics to develop an efficient and resilient sustainable supply chain production planning framework.

3.1. Fuzzy Optimization Approach

The framework employs a multi-objective fuzzy linear programming approach, structured into four phases: 1) Data Preparation, 2) Defuzzification, 3) Membership Function Development, and 4) Optimization Process, as depicted in Fig. 1.

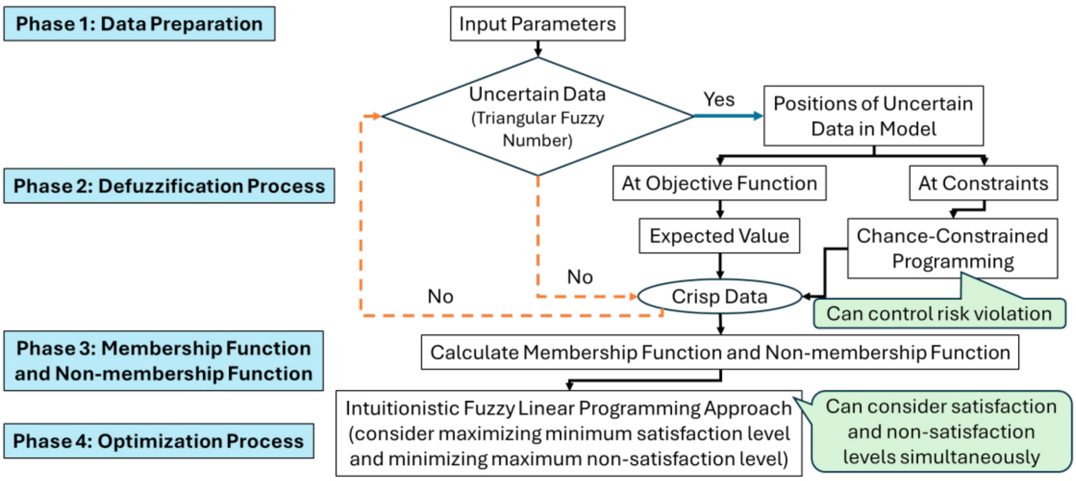

Fig. 1. The framework of fuzzy optimization approach.

Phase 1: Data Preparation - In this phase, parameters are classified as either crisp (precise and known) or uncertain (ambiguous or difficult to define). Uncertain parameters are represented using Triangular Fuzzy Numbers (TFNs).

Phase 2: Defuzzification Process - In this stage, uncertain parameters are converted into crisp values through defuzzification, with the method selected depending on whether the fuzzy parameters are part of the objective functions or constraints.

The Expected Value (EV) approach is introduced as a standard defuzzification method for objective functions, aimed at evaluating their average overall performance [11].

$$EV = \frac{(C^o + (2 \times C^m) + C^p)}{4} \tag{1}$$

where C^o, C^m, and C^p represent the objective coefficients in optimistic, most likely, and pessimistic scenarios, respectively.

Chance-Constrained Programming (CCP) uses the fuzzy measure of credibility to transform fuzzy data while ensuring a specified confidence level for constraints [12]. By selecting a credibility percentage (γ), CCP adjusts confidence levels, with higher values indicating greater reliability and lower risk of violation. A 100% confidence level covers all scenarios, while low confidence ($\gamma < 0.5$) is rarely used due to its limited reliability.

$$Cr\left\{\sum_{i=1}^{I} ax \leq \tilde{b_i}\right\} \geq \gamma$$

$$If\ (0 \leq \gamma < 0.5): ax \leq (1 - 2\gamma)b_i^o + (2\gamma)b_i^m \tag{2}$$

$$If\ (0.5 \leq \gamma \leq 1): ax \leq (2 - 2\gamma)b_i^m + (2\gamma - 1)b_i^p \tag{3}$$

where b_i^o, b_i^m, and b_i^p are values of available resources in optimistic situation, most likely situation, and pessimistic situation, respectively. γ is the percentage of credibility level, which is assigned to 80% in this study.

Phase 3: Membership and Non-membership Functions - In SCAPP, differing stakeholder priorities result multiple, non-comparable objectives. To standardize these, membership and non-membership functions are used to scale objectives from 0.0 to 1.0, representing levels of satisfaction and non-satisfaction.

- Membership Function for Minimization of the Objective Function

$$\mu_{z_i} = \begin{cases} 1, & z_i \leq z_i^{PIS} \\ \frac{z_i^{NIS} - z_i}{z_i^{NIS} - z_i^{PIS}}, & z_i^{PIS} \leq z_i \leq z_i^{NIS} \\ 0, & z_i \geq z_i^{NIS} \end{cases} \tag{4}$$

- Membership Function for Maximization of the Objective Function

$$\mu_{z_i} = \begin{cases} 1, & z_i \geq z_i^{PIS} \\ \frac{z_i - z_i^{NIS}}{z_i^{PIS} - z_i^{NIS}}, & z_i^{NIS} \leq z_i \leq z_i^{PIS} \\ 0, & z_i \leq z_i^{NIS} \end{cases} \tag{5}$$

where z_i^{NIS} is the maximum bound for minimizing the objective or the minimum bound for maximizing the objective, and z_i^{PIS} is the maximum bound for maximizing the objective or the minimum bound for minimizing the objective.

- Non-membership Function for Minimization of the Objective Function

$$\tau_{z_i} = \begin{cases} 1, & z_i \geq z_i^{PIS} \\ \frac{z_i - z_i^{NIS}}{z_i^{PIS} - z_i^{NIS}}, & z_i^{NIS} \leq z_i \leq z_i^{PIS} \\ 0, & z_i \leq z_i^{NIS} \end{cases} \tag{6}$$

- Non-membership Function for Maximization of the Objective Function

$$\tau_{z_i} = \begin{cases} 1, & z_i \leq z_i^{PIS} \\ \frac{z_i^{NIS} - z_i}{z_i^{NIS} - z_i^{PIS}}, & z_i^{PIS} \leq z_i \leq z_i^{NIS} \\ 0, & z_i \geq z_i^{NIS} \end{cases} \tag{7}$$

where z_i^{PIS} is the maximum bound for minimizing the objective or the minimum bound for maximizing the objective, and z_i^{NIS} is the maximum bound for maximizing the objective or the minimum bound for minimizing the objective.

Phase 4: Optimization Process - This phase aims to find the optimal solution in Multi-Objective Fuzzy Linear Programming (MOFLP) using Intuitionistic Fuzzy Linear Programming (IFLP). It does so by maximizing minimum satisfaction and minimizing maximum non-satisfaction levels across multiple objectives.

$$\begin{aligned} & Maximize\ (\mu_z - \tau_z) \\ & Subject\ to: x \in F(x) \\ & \qquad \mu_z < \mu_{z_i}, \qquad i = 1, 2, \dots, I \\ & \qquad \tau_z < \tau_{z_i}, \qquad i = 1, 2, \dots, I \end{aligned} \tag{8}$$

where μ_z represents the minimum satisfaction level among multiple objective functions, while μ_{z_i} denotes the satisfaction level of each individual objective function. τ_z represents the maximum non-satisfaction level among multiple objective functions, while τ_{z_i} denotes the non-satisfaction level of each individual objective function.

3.2. Resilience Metrics

Resilience metrics assess a system's ability to withstand and recover from disruptions. In supply chains, these metrics evaluate flexibility, redundancy, and recovery to ensure continued operations amid uncertainties and disruptions. They help organizations identify vulnerabilities and enhance strategies to maintain stability under challenging conditions. The procedure for calculating resilience metrics is outlined below.

- Step 1: Define resilience metrics and normalize the indicators to a scale (0 to 1) for comparability.
  1. Flexibility Metric: It evaluates the system’s ability to adapt to demand, capacity, and supply changes that can be calculated from number of feasible plans that can be adapted to disruption cases.

     $$Normalized\ Value\ (\%\ Flexibility) = \frac{Number\ of\ feasible\ plans}{Total\ number\ of\ disruption\ cases} \tag{9}$$

  2. Redundancy Metric: It measures the availability of backup suppliers or resources to ensure continuity that can be calculated from the number of feasible plans that inventory amounts are increased.

     $$Normalized\ Value\ (\%\ Redundancy) = \frac{Number\ of\ feasible\ plans\ (inventory\ increased)}{Total\ number\ of\ disruption\ cases} \tag{10}$$

  3. Recovery Capability Metric: It assesses how efficiently the system restores operations and minimizes disruption impact that can be calculated from the number of feasible plans that costs are increased.

     $$Normalized\ Value\ (\%\ Recovery\ Capability) = \frac{Number\ of\ feasible\ plans\ (costs\ increased)}{Total\ number\ of\ disruption\ cases} \tag{11}$$

- Step 2: Calculate resilience metrics

  $$RM = \sum_{i=1}^{I} w_i \times NS_i \tag{12}$$

  where w_i is the weight of each resilience metric (in this study, each weight is assigned equally 33% with the total weight summing to 1) and NS_i is the normalized score of each resilience metric.

4. Mathematical Model

Minimizing total supply chain operational costs is a critical objective in formulating an effective and sustainable supply chain plan, especially when costs are inherently uncertain.

$$\begin{aligned} Minimize\ \widetilde{TSCOC} = & \sum_{s=1}^{S}\sum_{r=1}^{R} \widetilde{FCS}_{sr} \times SS_{sr} + \sum_{m=1}^{M}\sum_{cm=1}^{CM} \widetilde{FCM}_{mcm} \times IM_{mcm} \\ & + \sum_{d=1}^{D}\sum_{cd=1}^{CD} \widetilde{FCD}_{dcd} \times ID_{dcd} + \sum_{m=1}^{M}\sum_{d=1}^{D} \widetilde{TCMD}_{md} \times TPQM_{md} \\ & + \sum_{s=1}^{S}\sum_{m=1}^{M}\sum_{r=1}^{R} \widetilde{TCSM}_{smr} \times TRQS_{tmr} + \sum_{d=1}^{D}\sum_{c=1}^{C} \widetilde{TCDC}_{dc} \times TPQD_{dc} + \sum_{s=1}^{S}\sum_{r=1}^{R} \widetilde{PurC}_{sr} \times \widetilde{PurC}_{sr} \\ & + \sum_{m=1}^{M} \widetilde{ProdC}_{m} \times PQM_{m} + \sum_{m=1}^{M}\sum_{r=1}^{R} \widetilde{MHC}_{rm} \times SSQM_{mr} + \sum_{d=1}^{D} \widetilde{DHC}_{d} \times SSQD_{d} \end{aligned} \tag{13}$$

Companies increasingly recognize the importance of sustainability, while consumers demand ethical practices. Integrating social and environmental factors into supply chains is essential for compliance and reputation [13]. This study evaluates each supply chain echelon's social and environmental performance using expert judgment, assigning weighted scores (W_i) and ratings (R_i), where higher scores indicate better performance.

$$Social/Environmental\ Performance\ Score = \sum_i^I W_i R_i \quad (14)$$

The total social performance score, calculated as the product of each echelon's social performance score and the quantity of transported raw materials or products, is maximized, as expressed in Equation (15). Similarly, the total environmental performance score, determined by multiplying each echelon's environmental performance score by the quantity of transported raw materials or products, is also maximized, as indicated in Equation (16).

$$Maximize\ SPC = \sum_{s=1}^{S}\sum_{m=1}^{M}\sum_{r=1}^{R} SPCS_{sr} \times TRQS_{tmr} + \sum_{m=1}^{M}\sum_{d=1}^{D} SPCM_m \times TPQM_{md} + \sum_{d=1}^{D}\sum_{c=1}^{C} SPCD_d \times TPQD_{dc} \quad (15)$$

$$Maximize\ EPC = \sum_{s=1}^{S}\sum_{m=1}^{M}\sum_{r=1}^{R} EPCS_{sr} \times TRQS_{tmr} + \sum_{m=1}^{M}\sum_{d=1}^{D} EPCM_m \times TPQM_{md} + \sum_{d=1}^{D}\sum_{c=1}^{C} EPCD_d \times TPQD_{dc} \quad (16)$$

Constraints

$$\sum_{m=1}^{M} TRQS_{tmr} \le ARM_{sr} \quad \forall r,s \quad (17)$$
$$ARM_{sr} \le SCapRM_{sr} \times PR_{sr} \times SS_{sr} \quad \forall r,s \quad (18)$$
$$PQM_m \le \sum_{cm=1}^{CM} MCapP_{mcm} \times IM_{mcm} \quad \forall m \quad (19)$$
$$RPP_r \times PQM_m + SSQM_{mr} = \sum_{s=1}^{S} TRQS_{tmr} \quad \forall r,m \quad (20)$$
$$SSQM_{mr} \ge SSRM_{mr} \times RPP_r \times PQM_m \quad \forall r,m \quad (21)$$
$$SSQM_{mr} \le SMCap_{mr} \times IM_{mcm} \quad \forall r,m,cm \quad (22)$$
$$PQM_m = \sum_{d=1}^{D} TPQM_{md} \quad \forall m \quad (23)$$
$$\sum_{m=1}^{M} TPQM_{md} \le \sum_{cd=1}^{CD} SDCap_{dcd} \times ID_{dcd} \quad \forall d \quad (24)$$
$$\sum_{m=1}^{M} TPQM_{md} - SSQD_d = \sum_{c=1}^{C} TPQD_{dc} \quad \forall d \quad (25)$$
$$SSQD_d \ge SSRD_d \times \sum_{m=1}^{M} TPQM_{md} \quad \forall d \quad (26)$$
$$\sum_{c=1}^{C} TPQD_{dc} = \widetilde{De}_c \quad \forall c \quad (27)$$

5. Case Study

A numerical case study models a supply chain where four suppliers provide two raw materials to two manufacturers with varying capacities. The manufacturers process these materials into a final product, distributed through three capacity-limited distribution centers to five customers with specific demand requirements.

Table 1. Values of input parameters.

Parameters	Values	Parameters	Values
RPP_r	(1, 1)	$SSRD_d$	(0.17, 0.23, 0.27)
$SPCS_{sr}$	(0.75, 0.80, 0.95, 0.62), (0.68, 0.85, 0.77, 0.88)	$\widetilde{PurC}_{sr}$	(1.25, 1.45, 0.85, 0.55), (0.75, 0.35, 1.15, 1.65)
$SPCM_m$	(0.85, 0.92)	$\widetilde{FCS}_{sr}$	(75, 85, 98, 65), (58, 50, 70, 90)
$SPCD_d$	(0.79, 0.87, 0.96)	$\widetilde{FCM}_{mcm}$	(8,500, 9,200), (7,900, 8,700)
$EPCS_{sr}$	(0.83, 0.78, 0.91, 0.75), (0.72, 0.67, 0.85, 0.89)	$\widetilde{FCD}_{dcd}$	(5,600, 6,300, 5,900), (6,500, 5,200, 6,800)
$EPCM_m$	(0.91, 0.78)	$\widetilde{ProdC}_m$	(2.25, 2.75)
$EPCD_d$	(0.86, 0.72, 0.68)	$\widetilde{MHC}_{rm}$	(2.46, 1.87)
$SCapRM_{sr}$	(700, 700, 700, 700), (700, 700, 700, 700)	$\widetilde{DHC}_d$	(2.87, 3.27, 3.65)
$MCapP_{mcm}$	(750, 670), (880, 590)	$\widetilde{TCSM}_{smr}$	[(1.23, 1.14, 1.72, 1.26), (1.41, 1.92, 1.34, 1.78)] [(1.56, 1.49, 1.85, 1.39), (1.17, 1.32, 1.68, 1.54)]
$SMCap_{mr}$	(450, 380), (350, 470)	$\widetilde{TCMD}_{md}$	(1.46, 1.38, 1.52), (1.94, 1.83, 1.75)

$SDCap_{dcd}$	(900, 900, 900), (900, 900, 900)	$\widetilde{TCDC}_{dc}$	(1.54, 1.26, 1.43, 1.71, 1.64), (1.29, 1.35, 1.48, 1.52, 1.94), (1.58, 1.67, 1.21, 1.45, 1.76)
$SSRM_{mr}$	(0.15, 0.25), (0.22, 0.18)	$\widetilde{De}_{c}$	(225, 246, 289, 217, 263)

6. Results

6.1. Results of fuzzy optimization approach

The optimal results show a minimum total supply chain operational cost of $70,631, a maximum social performance scores of 7,100 scores, and a maximum environmental performance scores of 7,215.4 scores, as shown in Table 2.

Table 2. Results of fuzzy optimization approach.

	Minimizing total supply chain operational costs	Maximizing social performance scores	Maximizing environmental performance scores
Objective Values	$70,631	7,100 scores	7,215.4 scores
Satisfaction Level	67.62%	69.72%	67.62%
Non-Satisfaction Level	32.37%	30.28%	32.37%

6.2. Results of measuring resilience metrics of models under disruptions

In this study, the probability distribution of disruption level is presented in Table 3, where the disruption levels are categorized into 6 cases.

Table 3. Probability distribution of disruption levels.

	% Disruption	Probability	Samples		% Disruption	Probability	Samples
CASE1: Very high	50%	4%	2	CASE4: Low	20%	12%	6
CASE2: High	40%	8%	4	CASE5: Very low	10%	16%	8
CASE3: Moderate	30%	10%	5	CASE6: None	0%	50%	25

This study evaluates the proposed fuzzy linear programming model by varying the capacities of suppliers, manufacturers, and distribution centers. Disruptions such as raw material shortages, machinery breakdowns, and labor shortages impact each stage. By incorporating these variations, the model assesses the system's ability to adapt to disruptions, ensuring supply chain efficiency and sustainability. This evaluation provides decision-makers with insight into the impact of reliability and underscores the importance of flexible, resilient supply chain design.

Table 4. Results of disruption cases and implementation cases.

Supplier disruption										
Case	Total supply chain costs		Total social scores		Total environmental scores		Probability distribution of handling disruption		Resilience Index	
	D	I	D	I	D	I	D	I	D	I
1	0	$74,227.00	0	5745.1	0	5948.1	0%	100%	F = 27.72%	F = 33.00%
2	0	$77,442.00	0	6562.0	0	6718.2	0%	100%	R = 27.72%	R = 33.00%
3	$64,672.33	$70,582.60	5,446.60	6049.7	5,680.10	6303.9	60%	60%	RC = 14.93%	RC =13.80%
4	$66,520.00	$66,520.00	6,021.40	6021.4	6,212.08	6212.1	100%	100%	Total = 70.37%	Total = 79.77%
5	$73,150.25	$73,150.25	6,404.85	6404.9	6,570.09	6570.1	100%	100%		
6	$75,002.84	$75,002.84	6,990.12	6990.1	7,117.54	7117.5	100%	100%		

Manufacturer disruption										
Case	Total supply chain costs		Total social scores		Total environmental scores		Probability distribution of handling disruption		Resilience Index	
	D	I	D	I	D	I	D	I	D	I
1	0	$73,674.50	0	6123.9	0	6241.8	0%	100%	F = 30.36%	F = 33.00%
2	$71,942.00	$73,275.00	6,504.30	6672.3	6,665.35	6839.3	50%	100%	R = 30.36%	R = 33.00%
3	$74,618.60	$74,618.60	6,821.96	6822.0	7,036.82	7036.8	100%	100%	RC = 15.17%	RC =14.40%
4	$75,131.83	$75,131.83	7,092.70	7092.7	7,159.37	7159.4	100%	100%	Total = 75.89%	Total = 80.39%
5	$76,997.75	$76,997.75	7,112.66	7112.7	7,196.39	7196.4	100%	100%		
6	$75,002.84	$75,002.84	6,990.12	6990.1	7,117.54	7117.5	100%	100%		
Distribution center disruption										
Case	Total supply chain costs		Total social scores		Total environmental scores		Probability distribution of handling disruption		Resilience Index	
	D	I	D	I	D	I	D	I	D	I
1	$89,165.00	None	6,835.75	None	6,890.35	None	100%	None	F = 33.00%	None
2	$85,115.00		7,360.30		7,354.13		100%		R = 33.00%	
3	$79,915.80		6,999.96		7,105.54		100%		RC = 15.46%	
4	$75,363.17		7,146.38		7,211.35		100%		Total = 81.46%	
5	$77,433.13		7,081.65		7,153.50		100%			
6	$75,002.84		6,990.12		7,117.54		100%			
Supply chain disruption										
Case	Total supply chain costs		Total social scores		Total environmental scores		Probability distribution of handling disruption		Resilience Index	
	D	I	D	I	D	I	D	I	D	I
1	0	$85,894.00	0	5739.0	0	5768.1	0%	100%	F = 27.06%	F = 33.00%
2	0	$84,170.25	0	6552.0	0	6579.6	0%	100%	R = 27.06%	R = 33.00%
3	$74,040.50	$78,294.20	5,496.50	6376.2	5,630.75	6429.5	40%	100%	RC = 13.24%	RC =12.80%
4	$72,541.17	$72,541.17	6,237.85	6237.9	6,345.98	6346.0	100%	100%	Total = 67.36%	Total = 78.77%
5	$75,509.25	$75,509.25	6,681.79	6681.8	6,764.33	6764.3	100%	100%		
6	$75,002.84	$75,002.84	6,990.12	6990.1	7,117.54	7117.5	100%	100%		

*Note: D = Disruption case, I = Implemented case, F = Flexibility, R = Redundancy, RC = Recovery capability.

According to Table 4, disruptions over 30% for suppliers and 40% for manufacturers have a significant impact on the supply chain. To address this, the study introduces a backup supplier with 700 units capacity and 500 units of subcontracted production. After implementing these measures, all disruption cases (CASE1-CASE6) are manageable. Flexibility and redundancy indices improve, with 100% of disruptions effectively handled. However, the recovery capability index decreases slightly due to the higher costs associated with using backup suppliers and subcontracted production.

7. Conclusions and Future Work

This paper presents a comprehensive fuzzy optimization framework for sustainable supply chain planning under uncertainty, explicitly incorporating resilience metrics to enhance strategic decision-making. By addressing uncertainties in costs, demands, and potential disruptions, the proposed approach empowers supply chain managers and policymakers to make informed, data-driven decisions through the combined use of chance-constrained programming and intuitionistic fuzzy linear programming. Key findings demonstrate how aligning sustainability objectives with resilience capabilities enable decision-makers to develop supply chain strategies that are not only cost-effective and socially and environmentally responsible but also robust against unforeseen disruptions. The framework's integration of flexibility, redundancy, and recovery metrics facilitates proactive risk management, ensuring operational continuity and minimizing vulnerability in volatile conditions.

From a policy perspective, this framework provides valuable insights for regulators and industry leaders seeking to establish guidelines that promote sustainable and resilient supply chains. It supports the development of standards that encourage investments in backup resources, adaptive planning, and risk mitigation practices critical for long-term supply chain stability. Moreover, its applicability across various sectors underscores its potential for broader operational deployment, particularly in industries where supply chain disruptions can have significant economic and social and environmental consequences. The practical value of the framework is demonstrated through a detailed case study, which highlights its effectiveness and adaptability to real-world complexities faced by supply chain professionals. Future research could focus on expanding the framework's scope by incorporating dynamic policy scenarios and regulatory constraints, enabling decision-makers to evaluate trade-offs between sustainability, resilience, and compliance in real time. Further exploration into multi-tier supply chain networks and cross-sector collaboration mechanisms could also provide deeper insights into systemic risks and resilience strategies. By extending this foundation, future studies can contribute to the development of globally resilient supply chains that are capable of thriving amid increasing environmental, social, and economic uncertainties.

Appendix

Table 5. Mathematical notations of indexes, parameters, and decision variables.

Indexes, Parameters, & Decision variables	Meaning	Indexes, Parameters & Decision variables	Meaning
r	Index of raw materials, $r = 1, \ldots, R$	$\widetilde{PurC}_{sr}$	Fuzzy purchasing cost of raw materials r from suppliers s
s	Index of suppliers, $s = 1, \ldots, S$	$\widetilde{FCS}_{sr}$	Fuzzy fixed cost of making a contract with suppliers s
m	Index of manufacturers, $m = 1, \ldots, M$	$\widetilde{FCM}_{mcm}$	Fuzzy fixed cost of installing factory of manufacturers m with different manufacturers' capacity levels cm
d	Index of distribution centers, $d = 1, \ldots, D$	$\widetilde{FCD}_{dcd}$	Fuzzy fixed cost of installing distribution centers d with different distribution centers' capacity levels cd
c	Index of customers, $c = 1, \ldots, C$	$\widetilde{ProdC}_{m}$	Fuzzy producing cost for a product at manufacturers m
cm	Index of capacity levels of manufacturers, $cm = 1, \ldots, CM$	$\widetilde{MHC}_{rm}$	Fuzzy holding cost of raw materials r at manufacturers m
cd	Index of capacity levels of distribution centers, $cd = 1, \ldots, CD$	$\widetilde{DHC}_{d}$	Fuzzy holding cost of products at distribution centers d
RPP_r	Amount of required raw materials r for producing a unit of product	$\widetilde{TCSM}_{smr}$	Fuzzy transporting cost of raw materials r from suppliers s to manufacturers m
SPC	Social performance score	$\widetilde{TCMD}_{md}$	Fuzzy transporting cost of products from manufacturers m to distribution centers d
$SPCS_{sr}$	Social performance score of supplier s for raw material r	$\widetilde{TCDC}_{dc}$	Fuzzy transporting cost of products from distribution centers d to customers c
$SPCM_m$	Social performance score of manufacturers m for a product	$\widetilde{De}_{c}$	Fuzzy demand of customers c
$SPCD_d$	Social performance score of distribution centers d for a product	PR_{sr}	If suppliers s can provide raw materials r equal to 1, otherwise 0.
EPC	Environmental performance score	SS_{sr}	If suppliers s is selected for providing raw materials r

			equal to 1, otherwise 0.
$EPCS_{sr}$	Environmental performance score of supplier *s* for raw material *r*	IM_{mcm}	If factory of manufacturers *m* is installed with capacity level *cm* equal to 1, otherwise 0.
$EPCM_m$	Environmental performance score of manufacturers *m* for a product	ID_{dcd}	If distribution centers *d* is installed with capacity level *cd* equal to 1, otherwise 0.
$EPCD_d$	Environmental performance score of distribution centers *d* for a product	$TRQS_{tmr}$	Amount of transported raw materials *r* from suppliers *s* to manufacturers *m*
$SCapRM_{sr}$	Capacity of suppliers *s* for raw materials *r*	$TPQM_{md}$	Amount of transported products from manufacturers *m* to distribution centers *d*
$MCapP_{mcm}$	Production capacity *cm* of manufacturers *m* for manufacturing products	$TPQD_{dc}$	Amount of transported products from distribution centers *d* to customers *c*
$SMCap_{mr}$	Capacity of manufacturers *m* for storing raw materials *r*	PQM_m	Amount of produced products at manufacturers *m*
$SDCap_{dcd}$	Capacity of distribution centers *d* for storing products	$SSQM_{mr}$	Amount of safety stock of raw materials *r* at manufacturers *m*
$SSRM_{mr}$	Safety stock of raw materials *r* at manufacturers *m*	$SSQD_d$	Amount of safety stock of products at distribution centers *d*
$SSRD_d$	Safety stock of products at distribution centers *d*	ARM_{sr}	Amount of raw materials *r* allocated to suppliers *s*

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