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Designing Antifragile and Agile Food Supply Chains

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Abstract

Playing a critical role in any country, the food industry must guarantee a steady availability of food to consumers. Food supply chains are often vulnerable and unstable, particularly during crises. This vulnerability arises from various challenges and their associated consequences. Currently, stakeholders are being urged to improve supply chain risk management to address multiple disruptive and operational risks. This study proposes an antifragile and agile food Supply Chain Network Design (SCND) that integrates concepts of resiliency, robustness and risk. The model's objective cost function employs combining robust stochastic optimization with Entropic Value at Risk (EVaR). Antifragility is introduced through learning effects on variable parameters and resiliency and agility through flexible capacity and multi-resource and demand satisfaction constraints. The model's performance, including antifragility, is compared against a model without it, showing a cost reduction of 0.42%. The model's application is evaluated using a numerical example, conducting a sensitivity analysis on the antifragility coefficient. Lastly, the research addresses managerial insights and practical implications.

Keywords: Food supply chain network design, Antifragility, Agility, Resilience, Risk.

1 | Introduction

Food significantly impacts the global economy and the well-being of populations, but its production and supply are highly sensitive to several factors such as climate conditions [1]. When external factors and disruptions such as climate change affect elements of the food system, including supply, access, and consumption, food security is jeopardized [2]. The intricate connections among supply networks, economic globalization, and climate change create a dual burden on society. Despite the uncertainties surrounding climate change, it is clear that both climate change and globalization will affect numerous regions, industries, ecosystems, and social groups [3]. Every component of the food supply chain—production, processing, distributing, retailing, and consumption—is vulnerable to environmental changes and natural disruptions.

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Beside climate changes, the COVID-19 pandemic, increasing reliance on raw materials, and conflicts and wars are just a few of the critical issues currently dominating public discourse and affecting global supply chains across various industries. The food industry, in particular, faces significant challenges that need to be understood, as it has always been a crucial sector for any nation [4]. Ensuring a continuous supply of food to consumers is the ultimate goal of this industry [5]. However, achieving the continuous availability of a wide range of food products leads to increasingly complex requirements and challenges for the supply chain and the stakeholders involved [6].

Disorder, which includes randomness, volatility, errors, stressors, uncertainty, variability, and incomplete knowledge, has become a fundamental aspect of today's business environment [7]. What if we adopt a positive perspective on disorder and embrace it? What if we create a supply chain that can benefit from disorder, both financially and in terms of social reputation? Unlike robust or resilient supply chains, an antifragile supply chain thrives on disorder and excels in randomness. In essence, robust and resilient supply chains lie on a spectrum from fragile to antifragile [8]. For instance, the managing director of a custom packaging company, speaking at an executive industry panel in December 2020 in Australia, revealed that the company not only survived but actually thrived during the COVID-19 pandemic, achieving approximately 150% growth in 2020.

Antifragile and agile food Supply Chain Network Design (SCND) represents a novel approach in the field of food SCND (*Fig. 1*). This design incorporates the concept of antifragility, which enhances the ability of facilities to manage disruptions such as stressors, fluctuations, volatility, and shocks [9]. There are four strategic shifts essential for developing an antifragile supply chain: transitioning from resilience to antifragility, innovating mental models instead of just supply chains, shifting from forecasting demand of market to enabling real-time, rapid responses, and Shifting from external production outsourcing to establishing strategic partnerships [10].

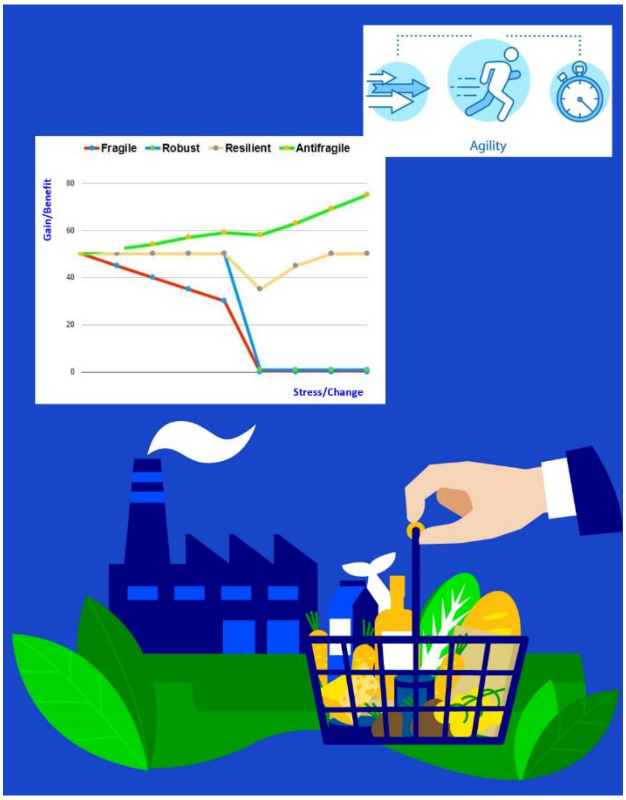

Fig. 2. Antifragility and agility concepts in food SCND.

Transitioning to antifragility allows for network flexibility in the face of complex situations and varying products, addressing demand fluctuations effectively (Lotfi et al., 2023) [11]. Consequently, the optimal approach is to develop an antifragile food SCND that can respond to demand with agility and a risk-averse strategy.

This research is structured into six sections. The second section covers the literature review and recent studies, highlighting research gaps. The third section details the problem mathematical model, linearization, and solution approach. The result section presents a numerical example, along with results and sensitivity analysis. Insights and practical perspectives for managers are provided in the discussion next section. Finally, in the last section, conclusions are drawn and recommendations for further studies are proposed.

2|Literature Review

A substantial amount of research has addressed various uncertainties, including demand, transportation costs, and holding costs, as significant challenges in supply chain management. Numerous methods have been developed to manage these uncertainties, including stochastic programming, simulation, fuzzy sets, and robust optimization. Although many of these methods have been applied in the food industry, new concepts like agility and antifragility, which have not been previously defined in this field, can now be applied and combined.

Reviewed the current understanding of the food supply chain's vulnerability to climate change and identified existing literature that could inform future research, policy, and decision-making to improve the food supply chain's resilience [1]. Developed a multi-objective mathematical model that incorporates uncertainty and sustainability criteria to optimize production rates. The model aims to improve distribution across various demand markets, minimize total costs, address social issues, and reduce negative environmental impacts such as CO_2 emissions and waste products. To solve the proposed model, a combination of exact, meta-heuristic, and hybrid meta-heuristic algorithms were utilized [12]. Arabsheybani and Arshadi Khasmeh [13] created a robust bi-objective multi-product mathematical model that addresses resiliency and uncertainty within a multi-period, multi-item SCND. Their approach facilitates coordination between production planning, distribution, supplier selection, and order allocation. Coordinate a green supply chain incorporating dairy recycling, involving suppliers, retailers, and manufacturers in a multi-item, multi-product, and multi-level framework [14]. Bottani et al. [15] tackle the issue of resilient food supply chains by proposing a bi-objective mixed-integer mathematical model focused on maximizing total profit over a year and minimizing total lead time, utilizing the Ant Colony optimization algorithm for solutions. Martins et al. [16] address the redesign of food bank supply chains by developing a multi-objective mathematical model that simultaneously considers sustainable factors, employing the Lexicographic approach to obtain non-dominated results. Allaoui et al. [17] use an Analytic Hierarchy Process (AHP) and Ordered Weighted Averaging (OWA) method in the first stage, with results from this stage applied in the second stage to solve a developed multi-objective mathematical model. This approach generates a Pareto frontier to assist managers in decision-making. The model's efficiency and effectiveness are demonstrated through its implementation in an agro-food company.

Chen and Chen [18] introduced a two-stage Distributionally Robust Optimization (DRO) model with Ambiguous Chance Constraints (ACC) to address the Resilient Supply Chain Network Design (RSCND) problem. This model aims to offer decision support for planning supply chain networks amidst demand uncertainty and potential disruption scenarios. Mu et al. [19] defined resilient food supply chains in terms of food safety and outlined a procedure for assessing this resilience. They also demonstrated how to quantify and enhance a resilient food supply chain by presenting a numerical example in a case study. Yazdani et al. [20] created a decision-making model utilizing the Best Worst Method (BWM) and the Fuzzy Measurement of Alternatives and Ranking according to Compromise Solution (fuzzy MARCOS) to evaluate the resiliency of key players in the Food Supply Chain Management (FSCM) concerning various resiliency and risk factors. The model's reliability was tested through sensitivity analysis. Bottani et al. [21] conducted research aimed at establishing a framework to assess supply chain performance within the food sector. The approach relied on the LARG (Lean, Agile, Resilient, and Green) perspectives, integrating a thorough review of relevant literature and metrics specific to the food industry. This facilitated the creation of a suitable performance measurement system tailored for food supply chains.

This research aims to design an innovative antifragile and agile food SCND by incorporating antifragility through the impact of learning on variable parameters (variable costs), and enhancing resiliency and agility with flexible capacity and demand satisfaction constraints into the model.

3 | Describing the Model

This research aims to design a novel SCND that emphasizes the significance of antifragility and agility concepts. The SCN includes farms, producers, distribution centers, retailers, and customers (Figure 2). The strategies proposed include an antifragility strategy, which utilizes learning and the experience curve effect by incorporating constraints into the model [22]. An agility approach is implemented through minimum satisfaction demand constraints [23]. Lastly, resiliency and reliability are ensured by making facility capacity dependent on different scenarios [24].

Fig. 2. Food SCND.

Assumptions include allowing partial demands based on agility levels, enforcing general SCND limitations like flow and capacity to maintain agility, and using scenario-dependent facility capacities for robustness and reliability. To handle demand fluctuations, a hybrid risk-averse and stochastic robust optimization approach is suggested. Additionally, antifragility through learning impacts variable parameters such as cost, with a formula used to compute EVaR under the assumption of a normal distribution.

Indices

$f \in \{1,2,...,F\}$	Farms (suppliers)
$m \in \{1,2,...,M\}$	Manufacturers (producers)
$d \in \{1,2,...,D\}$	Distribution Centers (DC)
$r \in \{1,2,...,R\}$	Retailers
$p \in \{1,2,...,P\}$	Products
$t \in \{1,2,...,T\}$	Periods
$s \in \{1,2,...,S\}$	Scenarios

Parameters

`	Fixed cost for farm f
C_m	Fixed cost for manufacturer m
C_d	Fixed cost for DC d
C_r	Fixed cost for retailer r
Cfm_{fmp1s}	Transferring cost from farm f to manufacturer m for product p in period t = 1 for scenario s
Cmd_{mdp1s}	Transferring cost from manufacture m to DC d for product p in period t = 1 for scenario s
Cdr_{drp1s}	Transferring cost from DC d to retailer r for product p in period t = 1 for scenario s
Cr_{rp1s}	Variable cost in retailer r for product p in period t = 1 for scenario s
$Capf_{fpts}$	Maximum capacity of farm f for product p in period t for scenario s

$Capm_{mpts}$	Maximum capacity of manufacture p for product p in period t for scenario s
$Capd_{dpts}$	Maximum capacity of DC d for product p in period t for scenario s
$Capr_{rpts}$	Maximum capacity of retailer r for product p in period t for scenario s
D_{pts}	Product p demand in period t for scenario s
P_s	Probability of scenario s
θ	Coefficient of conservatism
ν	Level of confidence
AL_f	Level of availability for farm f
AL_m	Level of availability for manufacturer m
AL_d	Level of availability for DC d
AL_r	Level of availability for retailer r
λ	Agility (responsive) rate
φ_1	Number of farms required for activation
φ_2	Number of DCs required for activation
μ	Coefficient of antifragility
α_f	Deteriorating percentage of the product by farms
β_m	Waste percentage of the product by the manufacturers

Decision Variables

XF_f	1 if farm f is established; else 0
XM_m	1 if manufacturer m is established; else 0
XD_d	1 if DC d is established; else 0
XR_r	1 if retailer r is established; else 0
Q_{fmpts}	Shipped quantity from farm f to manufacturer m for product p in period t for scenario s
Q_{mdpts}	Shipped quantity from manufacturer m to DC d for product p in period t for scenario s
Q_{drpts}	Shipped quantity from DC d to retailer r for product p in period t for scenario s
Q_{rpts}	Shipped quantity from retailer r to customer for product p in period t for scenario s

Auxiliary variables

TC_s	Total fixed and variable costs for scenario s
FC	Total fixed cost
VC_s	Total variable cost for scenario s
δ	Auxiliary variables for linearization of the max function
ω_{pts}	Surplus variable for demand satisfaction,
a_s, b_s	Auxiliary variables for linearization of the absolute function

Mathematical model

$$\text{Min } Z = (1-\theta)\sum_s P_s\ TC_s + \theta\left(\max_s(TC_s) + EVaR(TC_s)\right)/2, \tag{1}$$

s.t.

$$TC_s = FC + VC_s, \tag{2}$$

$$FC = \sum_f C_f XF_f + \sum_m C_m XM_m + \sum_d C_d XD_d + \sum_r C_r XR_r, \tag{3}$$

$$VC_s = \sum_p \sum_t \left(\begin{array}{l} \sum_f \sum_m Cfm_{fmp1s} Q_{fmpts} + \sum_m \sum_d Cmd_{mdp1s} Q_{mdpts} + \\ \sum_d \sum_r Cdr_{drp1s} Q_{drpts} + \sum_r Cr_{rp1s} Q_{rpts} \end{array} \right), \text{for all s,} \tag{4}$$

$$\sum_r Q_{rpts} + \omega_{pts} = D_{pts}, \quad \text{for all } p, t, s, \tag{5}$$

$$\sum_d Q_{drpts} = Q_{rpts}, \quad \text{for all } r, p, t, s, \tag{6}$$

$$\sum_m Q_{mdpts} \times (1 - \beta_m) = \sum_r Q_{drpts}, \quad \text{for all } d, p, t, s, \tag{7}$$

$$\sum_f Q_{fmpts} \times (1 - \alpha_f) \ge \sum_d Q_{mdpts}, \quad \text{for all } m, p, t, s, \tag{8}$$

$$\sum_m Q_{fmpts} \le AL_f Capf_{fpts} XF_f, \quad \text{for all } f, p, t, sm, \tag{9}$$

$$\sum_m Q_{mdpts} \le AL_m Capm_{mpts} XM_m, \quad \text{for all } m, p, t, s \tag{10}$$

$$\sum_m Q_{drpts} \le AL_d Capd_{dpts} XD_d, \quad \text{for all } d, p, s, t, \tag{11}$$

$$Q_{rpts} \le AL_r Capr_{rpts} XR_r, \quad \text{for all } r, p, s, t, \tag{12}$$

$$\sum_f XF_f \ge \varphi_1, \tag{13}$$

$$\sum_d XD_d \ge \varphi_2, \tag{14}$$

$$\sum_r \sum_p \sum_t \sum_s Q_{rpts} \Big/ \sum_p \sum_t \sum_s D_{pts} \ge \lambda, \tag{15}$$

$$Cfm_{fmpts} = Cfm_{fmp1s} \left(\frac{Q_{fmpts}}{Q_{fmp1s}} \right)^{\frac{-Ln(\mu)}{Ln(2)}}, \quad \text{for all } f, m, p, t \ge 2, s \tag{16}$$

$$Cmd_{mdpts} = Cmd_{mdp1s} \left(\frac{Q_{mdpts}}{Q_{mdp1s}} \right)^{\frac{-Ln(\mu)}{Ln(2)}}, \quad \text{for all } m, d, p, t \ge 2, s \tag{17}$$

$$Cdr_{drpts} = Cdr_{drp1s} \left(\frac{Q_{drpts}}{Q_{drp1s}} \right)^{\frac{-Ln(\mu)}{Ln(2)}}, \tag{18}$$
$$\text{for all } d, r, p, t \ge 2, s$$

$$Cr_{rpts} = Cr_{rp1s} \left(\frac{Q_{rpts}}{Q_{rp1s}} \right)^{\frac{-Ln(\mu)}{Ln(2)}}, \quad \text{for all } r, p, t \ge 2, s \tag{19}$$

$$XF_f, XM_m, XD_d, XR_r \in \{0,1\}, \tag{20}$$
$$\text{for all } f \in F, \text{for all } m \in M, \text{for all } d \in D, \text{ for all } r \in R$$

$$Q_{fmpts}, Q_{mdpts}, Q_{drpts}, Q_{rpts} \ge 0, \quad \text{for all } f \in F, \tag{21}$$
$$\text{for all } m \in M, \text{for all } d \in D, \text{for all } r \in R, \text{for all } p \in P, \text{for all } t \in T, \text{for all } s \in S$$

The objective *Function (1)* aims to minimize the cost function, which includes the expected value, EVaR, and maximum cost. The objective function form that accounts for risks and robustness against demand fluctuation is introduced by using the max function for the worst-case and EVaR functions as risk criteria. *Constraint (2)* summarize the total costs for each scenario. *Constraint (3)* establish the total fixed cost of activating facilities in SCND. *Constraint (4)* specify the total variable cost for product shipment within the facility flow. *Constraints (5)* to *(8)* are designed to balance the flow of facilities. *Constraints (9)* to *(14)* ensure that the output amount is within the flexible capacity of the facility. It should be noted that in *Constraints (7)* and *(8)*, the removal of deteriorated products from farm outputs and production waste from producers is taken into account, respectively. *Constraint (15)* set the level of demand satisfaction as an agile and responsive measure that must exceed the threshold coefficient. *Constraints (16)* to (19) address antifragile variables, with an antifragile approach based on the learning rate to reduce these variables. *Constraint (20)* involve location and binary variables indicating activation in SCND. *Constraint (21)* cover forward flow and positive variables.

Linearizing nonlinear functions

To transform NLP to LP, it is preferable to use the linearization method for the objective *Function (1)*. This adjustment enhances computation time as follows:

$$\text{Min}\, Z = (1-\theta)\sum_s P_s\ TC_s + \theta\left(\delta + \text{EVaR}\left(TC_s\right)\right)/2, \tag{22}$$

s.t.

$$\begin{aligned}&\text{EVaR}\left(TC_s\right) \approx \sum_s P_s\ TC_s,\\ &+\sum_s P_s\left(a_s + b_s\right)\sqrt{-2\text{Ln}(\nu)},\end{aligned} \tag{23}$$

$$TC_s - \sum_s P_s TC_s = a_s - b_s,\ \text{for all s}, \tag{24}$$

$$a_s, b_s \geq 0,\ \text{for all s}, \tag{25}$$

$$\delta \geq TC_s,\ \text{for all s}, \tag{26}$$

Computational results

A numerical example is generated and tested to validate the mathematical model. It is demonstrated by its numbers of farms (F=3), processing centers (M=3), distribution centers (D=3), retailers(R=3) of processed products (P=3) at periods (P=3) and under scenarios (S=3). Table 1 presents the values of the parameters of the model. The model was run on a computer with Intel® Core ™ i7-8750H CPU @ 2.20GHz specifications using Lingo software.

Table 1. model parameters setting.

Parameter	Value	Unit
C_f	Uniform ~ [2000, 4000]0.1000	Dollar
C_m	Uniform ~ [8000, 10000]0.1000	Dollar
C_d	Uniform ~ [6000, 8000]0.1000	Dollar
C_r	Uniform ~ [2000, 4000]0.1000	Dollar
Cfm_{fmp1s}	Uniform ~ [3000, 4000]/1000	Dollar
Cmd_{mdp1s}	Uniform ~ [5000, 6000]/1000	Dollar
Cdr_{drp1s}	Uniform ~ [3000, 4000]/1000	Dollar
Cr_{rp1s}	Uniform ~ [1000, 2000]/1000	Dollar
$Capf_{fpts}$	Uniform ~ [1000, 2000].(0.5.(s-1)/(|S|)+1)	Kg
$Capm_{mpts}$	Uniform ~ [10000, 11000].(0.5.(s-1)/(|S|)+1)	Kg
$Capd_{dpts}$	Uniform ~ [1000, 2000].(0.5.(s-1)/(|S|)+1)	Kg
$Capr_{rpts}$	Uniform ~ [1000, 2000].(0.5.(s-1)/(|S|)+1)	Kg

Table 1. Continued.

Parameter	Value	Unit
D_{pts}	Uniform ~ [5000, 6000].(0.2.(s-1)/(|S|)+1)	Kg
$P_s = 1/\|S\|,\ \theta = 50,\ \nu = 5,$		Percentage
AL_f, AL_m, AL_d, AL_r = Uniform ~ $[95,\ 98]$,		
$\lambda = 85,\ \mu = 40,\ \alpha_f = 0.01,\ \beta_m = 0.02.$		
$\varphi_1 = 2,\ \varphi_2 = 2.$		Number

The comparison between the main problem with antifragility and without antifragility is analyzed. It is found that the cost of the problem with antifragility is 0.42% lower than without antifragility, indicating that it performs better when antifragility is considered (*Table 2*) (*Figure 3*).

Table 2. Results and comparison.

Problem	Cost (thousand dollars)		
$\|F\|.\|M\|.\|D\|.\|R\|.\|P\|.\|T\|.\|S\|$	With antifragile	Without antifragile	Gap
3.3.3.3.3.3.3	105998.69	106454.48	- 0.42%

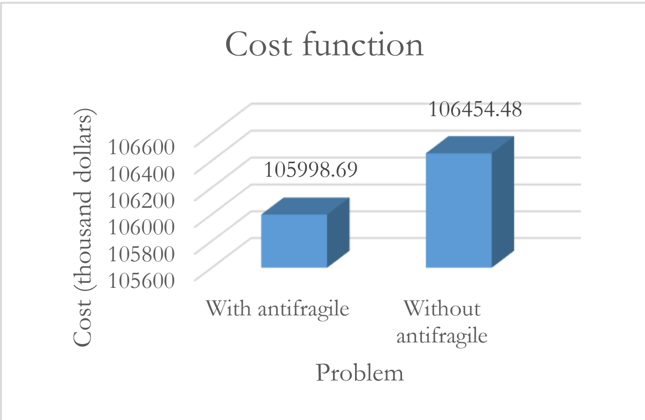

Fig. 3. Results and comparison.

The antifragility coefficient (μ) is adjusted between 10% and 40% for sensitivity analysis. An increase in the antifragility coefficient results in a decrease in the cost function (*Table 3* and *Figure 4*).

Table 3. Changing the antifragility coefficient.

Antifragility coefficient (μ)	Cost (Thousand dollars)	Cost variability
0%	106454.48	0.42%
10%	106390.89	0.37%
20%	106253.09	0.24%
30%	106125.89	0.12%
40%	105998.69	0.00%

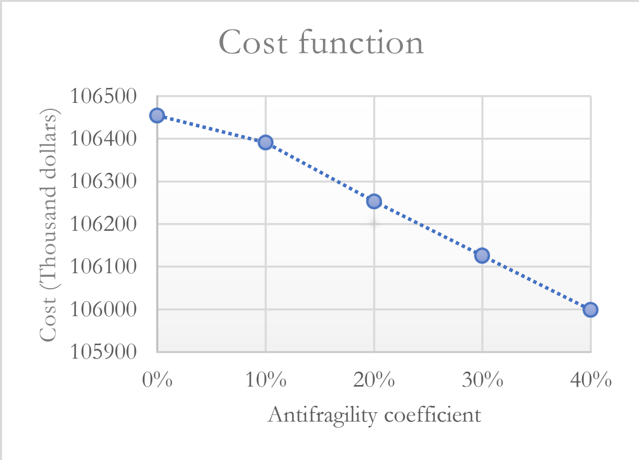

Fig. 4. Impact of antifragility coefficient variation on the cost function.

Discussion and managerial insights

The antifragility requirement enables the utilization of chaos, disorder, or volatility, leading to organizational improvement. In this study such a requirement has been proposed in the food SCND area. This research compared models with and without embedded antifragility. The results indicate that the cost is lower when antifragility is considered. Furthermore, increasing the antifragility coefficient reduces the cost function.

This style of mathematical modeling can be applied to all SCNDs. The model is proposed with a new design theme that incorporates resilience for facilities, antifragility, and robustness against disruptions. Consequently, it is advantageous for all stakeholders in SCND. In the context of pandemics like COVID-19 and other disasters, this approach is utilized to counter disruptions and enhance SCND performance.

4 | Conclusions

This research proposes a SCND framework incorporating antifragility and agility while addressing resiliency, robustness, and risk. A robust stochastic optimization method integrates expected value, EVaR, and maximum cost to minimize a new cost function. A numerical example optimizes the locations and flow quantities for all SCND components (farms, manufacturers, distribution centers, and retailers). The findings include comparing the main problem with and without antifragility shows that it costs 0.42% less, demonstrating better performance with antifragility.

Specific products in the food industry, each with unique attributes, can be designed using the supply chain network. Further studies should consider incorporating coherent risk criteria, as well as integrating digital and green technologies (such as blockchain, IoT, RFID, and renewable energy). Future research should include sustainability criteria, including environmental and social aspects. Additionally, adding other objectives and employing multi-objective optimization methods can enhance the model. Due to the significant computational burden associated with increasing the problem's dimensions, future research could benefit from using heuristic and metaheuristic algorithms.

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Data Availability

All data generated or analyzed during this study are included in this published article. Further inquiries can be directed to the corresponding author.

Conflicts of 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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