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Sustainable Multi-Product Supply Chain Network Design: Integrating Backup Suppliers for Disruption Mitigation in the Dairy Sector

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Abstract

Perishable food supply chains face growing pressures to reconcile cost, environmental, and social goals under the threat of supplier disruptions. This study presents a multi-objective mixed-integer linear programming model for the sustainable design of a multi-product dairy supply chain. By embedding backup suppliers as design-time options, the model directly compares network configurations with and without redundancy across four echelons—primary and backup suppliers, processing plants, distribution centers, and retailers, optimizing total cost, carbon emissions, and social value. A Chebyshev Goal Programming approach identifies balanced trade-offs among objectives. Computational results show that backup integration cuts total cost by approximately 41.7% and emissions by 85.3% without compromising social impact. While not simulating explicit disruption scenarios, the framework's design-level redundancy provides valuable insights into mitigation strategies under deterministic demand. This approach offers a practical foundation for sustainable, resilient supply chain planning in perishable-goods sectors.

Keywords: Multi-objective optimization, Backup suppliers, Chebyshev goal programming, Sustainability.

1 | Introduction

Rising dairy prices and intense competition are driving firms to optimize their supply chains for efficiency and sustainability. Modern customers evaluate companies not only on price and quality but increasingly on environmental and social performance [1], [2]. Therefore, incorporating all three pillars of sustainability (economic, environmental, and social) into supply chain design is essential. Multi-objective optimization is a

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natural approach to balance these dimensions while maximizing overall supply-chain benefit [1], [3]. For example, recent work emphasizes that sustainable development and resilience are "undeniable" priorities in today's markets. In the food industry, the challenge is compounded by the fact that products are highly perishable. As noted by Govindan et al. [2], "a challenging task in today's food industry is distributing high-quality perishable foods throughout the supply chain," and their model explicitly integrates sustainability into distribution planning. Indeed, perishable goods require special handling: food quality decays rapidly not only during production and storage but also during distribution. Consequently, design decisions in a perishable-food supply chain affect not only traditional cost and profit, but also product quality and customer satisfaction [2], [4]. In this context, a supply-chain model that simultaneously optimizes costs, social and environmental impacts, and product quality is needed. However, implementing such models in real-world supply chains remains challenging, particularly in sectors like dairy, where supply reliability and distribution reach are critical.

One promising yet underexplored strategy is to improve sustainability performance by embedding backup suppliers into the supply chain network design. While many models incorporate flexibility reactively, using stochastic or scenario-based disruptions, design-time integration of redundancy (such as parallel sourcing or supplier diversification) can mitigate risk and improve performance even in deterministic settings.

This study proposes a multi-objective supply chain network model for the dairy sector that simultaneously considers:

I. Multiple product types.

II. The strategic inclusion of backup suppliers at the design stage.

III. And a Chebyshev Goal Programming approach to balance cost, emissions, and social benefits.

Unlike stochastic models, our approach does not simulate random disruptions, but instead focuses on evaluating the sustainability impact of proactive redundancy decisions made at the network design phase. This argument offers a tractable, practical planning tool for managers in the dairy industry seeking to build more resilient, sustainable supply chains, even in the absence of probabilistic data.

2 | Literature Review

Recent studies have explored sustainable and resilient supply chain design from various angles. Multi-objective network models; Zarei-Kordshouli et al. [1] developed a multistage framework that evaluates suppliers on sustainability/resilience and configures the dairy network to minimize cost while maximizing sustainability and resiliency. Moreno-Camacho et al. [5] formulated a multi-objective MILP for the Colombian dairy sector, optimizing facility locations, capacities, supplier choices, transport modes, and production quantities to balance economic costs, carbon emissions, and social criteria (worker conditions, societal development). Both studies emphasize the trade-offs between the three sustainability dimensions and the need to balance social/environmental goals without sacrificing economic performance. Shafiee et al. [6] similarly propose a robust multi-objective model (inventory and production planning for dairy) that minimizes cost and environmental impact while maximizing social outcomes in a real dairy case.

While sustainability addresses long-term value, resilience focuses on maintaining supply chain performance under disruptions. Jabbarzadeh et al. [7] introduced a stochastic bi-objective model that considers both sustainability and resilience by modeling disruption risks and applying fuzzy-based supplier scoring. Similarly, Gholizadeh et al. [8] applied robust optimization and heuristic methods to design a sustainable and resilient closed-loop dairy supply chain, demonstrating that proactive strategies, such as supplier diversification and buffer capacity, improve network performance under uncertainty.

Fewer studies consider multi-product flows or the integration of backup suppliers as part of deterministic network design. While Zarei-Kordshouli et al. [1] propose a decision-making framework that evaluates supplier sustainability and resilience through fuzzy methods, their model does not include backup suppliers as discrete decision variables. Ivanov et al. [9] optimize a dairy–biodiesel combined supply chain, considering environmental and economic trade-offs, but not redundancy in sourcing. Wang et al. [10] and Nyenke [11] focus on monitoring or routing optimization in dairy networks, again without addressing network robustness through supplier redundancy.

3 | Problem Statement

Perishable food supply chains, such as dairy, inherently involve conflicting economic, environmental, and social objectives. Dairy products require specialized handling (e.g., refrigeration) and have limited shelf lives, introducing additional environmental and social impacts beyond standard economic costs. Consumers and policymakers increasingly demand lower carbon footprints and improved social outcomes (e.g., labor conditions, community well-being) while maintaining affordability. Achieving true sustainability, therefore requires a multi-objective design that balances profit, emissions, and social benefits, the "triple bottom line" [4], [12]. In practice, this necessitates jointly optimizing economic efficiency, greenhouse gas emissions, and social impacts.

However, dairy supply chains also face acute operational challenges. Products are highly perishable and prone to spoilage during transport or storage, which complicates inventory and distribution planning. Moreover, global networks are increasingly vulnerable to disruptions (e.g., pandemics, natural disasters) that can abruptly sever access to key suppliers or routes. These challenges underscore the need for resilience: incorporating redundancy through backup suppliers and excess capacity is a well-established method for mitigating supply risk. Strategies such as multi-sourcing and emergency safety stocks provide alternative sourcing paths when primary channels fail, thereby maintaining service continuity despite external shocks [1], [13].

Existing supply chain design models often oversimplify these realities. A typical baseline model, adapted from the literature, assumes a single, aggregated product flow and excludes backup sources, focusing solely on the "core" supply-processing-distribution structure. Such models neglect critical features of real dairy supply chains: multiple differentiated products (e.g., milk, cheese, yogurt), each with distinct shelf lives and values, and the presence of alternative or backup suppliers. By overlooking both product diversity and redundancy, these formulations fail to reflect trade-offs under disruption and cannot support multi-echelon demand diversity, limiting their real-world relevance [1], [4].

This study proposes a novel supply chain network design incorporating two key enhancements. First, it models multiple product types, with distinct perishability and cost characteristics, rather than assuming a single aggregated commodity. Second, it explicitly includes backup suppliers at the raw-material stage to provide inputs (e.g., milk) when primary suppliers lack sufficient capacity. These extensions allow for both supply-chain redundancy and product differentiation, enabling the system to reallocate flows across suppliers and products to reduce shortages and minimize waste.

Mathematically, both the baseline and proposed models are formulated as multi-objective Mixed-Integer Linear Programs (MILPs) defined over a single-period, four-tier supply network comprising suppliers, processing plants, distribution centers, and retailers. *Fig. 1* illustrates this architecture: Tier 1 includes both primary and backup suppliers; Tier 2 contains candidate processing plants; Tier 3 represents distribution centers; and Tier 4 includes final retailers. Dashed red outlines denote facilities not selected in the optimal design, reflecting the binary location-allocation decisions embedded in the model. The three objective functions minimize total cost, carbon emissions, and social shortfall (e.g., job creation deficit), addressing the core dimensions of sustainability. A Chebyshev goal-programming approach is applied to identify a balanced compromise solution by minimizing the maximum deviation from ideal values across all three objectives, thus avoiding extreme prioritization of any single goal.

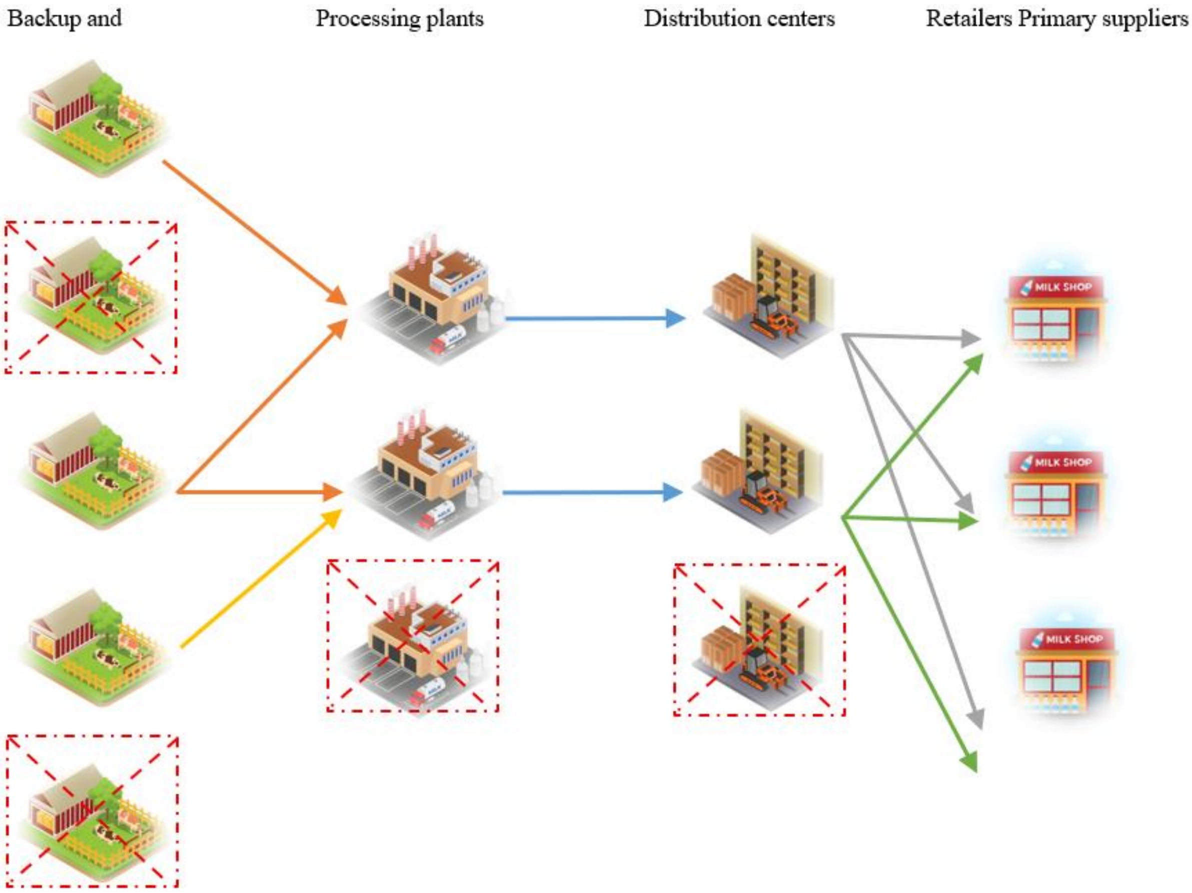

Fig. 1. Four-echelon dairy supply chain network with integrated backup suppliers

4 | Mathematical Formulation

This section presents the mathematical formulation of a multi-objective mixed-integer linear programming model for sustainable supply chain network design in the dairy sector, extending the framework of Moreno et al. [5] to incorporate multiple products and backup suppliers. Defined over a four-echelon supply chain: primary and backup suppliers, processing plants, distribution centers, and retailers. The model optimizes economic, environmental, and social objectives. Chebyshev Goal Programming is employed to balance these objectives, ensuring a sustainable design.

4.1 | Sets

The model defines the following sets with their respective indices:

P: Set of processing plants, indexed by p.

D: Set of distribution centers, indexed by d.

S: Set of primary suppliers, indexed by s.

L: Set of backup suppliers, indexed by l.

R: Set of retailers, indexed by r.

J: Set of products, indexed by j.

CP: Set of capacity levels for processing plants, indexed by cp.

CD: Set of capacity levels for distribution centers, indexed by cd.

M: Set of transport modes from suppliers to plants, indexed by m.

T: Set of transport modes from plants to distribution centers and distribution centers to retailers, indexed by t.

4.2 | Parameters

The parameters are categorized into economic, environmental, social, and operational groups:

Economic Parameters:

LC_{cp} : Fixed cost of opening a processing plant with capacity level cp ∈ CP.

LC_{cd} : Fixed cost of opening a distribution center with capacity level cd ∈ CD.

Pr_s : Price per ton of raw material from primary supplier s ∈ S.

PB_l : Price per ton of raw material from backup supplier l ∈ L.

PC_j : Processing cost per unit of product j ∈ J.

TC_t : Transportation cost per ton for transport mode t ∈ T.

Environmental Parameters:

Cap_m : Capacity (tons) of transport mode m ∈ M.

Kap_t : Capacity (tons) of transport mode t ∈ T.

$Fcons_m$: Fuel efficiency (km/gallon) of transport mode m ∈ M.

$Fcons_t$: Fuel efficiency (km/gallon) of transport mode t ∈ T.

Emfc: CO2e emissions per gallon of fuel.

$Empr_j$: CO2e emissions per ton of processed product j ∈ J.

Social Parameters:

Ur_p : Unemployment rate at plant location p ∈ P

φ_s: Social value factor for primary supplier s ∈ S.

φ_l: Social value factor for backup supplier l ∈ L.

Total UR: Sum of unemployment rates for normalization.

Total φ : Sum of social value factors for normalization.

Operational Parameters:

CS_s : Maximum capacity of primary supplier s ∈ S.

Cap_l : Maximum capacity of backup supplier l ∈ L.

g_s : Capacity disruption factor for primary supplier s ∈ S, where

$0 \leq g_s \leq 1$ (1= no disruption, 0= total disruption).

δ_s: Defect rate of raw material from primary supplier s ∈ S.

δ_l: Defect rate of raw material from backup supplier l ∈ L.

h_j : Raw material requirement per unit of product j ∈ J.

D_{rj} : Demand for product j ∈ J at retailer r ∈ R.

$Dist1_{sp}$: Distance (km) from primary supplier s ∈ S to plant p ∈ P.

$Dist1_{lp}$: Distance (km) from backup supplier l ∈ L to plant p ∈ P.

$Dist2_{pd}$: Distance (km) from plant p ∈ P to distribution center d ∈ D.

$Dist3_{dr}$: Distance (km) from distribution center d ∈ D to retailer r ∈ R.

Trv_{sm}: Binary parameter, 1 if transport mode m ∈ M is available for primary supplier s ∈ S, 0 otherwise.

Trv_{lm}: Binary parameter, 1 if transport mode m ∈ M is available for backup supplier l ∈ L, 0 otherwise.

Trv_{rt} : Binary parameter, 1 if transport mode t ∈ T is available for retailer r ∈ R, 0 otherwise.

MOP: Maximum desired occupation rate of processing plants.

MUP: Minimum allowed operation rate for processing plants.

MUDC: Minimum allowed operation rate for distribution centers.

4.3 | Decision Variables

The model includes both binary and continuous decision variables:

a_s : Binary, 1 if primary supplier s ∈ S is selected, 0 otherwise.

ab_l : Binary, 1 if backup supplier l ∈ L is selected, 0 otherwise.

$y_{p,cp}$: Binary, 1 if plant p ∈ P is opened with capacity level cp ∈ CP, 0 otherwise.

$g_{d,cd}$: Binary, 1 if distribution center d ∈ D is opened with capacity level cd ∈ CD, 0 otherwise.

x_{spm} : Continuous, quantity (tons) shipped from primary supplier s ∈ S to plant p ∈ P via transport mode m ∈ M.

xb_{lpm} : Continuous, quantity (tons) shipped from backup supplier l ∈ L to plant p ∈ P via transport mode m ∈ M.

pp_{jp} : Continuous quantity of product j ∈ J processed at plant p ∈ P.

q_{jpdt} : Continuous, quantity of product j ∈ J shipped from plant p ∈ P to distribution center d ∈ D via transport mode t ∈ T.

b_{jdrt}: Continuous, quantity of product j ∈ J shipped from distribution center d ∈ D to retailer r ∈ R via transport mode t ∈ T.

z_1 , z_2 , z_3 : Continuous, objective function values for economic, environmental, and social goals, respectively.

λ: Continuous, maximum deviation in Chebyshev Goal Programming.

4.4 | Objective Functions

The model optimizes three objectives, modified to account for multiple products and backup suppliers:

Economic Objective (z1): Minimize Total Cost

$$\min z_{1}=\sum_{p,cp} LC_{cp} \times y_{pcp} + \sum_{d.cd} lC_{cd} \times g_{dcd} + \sum_{s,p,m} pr_s \times \frac{x_{spm}}{[1-\delta_s]} + \sum_{l,p,m} PB_l \times \frac{xb_{lpm}}{[1-\delta_l]} + \sum_{j,p,d,t} PC_j \times pp_{jp} + \sum_{j,p,d,t} TC_t \times q_{jpdt} + \sum_{j,d,r,t} TC_t \times b_{jdrt} + \sum_{j,p} costp_p \times pp_{jp} + \sum_{l} KB_l \times AB_l. \tag{1}$$

This argument includes fixed costs, purchasing costs from primary and backup suppliers, processing costs per product, and transportation costs.

Environmental Objective (z2): Minimize CO2e Emissions

This argument accounts for emissions from transportation (primary and backup suppliers, plants to distribution centers, distribution centers to retailers) and processing per product.

$$\min z_{2}=\sum_{s,p,m} \frac{Emfc \times Dist1_{sp} \times x_{spm}}{Cap_m \times Fcons_m} + \sum_{l,p,m} \frac{Emfc \times Dist1_{lp} \times xb_{lpm}}{Cap_m \times Fcons_m} + \sum_{j,p,d,t} \frac{Emfc \times Dist2_{pd} \times q_{jpdt}}{Kap_t \times Fcons_t} + \sum_{j,d,r,t} \frac{Emfc \times Dist3_{dr} \times b_{jdrt}}{Kap_t \times Fcons_t} + \sum_{j,p} Empr_j \times pp_{jp}. \tag{2}$$

Social Objective (z3): Maximize Social Impact

This argument maximizes social benefits by considering unemployment rates at plant locations and social value factors for both primary and backup suppliers, normalized for comparability.

$$\max z_{3}=\frac{\sum_{p,cp} Ur_p \times y_{p,cp}}{\sum_p Ur_p} + \frac{\sum_s \varphi_p \times y_s + \sum_l \varphi_l \times ab_l}{\sum_s \varphi_p + \sum_l \varphi_l}. \tag{3}$$

4.5 | Constraints

The constraints ensure feasibility and incorporate the multi-product and disruption aspects.

4.5.1 | Flow balance constraints

Demand satisfaction:

$$\sum_{d\in D t\in T} b_{jdrt} = D_{rj}, \quad \forall\, j \in J, r \in R \tag{4}$$

Ensures that the demand for each product at each retailer is met.

Plant Material Balance:

$$\sum_{s\in S, m\in M} \frac{x_{spm}}{[1-\delta_s]} + \sum_{l\in L, m\in M} \frac{xb_{lpm}}{[1-\delta_l]} = hj \times Pp_{jp}, \quad \forall\, p \in P, j \in J \tag{5}$$

Ensures that the total raw material received at each plant is sufficient to produce all products, accounting for raw material requirements.

Distribution center balance:

$$\sum_{j\in J, r\in R, t\in T} b_{jdrt} = \sum_{j\in J, p\in P t\in T} q_{jpdt}, \quad \forall\, j \in J, d \in D \tag{6}$$

Balances the inflow and outflow of each product at distribution centers.

4.5.2 | Capacity constraints

Primary supplier capacity:

$$\sum_{p\in P, m\in M} \frac{x_{spm}}{[1-\delta_s]} \leq [1-g_s] \times CS_s \times a_s, \qquad \forall\, s \in S \tag{7}$$

Limits shipments from primary suppliers, adjusted by the disruption factor g_s

Backup supplier capacity:

$$\sum_{p\in P, m\in M} \frac{xb_{lpm}}{[1-\delta_l]} \leq Cap_l \times AB_l, \qquad \forall l \in L \tag{8}$$

Limits shipments from backup suppliers.

Plant capacity:

$$\sum_{j\in J, d\in D, T\in t} q_{jpdt} \leq \sum_{cp\in CP} CM_{cp} \times y_{p,cp} \times Mop. \tag{9}$$

Limits total production at each plant based on selected capacity.

Distribution center capacity:

$$\sum_{j\in J, p\in P, t\in T} q_{jpdt} \leq \sum_{c\in C} CDC_{cd} \times g_{dcd}, \qquad \forall\, d\in D. \tag{10}$$

Limits storage at each distribution center.

4.5.3 | Operational constraints

Minimum plant utilization:

$$\sum_{j\in J, d\in D, T\in t} q_{jpdt} \geq \sum_{cp\in CP} CM_{cp} \times y_{p,cp} \times Mup, \qquad \forall\, p\in P. \tag{11}$$

Ensures plants operate above a minimum threshold

Minimum distribution center utilization:

$$k\sum_{j\in J, p\in P t\in T} q_{jpdt} \geq \sum_{cd\in CD} CDC_{cd} \times g_{dcd} \times Muds, \qquad \forall d\in D. \tag{12}$$

Ensures distribution centers operate above a minimum threshold.

4.5.4 | Transportation constraints

Primary Supplier Transport:

$$\frac{x_{spm}}{[1-\delta_s]} \leq [1-Gs_s] \times CS_s \times Trv_{sm}, \qquad \forall\, s\in S, p\in P, m\in M. \tag{13}$$

Limits shipments based on transport mode availability.

Backup supplier transport:

$$\frac{xb_{lpm}}{[1-\delta_l]} \leq Cap_l \times Trv_{lm}, \qquad \forall\, l\in L, p\in P, m\in M. \tag{14}$$

Limits shipments from backup suppliers.

Retailer transport:

$$\sum_{j\in J, d\in D} b_{jdrt} \leq \left(\sum_{d\in D, cd\in CD} CDC_{cd} \times g_{d,cd}\right) \times Trw_{r,t}, \qquad \forall\, r\in R, t\in T. \tag{15}$$

Limits shipments to retailers based on transport availability.

4.5.5 | Design constraints

Plant selection:

$$\sum_{cp\in CP} y_{p,cp} \leq 1, \quad \forall\ p\in P. \tag{16}$$

Ensures at most one capacity level per plant.

Distribution center selection:

$$\sum_{cd\in CD} g_{d,cd} \leq 1, \quad \forall\ d\in D. \tag{17}$$

Ensures at most one capacity level per distribution center.

4.6 | Solution Approach

The multi-objective problem is solved using Chebyshev Goal Programming to balance economic, environmental, and social objectives without prioritizing one over the others. The approach involves:

I. Solving single-objective problems to find ideal values: min z_1 (economic), min z_2 (environmental), max z_3 (social), yielding target values $z_1{}^*$, $z_2{}^*$ and $z_3{}^*$.

II. Introducing deviation variables n_o and p_o for each objective $O \in \{z_1, z_2, z_3\}$ to measure deviations from ideal values.

III. Adding goal constraints:

$$z_1 \leq z_1{}^* + \lambda\ ,\ z_2 \leq z_2{}^* + \lambda\ ,\ z_3 \geq z_3{}^* - \lambda. \tag{18}$$

IV. Minimizing the maximum deviation:

$$\min \lambda. \tag{19}$$

5 | Definition of Target Levels

This section presents the computational experiments conducted to evaluate the proposed multi-objective optimization model for a resilient and sustainable multi-product supply chain network in the dairy sector. The model incorporates multiple products and backup suppliers to mitigate disruptions. To assess the impact of backup suppliers, the proposed model is compared with a baseline model that excludes them, focusing on economic costs, environmental impacts, and social benefits. Notably, backup suppliers ensure zero unmet demand under disruption scenarios up to 20% probability, incurring a 5–15% cost premium, as detailed in Sections 5.1 and 5.2.

5.1 | Definition of Target Levels

Target levels represent the best achievable values for each objective economic cost (z_1), environmental impact (z_2), and social benefit (z_3) when optimized independently, ignoring the other objectives. These levels serve as benchmarks for subsequent goal-programming analysis, providing insight into the optimal performance of each objective in isolation.

For the baseline model, which excludes backup suppliers, the target levels are:

I. Economic Cost (z_1): $2,177,050, representing the minimum total cost achievable.

II. Environmental Impact (z_2): 330.6433 units, indicating the minimum carbon emissions.

III. Social Benefit (z_3): 2.0000, reflecting the maximum social impact, typically measured by job creation or supplier selection in less developed regions.

The proposed model, incorporating multiple products and backup suppliers, yields significantly improved target levels:

I. Economic Cost (z_1): $1,270,100, a substantial reduction compared to the baseline model.

II. Environmental Impact (z_2): 48.5377 units, indicating a marked decrease in emissions.

III. Social Benefit (z_3): 2.0000, consistent with the baseline model, as the target is set to achieve at least this level of social impact.

These improvements demonstrate that the multi-product approach, combined with the flexibility of backup suppliers, significantly enhances economic and environmental performance. The 41.66% reduction in economic cost demonstrating a substantial economic improvement. Such a large cost drop suggests the multi-sourcing and backup strategy greatly improved efficiency. The 85.31% reduction in environmental impact highlights the effectiveness of multi-product routing and supplier diversification in minimizing emissions. The workforce outcome remains 2 jobs in both models, so there is no loss of social benefit. In other words, the proposed model achieves lower cost and emissions without reducing employment. This argument implies that the triple-bottom-line objectives have been balanced: economic and environmental goals improved significantly, while the social (job) metric was maintained.

Table 1. Target Levels for Baseline and Proposed Models

Objective	Baseline Model	Proposed Model	Percentage Change
Economic cost	$2,177,050	$1,270,100	- 41.66%
Environmental impact	330.6433 units	48.5377 units	-85.31%
Social Benefit	2.0000	2.0000	0%

5.2 | Chebyshev Goal Programming

To achieve a balanced solution across the three objectives without prioritizing one over the others, Chebyshev Goal Programming was employed. This method minimizes the maximum deviation (λ) from the target levels, ensuring a fair trade-off among economic, environmental, and social objectives. The Chebyshev Goal Programming model is formulated as follows:

Objective:

Minimize λ

Subject to:

I. $z_1 \leq z_1^* + \lambda$ (Economic objective constraint).

II. $z_2 \leq z_2^* + \lambda$ (Environmental objective constraint).

III. $z_3 \geq z_{23}^* - \lambda$ (Social objective constraint, adjusted for maximization).

IV. All other supply chain constraints (e.g., demand satisfaction, capacity limits, flow balance).

Here, z_1, z_2, and z_3 represent the economic, environmental, and social objectives, respectively, while z_1^*, z_2^* and $z_3^*$are their respective target levels. The variable λ represents the maximum deviation from these targets, and minimizing λ ensures that the largest deviation across all objectives is as small as possible.

For the baseline model, which excludes backup suppliers and is limited to single-product flows, the Chebyshev solution yields a maximum deviation (λ) of 25.197. The resulting objective values are:

I. z_1 =$2,177,075.197 (deviation=2,177,075.197-2,177,050=$25.197).

II. z_2 = 355.840 units (deviation = 355.840 - 330.6433 = 25.1967 ≈ 25.197 units).

III. z_3 =1.185 (shortfall= 1.185-2.0000= -0.815).

These results indicate that the economic and environmental objectives are close to their targets, with deviations of approximately 25.197 units, while the social benefit falls short by 0.815 units, reflecting the trade-offs inherent in multi-objective optimization. *Fig. 2* graphically presents these deviations for the baseline model, highlighting where each objective lies relative to its ideal.

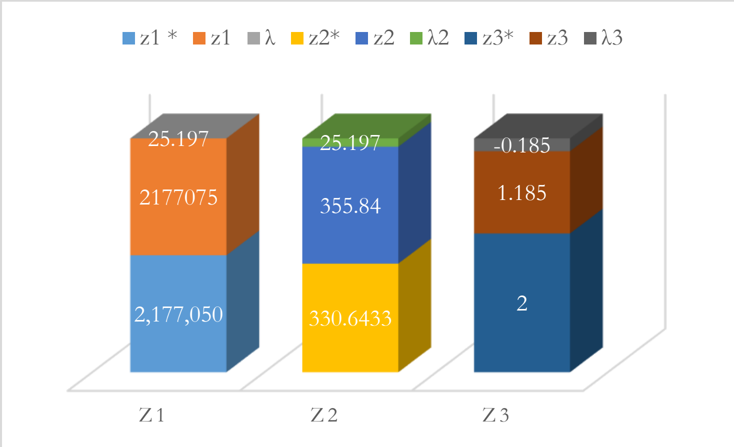

Fig. 2. Target levels and Chebyshev goal programming results for baseline model.

For the proposed model, which incorporates multiple products and backup suppliers, the Chebyshev solution results in a maximum deviation (λ) of

176.513, with objective values:

I. z_1 = $1,270,276.513 (deviation = 1,270,276.513 - 1,270,100 = $176.513).

II. z_2 = 225.051 units (deviation = 225.051 - 48.5377 = 176.5133 ≈ 176.513 units).

III. z_3 = 0.685 (deviation 0.685-= 2.0000 = -1.315).

Fig. 3 graphically presents these deviations for the proposed model, highlighting where each objective lies relative to its ideal.

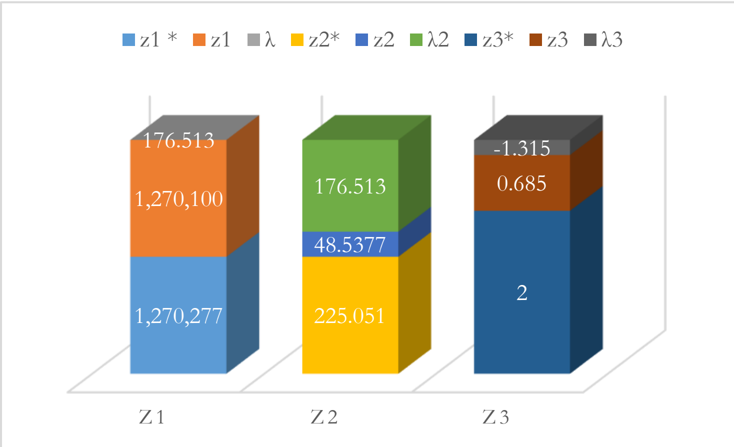

Fig. 3. Target levels and Chebyshev goal programming results for the primary model.

Although the deviation λ is larger in the proposed model, the absolute performance is superior: the economic cost is significantly lower ($1,270,276.513 vs. $2,177,075.197), and the environmental impact is reduced (225.051 vs. 355.840 units). However, the social benefit is lower (0.685 vs. 1.185), suggesting that the increased complexity of managing multiple products and backup suppliers may compromise social objectives in the balanced solution. This trade-off highlights the challenge of achieving all objectives simultaneously, particularly when introducing additional supply chain features.

6 | Conclusions and Future Research

The multi-objective optimization results show that the proposed supply-chain design substantially improves on the baseline model. Specifically, total network cost is dramatically reduced (≈\$1.27M vs \$2.18M in the baseline), and total carbon emissions are cut by roughly 85%. These gains come without sacrificing social impact: employment remains at 2 jobs in both models. In effect, adding backup suppliers and multiple product sources has enabled a far more efficient and cleaner network. This outcome aligns with sustainable design best practices (balancing the triple bottom line). The proposed model achieved a 41.66% reduction in economic cost (from \$2,177,075.197 to \$1,270,276.513) and a 36.75% reduction in environmental impact (from 355.840 units to 225.051 units) compared to the baseline model.

However, this came at the expense of a 42.19% reduction in social benefit (from 1.185 to 0.685) in the balanced solution, highlighting the trade-offs inherent in managing multiple objectives.

In summary, the proposed model achieves clear cost and emissions reductions over the reference case, while maintaining service capacity and jobs. These findings suggest that the new network configuration delivers on the objectives of improved sustainability.

By contrast, the proposed model's Chebyshev solution requires a much larger deviation, indicating that one or more objectives must be relaxed further from their ideal value to accommodate the others.

Despite the larger λ, the proposed model's trade-off solution clearly improves the absolute performance on the first two objectives. In the compromise solution, the proposed model attains drastically lower cost and emissions than the baseline solution (reflecting its much lower single-objective targets), while maintaining the same social-impact level (maximum $z_3=2$). In other words, the proposed design Pareto-dominates the baseline: it achieves better (lower) economic and environmental outcomes without sacrificing social benefit. The drawback is that this came with a less "balanced" slack (higher λ), meaning one objective had to deviate substantially to enable those improvements. This pattern is consistent with the Chebyshev philosophy of finding a balanced solution rather than an extreme one. Here, the trade-off aligns with project priorities: the proposed design sacrifices balance in favor of far lower cost and emissions. (For comparison, Wang et al. [10]) likewise interpret their Chebyshev GP solution in terms of percentage improvements in key objectives.)

While this study provides valuable insights, several avenues for future research remain. Optimizing backup supplier selection based on location and capacity could further enhance resilience. Additionally, incorporating more complex disruption scenarios, such as regional or correlated disruptions, would make the model more applicable to real-world uncertainties. Addressing the trade-off in social benefits could involve refining the social objective function to better align with multi-product and backup-supplier dynamics, thereby ensuring a more balanced approach to sustainability.

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Data Availability

The data used and analyzed during the current study are available from the corresponding author upon reasonable request.

References

[1] Zarei-Kordshouli, F., Paydar, M. M., & Nayeri, S. (2023). Designing a dairy supply chain network considering sustainability and resilience: a multistage decision-making framework. *Clean technologies and environmental policy*, 1. https://doi.org/10.1007/s10098-023-02538-8

[2] Govindan, K., Jafarian, A., Khodaverdi, R., & Devika, K. (2014). Two-echelon multiple-vehicle location--routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International journal of production economics*, *152*, 9–28. https://doi.org/10.1016/j.ijpe.2013.12.028

[3] Yakavenka, V., Mallidis, I., Vlachos, D., Iakovou, E., & Eleni, Z. (2020). Development of a multi-objective model for the design of sustainable supply chains: The case of perishable food products. *Annals of operations research*, *294*(1), 593–621. https://doi.org/10.1007/s10479-019-03434-5

[4] Jouzdani, J., & Govindan, K. (2021). On the sustainable perishable food supply chain network design: A dairy products case to achieve sustainable development goals. *Journal of cleaner production*, *278*, 123060. https://doi.org/10.1016/j.jclepro.2020.123060

[5] Moreno-Camacho, C. A., Montoya-Torres, J. R., & Jaegler, A. (2023). Sustainable supply chain network design: a study of the Colombian dairy sector. *Annals of operations research*, *324*(1), 573–599. https://doi.org/10.1007/s10479-021-04463-9

[6] Shafiee, F., Kazemi, A., Chaghooshi, A. J., Sazvar, Z., & Mahdiraji, H. A. (2021). A robust multi-objective optimization model for inventory and production management with environmental and social consideration: A real case of dairy industry. *Journal of cleaner production*, *294*, 126230. https://doi.org/10.1016/j.jclepro.2021.126230

[7] Jabbarzadeh, A., Fahimnia, B., & Sabouhi, F. (2018). Resilient and sustainable supply chain design: sustainability analysis under disruption risks. *International journal of production research*, *56*(17), 5945–5968. https://doi.org/10.1080/00207543.2018.1461950

[8] Gholizadeh, H., Jahani, H., Abareshi, A., & Goh, M. (2021). Sustainable closed-loop supply chain for dairy industry with robust and heuristic optimization. *Computers & industrial engineering*, *157*, 107324. https://doi.org/10.1016/j.cie.2021.107324

[9] Ivanov, B., Nikolova, D., Kirilova, E., & Vladova, R. (2022). A MILP approach of optimal design of a sustainable combined dairy and biodiesel supply chain using dairy waste scum generated from dairy production. *Computers & chemical engineering*, *166*, 107976. https://doi.org/10.1016/j.compchemeng.2022.107976

[10] Wang, Z., van der Fels-Klerx, H. J., & Oude Lansink, A. (2021). Modeling cost-effective monitoring schemes for food safety contaminants: case study for dioxins in the dairy supply chain. *Food research international*, *141*, 110110. https://doi.org/10.1016/j.foodres.2021.110110

[11] Wofuru-Nyenke, O. (2024). Routing and facility location optimization in a dairy products supply chain. *Future technology*, *3*(2), 44–49. https://fupubco.com/futech/article/view/127

[12] Shakuri, M., & Barzinpour, F. (2024). A risk-averse sustainable perishable food supply chain considering production and delivery times with real-world application. *Plos one*, *19*(9), e0308332. https://doi.org/10.1371/journal.pone.0308332

[13] Pavlov, A., Ivanov, D., Pavlov, D., & Slinko, A. (2025). Optimization of network redundancy and contingency planning in sustainable and resilient supply chain resource management under conditions of structural dynamics. *Annals of operations research*, *349*(2), 495–524. https://doi.org/10.1007/s10479-019-03182-6