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Integrating minimum cost flow and capacitated location in global supply chains under uncertainty

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ABSTRACT

Modern supply chain networks face significant challenges in balancing operational efficiency and resilience under diverse real-world uncertainties such as demand fluctuations and disruptions. To address these complexities, this study proposes an Integrated Capacitated Facility Location and Minimum Cost Flow Problem under Multi-Uncertainty (ICLMF-MU). The integrated multi-objective optimization model simultaneously optimizes total cost, service utility, and total risk while accounting for unmet demands and disruptions in supply chain network design. To deal with the NP-hardness of the problem, we propose an enhanced hybrid non-dominated sorting genetic algorithm II (NSGA-II). A novel bi-level evaluation strategy couples an exact linear programming (LP) solver to maintain flow balance with a greedy heuristic as a fallback mechanism. Through a three-stage benchmarking process, the algorithm demonstrates strong convergence and consistent performance. A large-scale numerical study (100 nodes) evaluates performance under diverse global trade environments, contrasting cost-sensitive goods against strategic resources prone to export controls. Pareto frontier trade-off analysis identifies a distinct Criticality Premium, confirming that strategic sectors require a substantially greater investment to withstand sanctions compared to commercial scenarios. Furthermore, regret analysis exposes a Robustness Paradox: the min-risk strategy exhibits the highest operational regret and lowest real-world resilience by limiting network scope. In contrast, the max-utility and balanced strategies demonstrate superior robustness. Sensitivity analysis confirms this implicit redundancy provides the structural capacity needed to absorb large demand surges, with the medical strategy demonstrating superior overall resilience under extreme demand. These findings imply that for critical supplies, true robustness is an emergent property of sufficient capacity investment rather than the optimization of theoretical risk indicators alone, offering guidance for designing resilient networks in an unstable global trade landscape.

1. Introduction

In the Supply Chain Network Design (SCND), two highly coupled decisions stand out as core pain points: identifying optimal facility locations and determining efficient material flow routing. Facility location selection and transportation routing have a significant impact on the overall network performance (Melo et al., 2009).

As a fundamental field of operations research, location science establishes the essential methodologies for solving facility location problems (FLP) (Laporte et al., 2019). The Capacitated Facility Location Problem (CFLP) addresses scenarios where multiple facilities

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jointly serve customers and each facility has limited capacity (Mousavi and Niaki, 2013). The foundational mathematical framework for CFLP was established by Khumawala (1974). The Minimum Cost Flow Problem (MCFP) focuses on optimizing goods flow routes across the supply chain network and revealing the relationships between transportation flows and facility placement (Ahuja et al., 1993). Existing research in this area involves designing robust flow distributions under uncertainty, such as route optimization with uncertain demand (Atamtürk and Zhang, 2007) and network structure design for dealing with edge failures (Matthews et al., 2019).

The integration of CFLP and MCFP is of great significance from both theoretical and practical perspectives, as flow routing and facility location are inherently interconnected and require collaborative optimization (Pirkul and Jayaraman, 1996). An integrated model considers both facility location and network design, providing a more realistic representation of operational conditions. For example, Shen et al. (2024) proposed a bi-level optimization framework for medical waste recycling, where facility location is determined at the upper level and vehicle routing (VRP) at the lower level. This hierarchical approach solves the two components in a sequential order rather than simultaneously, which restricts the full exploration of global trade-offs and may lead to suboptimal resilience in the final optimization. By developing such integrated models, a balance can be obtained between the optimization objective and practical realism, providing more effective support for decision-making.

In the increasingly competitive global market, geopolitical tensions and trade disputes are continuously escalating. It exposes supply chain networks to multiple sources of uncertainty, including disruptions, stochastic demand fluctuations, and export controls. These macro-environmental shocks have significantly heightened the risk and complexity of designing efficient, reliable, and economical supply chain networks, making resilience a critical competitive priority for enterprises. Consequently, strengthening supply chain performance requires not only cost efficiency but also the ability to deal with and adapt to various uncertainties.

Under environmental uncertainty, the traditional hierarchical approach to deal with location and route separately becomes unreliable. Sudden geopolitical events, such as unexpected trade sanctions, can cut off existing transportation routes. When these flow routes are disrupted, previously optimal facility locations may fail or become highly inefficient. Since the viability of the facilities is closely related to the connecting routes, optimizing facility locations and flow routings separately leads to suboptimal network performance, whereas their collaborative optimization is essential for enhancing both economic efficiency and resilience.

To ensure the efficiency and resilience of the network, significant uncertainties and various risks must be taken into account in modern supply chains. Supply chain disruptions, defined as the partial or total operational stagnation caused by unexpected events, have become major threats to system performance (Snyder et al., 2016; Govindan et al., 2017). Facility and transportation disruptions are particularly critical in supply chain network design, which may arise from natural disasters, equipment technical failures, traffic accidents, and increasingly geopolitical trade barriers. Ahmadi Digehsara et al. (2025) considered geopolitical disruptions such as tariff surges and sanctions. It helped decision-makers to choose more resilient locations and better sourcing strategies in global supply chains. Such disruptions reduce facility operational capacity or cut off key transportation connections, compromising the reliable flow of goods and services. To enhance network resilience, researchers have developed various robust design approaches. Heckmann et al. (2016) integrates risk preferences into FLP, discussing that risk-seeking decision-makers may accept higher value degradation to maintain strategic objectives. Kim et al. (2015) studied the impact of node or arc interruptions on network-wide disruptions. Additionally, An et al. (2014) also proposed a two-stage robust optimization model to address structural risks in location networks.

Beyond physical disruptions, supply chains face substantial demand uncertainty, and such uncertainty is often correlated with disruption events. For instance, during the COVID-19 pandemic, the demand for medical supplies surged while the demand for public services declined sharply. Similarly, trade conflicts often trigger volatile market changes. Sudden export bans or tariffs lead to panic buying and sharp fluctuations in regional demand. In recent years, much literature has increasingly emphasized demand risks. Akbarpour et al. (2020) explored the strategic design of integrated networks under unknown demand. In response to these challenges, scholars have developed network design models that consider multiple risk factors simultaneously. Lotfi et al. (2021) enhanced the resilience of supply chain network design (SCND) by incorporating renewable energy against demand disruptions and energy supply issues, using a two-stage robust stochastic optimization model. Lu and Cheng (2021) developed a resilient facility location model that simultaneously addresses capacity failures and correlated demand uncertainty. Cheng et al. (2021) studied a robust fixed-charge location problem involving demand uncertainty and facility disruption. Heckmann et al. (2023) provided a comprehensive framework for multiple uncertainties in facility location problem, focusing on single-objective optimization. More recently, Luo et al. (2025) further proposed a two-stage stochastic robust model that accounts for disruption uncertainty alongside large-scale demand fluctuations. Zhang and Kalcics (2026) considered demand uncertainty of CFLP incorporating service level restrictions. Zhang and Nickel (2026) focused on CFLP minimizing total cost and maximizing expected service satisfaction ratio under both node disruption and demand uncertainty.

To address these challenges, this study aims to integrate the Capacitated Facility Location Problem (CFLP) with the Minimum Cost Flow Problem (MCFP) to develop a comprehensive optimization model that addresses the increasing complexity of global trade networks. The resulting formulation is a multi-objective, nonlinear integer programming problem, laying a clear problem foundation for the subsequent methodological development.

To clearly highlight the contributions of this study relative to existing frameworks, Table 1 compares the proposed ICLMF-MU model with several representative and state-of-the-art studies from 2020 to 2026. While earlier models and the contemporary bi-level approach by Shen et al. (2024) have explored integrated decisions, our model advances the literature in two fundamental ways. It achieves a deeper structural integration by simultaneously optimizing CFLP and MCFP, which allows operational flow re-routing costs to act as a real-time feedback signal that penalizes non-resilient strategic locations during the optimization process. And the ICLMF-MU internalizes multi-uncertainty, capturing the complex, non-linear interplay between facility availability and network-wide commodity dynamics.

Table 1

Comparison of ICLMF-MU with representative and state-of-the-art literature.

Literature	Uncertainty Dimensions			Problem Type	Optimization Objective
	Demand	Disruption			
		Node	Flow		
Akbarpour et al. (2020)	✓	–	–	SCND	Multi
Lotfi et al. (2021)	✓	–	–	SCND	Single
Lu and Cheng (2021)	✓	✓	–	CFLP	Single
Cheng et al. (2021)	✓	✓	–	CFLP	Single
Shen et al. (2024)	✓	–	✓	CFLP, VRP	Single
Ahmadi Digehsara et al. (2025)	–	–	✓	CFLP	Single
Luo et al. (2025)	✓	✓	–	CFLP	Single
Zhang and Kalcsics (2026)	✓	–	–	CFLP	Single
Zhang and Nickel (2026)	✓	✓	–	CFLP	Multi
Our (ICLMF-MU)	✓	✓	✓	CFLP, MCFP	Multi

*Note: This table highlights the core distinctions against representative benchmarks in recent literature (2020–2026). VRP refers to the Vehicle Routing Problem. SCND refers to Supply Chain Network Design.

To address the complexity of the original multi-objective model, this study adopts the non-dominated sorting genetic algorithm II (NSGA-II). The standard NSGA-II is an efficient and widely applied evolutionary algorithm for multi-objective optimization. It employs fast non-dominated sorting, crowding distance, and elite strategy to approximate the Pareto optimal frontier (Deb et al., 2002). NSGA-II has demonstrated strong performance in various applications. It is successfully applied to general supply chain network design problems (Altıparmak et al., 2006), including specific models such as the Minimum Cost Flow Problem (MCFP) (Ghasemishabankareh et al., 2019). It also serves as the benchmark for facility location problems (FLP) (Bhattacharya and Bandyopadhyay, 2010). In research by Brahami et al. (2022), a supply chain network was designed by integrating simultaneously CFLP and transport network design. By integrating these capabilities, NSGA-II provides a solid theoretical foundation for solving the integrated uncertainties in our model.

This study proposes an Integrated Capacitated Facility Location and Minimum Cost Flow Problem under Multi-Uncertainty (ICLMF-MU). It aims to simultaneously optimize facility location, capacity allocation, and product flows under uncertainty. The model explicitly incorporates stochastic demand and multiple disruption risks, including supply shortages, transportation delays, and facility failures. It supports more resilient and adaptable decisions regarding facility location and flow distribution to provide strategic guidance in response to the current unstable global trade environment.

2. Problem description and modeling for resilient supply chain design

2.1. Multi-objective non-linear model under uncertainty (ICLMF-MU)

To address the challenges of facility planning in supply chains under uncertainties, an integrated Capacitated Facility Location and Minimum Cost Flow Problem under Multi-Uncertainty optimization model (ICLMF-MU) is proposed. The model is formulated to achieve a balance between economic efficiency, service quality, and resilience, while enabling a simultaneous optimization of facility location and network flow.

2.1.1. Model description

The ICLMF-MU model takes into account the more detailed aspects of uncertainty, including unmet needs and supply chain disruptions. Disruptions occur at the supply nodes i and along transportation arcs (i, j) . We consider operational risk and structural risk in the objective of resilience. This allows the model to effectively mitigate systemic risks. The model is structured to capture the mutual feedback between location and flow decisions under multi-uncertainty. In this framework, the surge in transportation costs acts as a feedback signal to the strategic layer, compelling the model to select more resilient facility locations that can buffer uncertainty rather than just minimizing static costs.

The sets, parameters and decision variables used in the formulation of the ICLMF-MU are shown in Table 2.

2.1.2. Objective function

The model optimizes three objectives: total cost, composite utility, and composite risk. The objective functions can be formulated as follows:

$$\min \quad Z_1 = \sum_{i \in S'} f_i y_i + \sum_{i \in D} u_i \varphi_i + \sum_{(i,j) \in A} c_{ij} x_{ij} + \sum_{(i,j) \in A} c_{ij}^{maint} \delta_{ij} \quad (1)$$

$$\max \quad Z_2 = \lambda_1 \beta + \lambda_2 \left(\frac{\sum_{(i,j) \in A} x_{ij} \cdot e^{-r_{ij} t_{ij}}}{\sum_{(i,j) \in A} x_{ij} + \epsilon} \right) \quad (2)$$

Table 2

Model notation: sets, parameters, and decision variables.

Identifier	Description
<i>Sets</i>	
V	Set of all nodes (vertices)
S	Set of fixed supply nodes, $S \subset V$
D	Set of demand nodes, $D \subset V$
T	Set of transit/hub nodes, $T \subset V$
A	Set of all potential arcs
S'	Set of potential facility nodes, $S' \subset V$
$\bar{d}_{\text{active}}$	Average degree of the activated network topology
V_{active}	Set of nodes connected by active arcs ($\delta_{ij} = 1$) in the solution
A_{active}	Set of all active arcs
<i>Parameters</i>	
s_i	Fixed supply capacity of an existing facility at node $i \in S$
$\bar{s}_i$	Maximum allowable supply capacity of node $i \in S'$
K_{ij}	Maximum flow capacity of arc $(i, j) \in A$
d_i	Demand at node $i \in D$
f_i	Fixed cost of setting up a facility at node $i \in S'$
c_{ij}	Transportation cost per unit of flow on arc $(i, j) \in A$
u_i	Penalty cost per unit of unsatisfied demand at node $i \in D$
c_{ij}^{maint}	Fixed maintenance cost for keeping arc (i, j) active
g_i, g_{ij}	Disruption probability of node $i \in V$ and arc $(i, j) \in A$
$\text{deg}(i)$	The degree (number of connections) of node $i \in V_{\text{active}}$ in the activated network
γ_i	The availability ratio of node $i \in V$
r_{ij}	Product freshness decay rate on arc $(i, j) \in A$
t_{ij}	Transportation time on arc $(i, j) \in A$
λ_1, λ_2	Weighting coefficients for the utility function components
w_{op}, w_{struct}	Weighting coefficients for the composite risk function components
μ_1, μ_2	Weighting coefficients for structural risk components
<i>Decision Variables</i>	
x_{ij}	Quantity of flow on arc $(i, j) \in A$
q_i, q'_i	Actual supply quantity from $i \in S$ and $i \in S'$
s'_i	Supply capacity allocated to potential facilities at node $i \in S'$
ϕ_i	Amount of unsatisfied demand at node $i \in D$
β	Network service level ratio
y_i	$\begin{cases} 1, & \text{if a supply facility is operational at } i \in S' \\ 0, & \text{otherwise} \end{cases}$
δ_{ij}	$\begin{cases} 1, & \text{if the flow from } i \text{ to } j \text{ is available} \\ 0, & \text{otherwise} \end{cases}$

$$\min Z_3 = w_{op} \cdot R_{op} + w_{struct} \cdot R_{struct} \quad (3)$$

The first objective Z_1 (Eq. (1)) minimizes total cost across four components: facility setup costs ($\sum_{i \in S'} f_i y_i$), penalty costs for unsatisfied demand ($\sum_{i \in D} u_i \phi_i$), transportation costs ($\sum_{(i,j) \in A} c_{ij} x_{ij}$), and network topology maintenance costs ($\sum_{(i,j) \in A} c_{ij}^{\text{maint}} du_{ij}$).

To better reflect real supply chain operations, the model simultaneously considers service quality and product reliability. A composite utility function is proposed. The second objective Z_2 (Eq. (2)) maximizes this composite utility function. It balances the service level β (the proportion of demand fulfilled) with the average freshness quality of the delivered products (the expected preservation level of goods upon delivery). The second term calculates the flow-weighted average freshness retention across the network. This component assigns equal weight $\lambda_1, \lambda_2 = 0.5$ to both service and freshness aspects.

The third objective Z_3 evaluates network resilience through a composite risk metric. Following the approach of Azaron et al. (2008), model risk is taken as a composite construct in supply chain network design, aiming to enhance the overall resilience and robustness of the system against the common systemic shocks in the volatile global trade environment. In formulation (3), composite risk concludes operational risk (R_{op}) and structural risk (R_{struct}).

Resilience Metric Components.

Operational risk (R_{op}) captures the disruption losses based on actual flows (Eq. (4)). In this equation, g_i and g_{ij} are the disruption probabilities of node i and arc (i, j) , respectively, considering various risks ranging from operational failures to geopolitical disruptions (e.g., sanctions or border closures). To ensure numerical stability and achieve a balanced multi-objective optimization, R_{op} is normalized by a scaling factor R_{op}^{max} (Eq. (5)), which is related to a worst-case scenario where total market demand is routed through the most unreliable network components. A routing redundancy multiplier ($\rho = 2.0$ in our experiments) reflects the typical path depth in a multi-echelon network (e.g., $S \rightarrow T \rightarrow D$).

Structural risk (R_{struct}) consists of two components: physical topology risk (R_{topo} , which measures network connectivity), and flow concentration risk (R_{HHI} , which measures flow distribution).

The topology risk component R_{topo} penalizes networks with low node connectivity to encourage a well-connected and redundant structure. Snyder and Daskin (2005) observed that reliable networks activated more facilities to promote redundancy and maintained stable performance under disruptions. Research by LaRocca and Guikema (2015) showed that higher node connectivity enhanced network resilience when failures occurred. This connectivity is quantified by the average degree $\bar{d}_{active}$ within the active node set V_{active} (where $\delta_{ij} = 1$), with $\deg(i)$ denoting the incident connections for each node $i \in V_{active}$. An inverse decay penalty function is adopted for R_{topo} to reflect the diminishing marginal returns of additional connectivity.

To ensure that this metric R_{topo} provides sufficient gradient for the optimization and aligns with the scale of other risk components, a scaling parameter $\Theta = 10$ maps the raw connectivity metrics into a normalized range. A detailed sensitivity analysis justifying the selection and robustness of Θ is provided in Appendix A. A small constant ϵ is introduced to prevent numerical instability in the calculations.

To address single-route dependency, where flow remains overly concentrated despite a connected topology. We introduce the Herfindahl-Hirschman Index (HHI), denoted as R_{HHI} . R_{HHI} is inherently bounded within $[0, 1]$ based on flow ratios and thus requires no additional scaling. This metric penalizes skewed flow distribution, encouraging the algorithm to distribute traffic across multiple active routes. The flow on an arc (i, j) is normalized by the total network throughput $\sum x_{uv}$ across all active arcs (Eq. (8)). This diversification is designed for mitigating the impact of targeted trade blockades on specific logistics channels.

In this study, both operational and structural risks carry equal weight $w_{op}, w_{struct} = 0.5$. Within the structural risk component R_{struct} , the sub-weights are also equally distributed with $\mu_1, \mu_2 = 0.5$ to provide a neutral baseline for the robustness paradox analysis.

$$R_{op} = \frac{1}{R_{op}^{\max}} \left[\sum_{(i,j) \in A} x_{ij} g_{ij} + \sum_{i \in V} g_i \left(\sum_{j: (i,j) \in A} x_{ij} \right) \right] \quad (4)$$

$$R_{op}^{\max} = \rho \cdot \sum_{k \in D} d_k \cdot \left(\max_{i \in V} g_i + \max_{(i,j) \in A} g_{ij} \right) \quad (5)$$

$$R_{struct} = \mu_1 \cdot R_{topo} + \mu_2 \cdot R_{HHI} \quad (6)$$

$$R_{topo} = \frac{\Theta}{\bar{d}_{active} + \epsilon}, \quad \text{where } \bar{d}_{active} = \frac{1}{|V_{active}|} \sum_{i \in V_{active}} \deg(i) \quad (7)$$

$$R_{HHI} = \sum_{(i,j) \in A} \left(\frac{x_{ij}}{\sum_{(u,v) \in A} x_{uv}} \right)^2 \quad (8)$$

2.1.3. Constraints

The feasibility of the solution is governed by the following constraints:

$$\beta = 1 - \frac{\sum_{i \in D} \varphi_i}{\sum_{i \in D} d_i} \quad (9)$$

$$\sum_{j: (j,i) \in A} x_{ji} - \sum_{j: (i,j) \in A} x_{ij} = \begin{cases} -q_i, & i \in S, \\ -q'_i, & i \in S', \\ d_i - \varphi_i, & i \in D, \\ 0, & \text{otherwise,} \end{cases} \quad \forall i \quad (10)$$

$$0 \leq x_{ij} \leq K_{ij} \delta_{ij}, \quad \forall (i, j) \in A \quad (11)$$

$$0 \leq q_i \leq \gamma_i s_i, \quad \forall i \in S \quad (12)$$

$$0 \leq q'_i \leq \gamma'_i s'_i, \quad \forall i \in S' \quad (13)$$

$$s'_i \leq \bar{s}_i y_i, \quad \forall i \in S' \quad (14)$$

$$\lambda_1 + \lambda_2 = 1, \quad w_{op} + w_{struct} = 1, \quad \mu_1 + \mu_2 = 1 \quad (15)$$

$$x_{ij}, q_i, q'_i, \varphi_i \geq 0, \quad \forall i, j \quad (16)$$

$$y_i, \delta_{ij} \in \{0, 1\}, \quad g_i, \gamma_i \in [0, 1] \quad (17)$$

The set of constraints (10) ensures flow balance throughout the network. At supply nodes, the net outflow is equal to the actual supplied quantity. At demand nodes, the net inflow must satisfy the required demand, with φ_i representing the unmet demand at node i . Transit nodes maintain a strict zero net flow, ensuring conservation of flow.

Constraint (11) links flow decisions to the network topology via the binary variable δ_{ij} , representing Arc Activation. In this model, Arc Activation is defined as the tactical decision to ensure a link's operational readiness under uncertainty. Flow x_{ij} is permitted only when the arc is activated ($\delta_{ij} = 1$), indicating a pre-disaster commitment of resources (e.g., transport contracts or maintenance) that makes the link available for immediate rerouting. This variable is essential for optimizing strategic redundancy, as it allows the model to configure a resilient topology that balances activation costs against disruption risks. In resilient network design, activating all potential arcs is often cost-prohibitive. By treating δ_{ij} as a decision variable, the model identifies the optimal subset of arcs that

maximizes resilience at minimum cost. A higher activation rate increases structural redundancy (alternative path availability), which serves as the fundamental mechanism for maintaining service levels when primary arcs suffer disruptions. The maximum flow x_{ij} is bounded by the arc capacity K_{ij} .

Facility supply capacity is influenced by disruptions and facility availability. Existing pre-established supply nodes ($i \in S$) have fixed supply capacities s_i , while potential alternative supply nodes ($i \in S'$) have variable supply quantities s'_i that are determined through optimization. Routine operational factors diminish effective capacity through an availability ratio $\gamma_i \leq 1$. The capacity constraints account for these disruption effects. Only activated facilities may assign capacity by linking supply quantities to the binary activation variable y_i , as enforced by constraint (14). Constraint (15) normalizes the weighting factors across all components of the utility and risk functions, ensuring a balanced contribution from each element.

The proposed ICLMF-MU model represents an integration of capacitated facility location and flow distribution under multiple uncertainties, including demand fluctuations and disruption at supply nodes and transportation arcs. It optimizes three objectives, total economic cost (Z_1), composite utility (Z_2), and composite risk (Z_3). Objective Z_3 quantifies network resilience through a combination of operational and structural metrics. The structural risk consists of physical topology risk (R_{topo}) and flow concentration risk (R_{HHI}). The objective risk provides a robust mathematical framework to mitigate systemic risks in global supply chains.

2.2. An illustrative example

To illustrate the proposed ICLMF-MU model, a representative multi-echelon network example is presented in Fig. 1. This example maps the parameter components onto a physical topology to display the model's logic and mechanisms.

The network consists of four distinct node types: two fixed supply nodes ($S = \{S1, S2\}$), two potential supply nodes ($S' = \{S1', S2'\}$), four transit nodes ($T = \{T1 \dots T4\}$), and two demand nodes ($D = \{D1, D2\}$). At the strategic level, the model determines the binary activation of candidate nodes ($y_i \in \{0, 1\}$) and potential arcs ($\delta_{ij} \in \{0, 1\}$). As shown in the figure, active transportation links are represented by solid arrows. Potential links appear as dashed arrows that are operational only upon the activation ($y_i = 1$) of candidate nodes (S').

This structure incorporates supply chain disruption scenarios. For instance, the red zigzag arrow g_1 represents a failure at the primary supply node $S1$. The activation of the potential node $S1'$ and its associated links (dashed arrows) serves as a redundancy strategy to mitigate the disruption risks (g_1), providing a robust measure against disruption uncertainty. The model optimizes the flow distribution (x_{ij}) constrained by arc capacities (K_{ij}) and demand requirements (d_i). Flexible transshipment operations are facilitated by flows between transit nodes (e.g., $T3 \rightarrow T4$), allowing for dynamic rerouting.

Each transportation arc (i, j) is characterized by a unit cost c_{ij} and maintenance costs c_{ij}^{maint} . Each demand node D_i faces a deterministic demand d_i , with incurring a penalty φ_i for any unsatisfied demand. All these costs are integrated into the economic objective

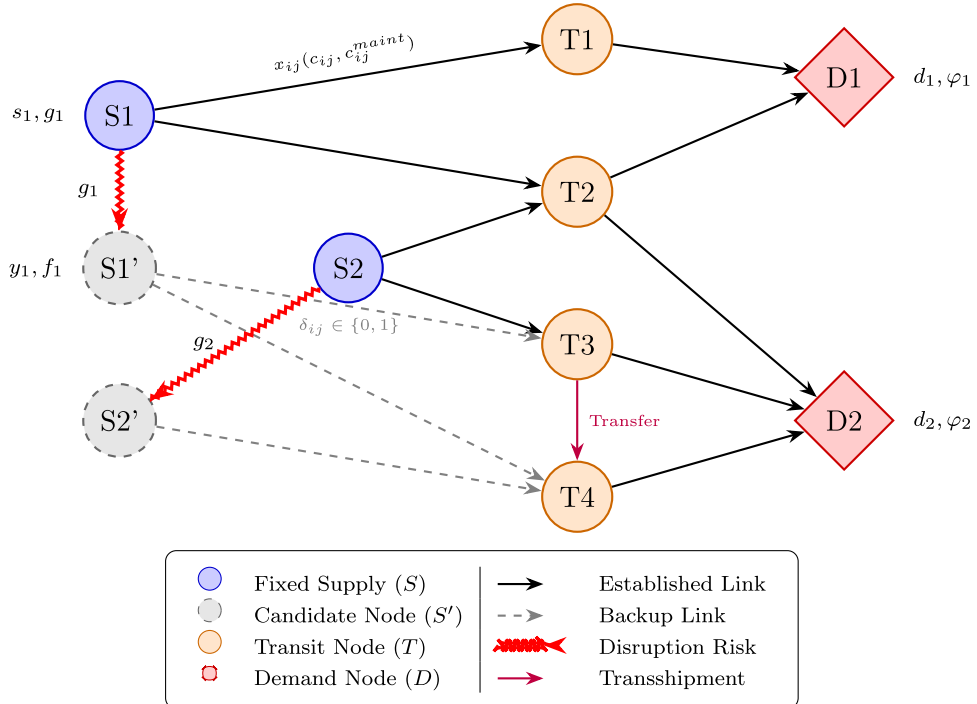


Fig. 1. Illustrative example of the multi-echelon supply chain network under uncertainties.

Z_1 . Accounting for product perishability during transit, each flow is penalized by the decay rate r_{ij} and transport time t_{ij} , directly influencing the composite utility Z_2 .

This framework of the illustrative example Fig. 1 transforms the theoretical multi-objective optimization into a functional process that balances economic efficiency, service quality, and resilience.

3. Solution methodology: a hybrid evolutionary approach and validation

The proposed multi-objective model (ICLMF-MU) integrates the MCFP and CFLP. Since the CFLP is well-known to be NP-hard (Daskin, 1995), the proposed model is inherently NP-hard, making it difficult to obtain exact solutions for large-scale instances. Therefore, this study develops an Enhanced Hybrid NSGA-II method. To effectively manage the complexity of this problem, we propose a hierarchical algorithmic framework (as illustrated in Fig. 2). This structured approach establishes a solid cognitive foundation by ensuring that each component of the proposed meta-heuristic is rigorously validated before being applied to the full-scale problem.

To validate the effectiveness and necessity of this algorithm, the framework is implemented through a three-stage benchmarking process using linearized approximations of the original model: (1) Single-objective validation: Comparing the Repair-based Genetic Algorithm (rGA, Algorithm 5) with the Weighted Exact Method (Algorithm 4); (2) Multi-objective validation: Comparing the proposed Enhanced Hybrid NSGA-II (Algorithm 1) with the exact ϵ -constraint method (Algorithm 6); (3) Algorithmic ablation study: Evaluating the individual contributions of the proposed enhancements to justify the hybrid architecture. This three-stage comparison verifies the performance and scalability of the proposed approach. Once validated, the Enhanced Hybrid NSGA-II (Algorithm 1), which is supported by a Tactical Support Layer (Algorithms 2–7) for solution repair and operational sub-problems, is then applied to solve the full non-linear ICLMF-MU model. This progression ensures that the comprehensive large-scale case analysis presented in the subsequent sections is built upon a verified algorithm.

3.1. Phase I validation: single-objective linear benchmark analysis

3.1.1. Performance benchmarking on a linearized model

To verify the effectiveness of the heuristic algorithm, the original multi-objective model (ICLMF-MU) is simplified into a linearized single-objective benchmark model.

In the original ICLMF-MU model, the first objective (Z_1) is inherently linear. However, the objectives Z_2 (Composite Utility) and Z_3 (Composite Risk) contain non-linear terms. The non-linearity stems primarily from the fractional term used for average freshness in Z_2 and the structural risk component (R_{struct}) in Z_3 . The structural risk component (R_{struct}) includes the inverse of the network's

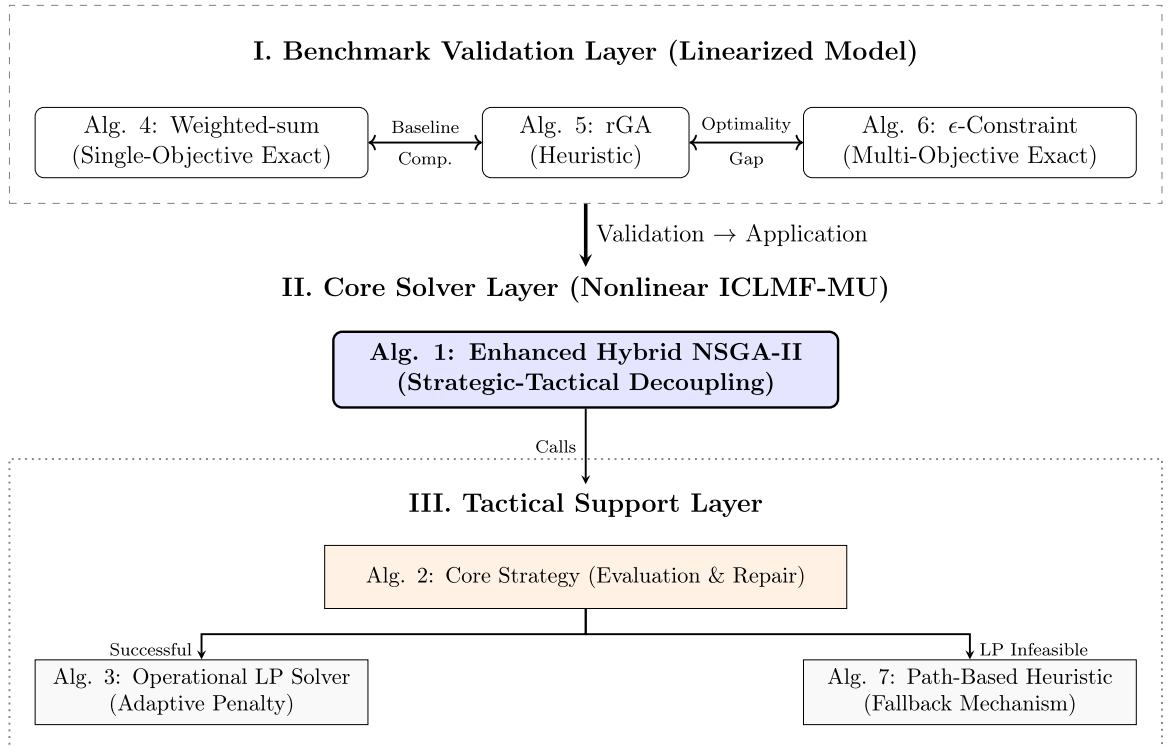


Fig. 2. Design logic of the algorithmic framework.

average node degree (R_{topo}) and the quadratic relationship of flow concentration (R_{HHI}). These nonlinear features make the original model incompatible with standard MILP solvers.

To construct a benchmark for evaluating the heuristic algorithm, we develop simplified proxy objectives: Z_2^{linear} and Z_3^{linear} .

For the freshness utility term in Z_2 , it is originally calculated as a flow-weighted average. The flow-dependent denominator ($\sum x_{ij}$) is replaced by the constant total demand D ($\sum_{d \in D} d_k$). And the sum is restricted to include only flow successfully reaching the demand nodes (consistent with the MILP formulation). This approximation transforms the utility term into a purely linear function.

To approximate the structural robustness within a linear framework, the complex non-linear structural risk R_{struct} is replaced by a linear proxy for network redundancy, denoted as Red_{net} . This proxy promotes network redundancy by incorporating a structural benefit term that is proportional to the number of activated potential facilities ($\sum y_i$). Since we are minimizing risk, this benefit appears with a negative sign in the objective. The formulas for the linearized benchmark model are presented below:

$$\max \quad Z_2^{\text{linear}} = \lambda_1 \cdot \beta + \lambda_2 \cdot \frac{\sum_{(i,j) \in A} x_{ij} \cdot e^{-r_{ij} t_{ij}}}{D} \quad (18)$$

$$\min \quad Z_3^{\text{linear}} = w_{\text{op}} \cdot R_{\text{op}} - w_{\text{struct}} \cdot Red_{\text{net}} \quad (19)$$

$$\text{where: } Red_{\text{net}} = \frac{1}{|S'|} \sum_{i \in S'} y_i \quad (20)$$

This three-objective linearized model is solved by the Weighted Sum Method (WSM), which combines multiple objectives into a single comprehensive function through a weighted linear combination (Miettinen, 1999; Marler and Arora, 2010). However, due to the significant magnitude differences between objectives (e.g., cost $\approx 10^4$ vs. Utility ≈ 1), normalization factors are introduced to ensure balanced optimization. The aggregated function is defined as:

$$\min \quad W = w_1 \frac{Z_1}{N_1} - w_2 Z_2^{\text{linear}} + w_3 \frac{Z_3^{\text{linear}}}{N_3} \quad (21)$$

subject to:

$$\text{all model constraints (Equations 4– dummyTXdummy–(17)} \quad (22)$$

$$w_1, w_2, w_3 \geq 0 \quad (23)$$

$$w_1 + w_2 + w_3 = 1 \quad (24)$$

Since the aggregated objective function is expressed as a minimization problem and Z_2 is originally a maximization objective, a negative sign is applied to its weight w_2 . As a result, the complete linearized benchmark model minimizes normalized Z_1 , maximizes Z_2 and minimizes normalized Z_3^{linear} , all subject to the same constraints as the original model. Where N_1 represents the theoretical maximum cost (Z_1^{max}) and N_3 represents the maximum operational risk ($R_{\text{op}}^{\text{max}}$). Both normalization factors are pre-calculated based on the problem parameters. The complete process is described in Algorithm 4 of Appendix B.

3.1.2. Heuristic approach for the benchmark: repair-based GA

The Genetic Algorithm (GA) is a global search heuristic inspired by biological evolution (Goldberg, 1989). It has been proven effective across a wide range of supply chain optimization problems, ranging from facility location problems (Gen and Cheng, 2000; Melo et al., 2009; Jaramillo et al., 2002; Mousavi and Niaki, 2013) to complex network design (Altıparmak et al., 2006; Iris and Serdarasan, 2012). In this study, we adopt a baseline rGA to solve the single-objective linearized benchmark model.

However, directly applying a standard GA to the ICLMF-MU model is challenging. Preliminary experiments reveal that standard genetic operators blindly disrupt the delicate flow balance constraints, producing almost no feasible solutions. Therefore, to address this issue and establish a valid baseline for comparison, this implementation explicitly integrates the proposed enforceFlowBalance mechanism (Heuristic and LP Repair) into the GA. We refer to this modified approach as the Repair-based Genetic Algorithm (rGA). This approach ensures that the baseline algorithm can effectively search the highly constrained search space. By comparing the results of rGA against the exact MILP solution, we establish a rigorous performance baseline to evaluate the search efficiency and solution quality of the proposed framework. The complete process is shown in Algorithm 5 of Appendix C.

3.1.3. Comparative analysis of benchmark results

To ensure a fair and strict comparison, the Repair-based GA and the exact MILP solver were executed within the same computational environment (MATLAB R2023b). The analysis was conducted on a small-scale instance (10 nodes). To evaluate the performance boundaries of the algorithms, a high-sensitivity parameter setting ($u \approx 100 \times$ transport cost) was employed to amplify structural differences between solutions. The objective weights were set to $(w_1, w_2, w_3) = (0.4, 0.3, 0.3)$ to provide a balanced assessment among cost, linearized utility, and linearized risk. Key parameters used in this benchmark test are listed in Table 3.

Under these conditions, the rGA was executed 20 independent times. The best solution, which matched the exact solver's weighted objective (W) to four decimal places, was selected for the detailed comparison shown in Table 4. As evidenced by the results, the rGA successfully locates a solution that is functionally equivalent to the global optimum derived by the Exact Solver for this linearized benchmark. The final objective value is nearly the same for both methods. While minor internal structural variations exist, the corresponding deviations across Total Cost (Z_1), Utility (Z_2^{linear}), and Risk (Z_3^{linear}) are marginal. This confirms that the proposed

Table 3
rGA parameters for the benchmark comparison.

Parameter	Value
Network Structure	10 Nodes 2 Supply, 2 Potential, 4 Transit, 2 Demand
Population Size / Max Generations	200 / 100
Crossover Probability (p_c)	0.8
Mutation Probability (p_m)	0.2

Table 4
Comparison of repair-based genetic algorithm and exact solver results.

Metric	rGA	Exact Solver
<i>Performance Metrics</i>		
Final Objective Value	-0.3929	-0.3930
Total Cost (Z_1)	13,091.53	13,062.85
Utility (Z_2^{linear})	1.5301	1.5301
Risk (Z_3^{linear})	50.3866	50.3251
Service Level (%)	100.0	100.0
<i>Decision Variables</i>		
Total Active Facilities	4	4
Arc Activation (%)	85.7%	71.4%
Total Network Flow	1690.6	1690.6

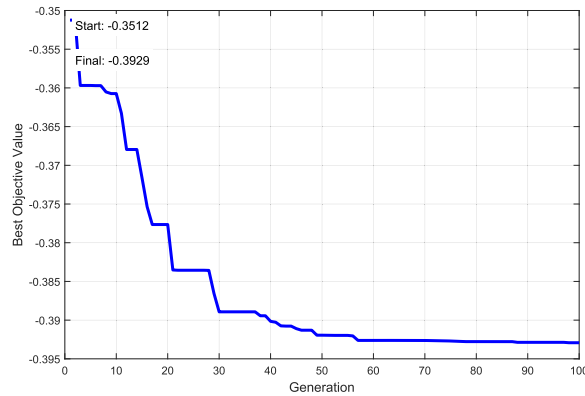


Fig. 3. rGA convergence curve.

rGA possesses the search capability to approximate the global optimum with high precision under a specific benchmark scenario.

Both methods activate four facilities, achieve 100.0% service levels and maintain an identical total network flow of 1690.6. However, a surprising pattern emerges in arc activation: the rGA activates substantially more of the network (85.7%) compared to the Exact Solver (71.4%). This indicates that the rGA generates a high degree of structural redundancy (physical density) by activating low-value arcs that do not contribute to resilience. The Exact Solver achieves strategic redundancy, delivering superior resilience through a leaner, more precisely configured topology that only deploys structural backups where they actively mitigate risk.

Fig. 3 shows the rGA convergence curve. The objective improves rapidly from an initial value of -0.3512 to a stable near-optimal value of -0.3929 , confirming that the evolutionary search effectively explores the solution space.

To assess system resilience, both solutions were evaluated under three uncertainty scenarios (Fig. 4). While performance remains comparable during demand surges and facility shutdowns, a clear difference emerges under critical arc failure. The Exact Solver maintains a low operational cost (1.435×10^4) via strategic redundancy (purposeful allocation of physical network connections to balance cost and resilience). In contrast, despite achieving an identical baseline objective, the rGA's cost spikes to 6.546×10^4 . This reveals that the rGA converges to a fragile network design and achieving an equivalent baseline objective does not guarantee actual structural resilience.

Fig. 5 shows the network topologies. The Exact Solver builds a structured network with precise connections and essential cycles for rerouting. The rGA topology appears less organized. Although it satisfies all static demands, it lacks the systematic backup routes required to absorb critical failures, directly explaining the vulnerability in the robustness analysis.

In summary, while the rGA successfully finds a high-quality solution that matches the optimum under static conditions, the exact solver exploits the full mathematical structure of the linear model to produce a more robust and structurally efficient network. The robustness analysis reveals that objective value equivalence does not imply matching structural quality. This confirms the necessity

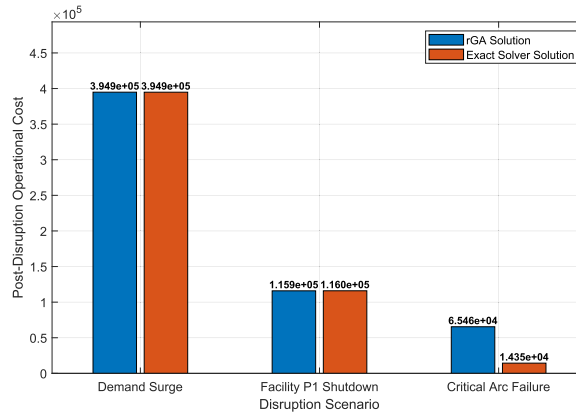


Fig. 4. Comparative robustness analysis: rGA vs. exact solver.

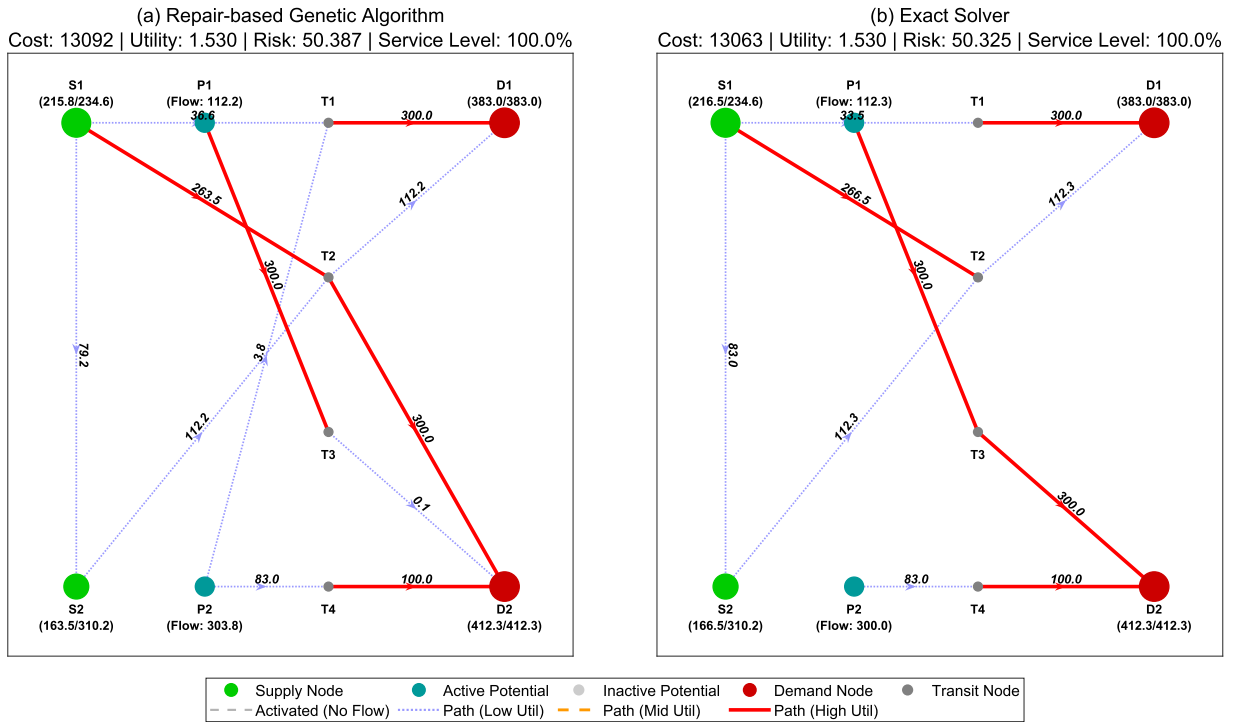


Fig. 5. Optimal network topology by the repair-based genetic algorithm vs. the exact solver.

of the proposed full non-linear ICLMF-MU model and the Enhanced NSGA-II approach to directly incorporate resilience into the optimization.

3.2. Phase II validation: multi-objective linear benchmark analysis

3.2.1. Exact method of the linearized multi-objective model

Following the validation of the single-objective model, we now extend the analysis to the multi-objective case to evaluate the performance of the improved NSGA-II. To establish a reliable benchmark for comparison, the original model (ICLMF-MU) is converted into a multi-objective linear model, and the problem is solved by an exact method. As described in Eqs. (18)–(20), the simplified proxy functions Z_2^{linear} and Z_3^{linear} are introduced, while all model constraints (Eqs. (9)–(17)) remain unchanged. To obtain the reference Pareto-optimal front P_{ref} , the ϵ constraint method (Chankong and Haimes, 1983) is employed. In this approach, one objective (Z_1 in this study) is set as the primary objective function, while other objective functions are transformed into constraints. This method

Table 5
Strategic vs. tactical layer: a comparative summary.

Feature	Strategic Layer	Tactical Layer
Core Decision	Facility & Capacity (y, s')	Flow, Routing & Shortage (x, δ, φ)
Decision Horizon	Long-term / Static	Short-term / Dynamic
Solver Logic	Evolutionary (NSGA-II)	Deterministic (LP / Heuristic)
Variable Nature	Discrete / Combinatorial	Continuous / Constrained
Search Focus	Global Exploration	Local Feasibility
Functional Role	Structure Definition	Performance Evaluation
Supply Chain Level	Corporate / Top-level Planning	Operational / Execution

generates a benchmark Pareto front representing the true trade-offs among three objectives. More details are shown in [Algorithm 6](#) of [Appendix D](#).

3.2.2. Heuristic approach: enhanced hybrid NSGA-II

Although exact methods can provide the optimal solution for linearized benchmark models, they become computationally intractable for the original nonlinear multi-objective problems, particularly for large supply chain networks. Due to the NP-hard nature of the ICLMF-MU model, the solution space and computational time grow exponentially with network scale.

The ICLMF-MU model presents a multi-scale challenge due to the complex coupling of long-term infrastructure decisions and short-term operational flows. To address this, we propose a strategic-tactical decoupling framework, as summarized in [Table 5](#). By delegating high-dimensional flow constraints to the specialized sub-solvers in the Tactical Layer, the Strategic Layer (NSGA-II) avoids the curse of dimensionality and focuses exclusively on optimizing the discrete combinatorial backbone of the network. This bi-level partitioning effectively balances global exploration with local precision, reducing computational complexity while closely mirroring the hierarchical decision-making structure of real-world supply chains.

Algorithm 1: Enhanced Hybrid NSGA-II.

Serving as the core solver for the nonlinear ICLMF-MU model, [Algorithm 1](#) is invoked by the main optimization system and triggers [Algorithm 2](#) for solution evaluation. To address the problem complexity, we propose an Enhanced Hybrid NSGA-II. Building upon the foundational principles of the standard NSGA-II, our proposed algorithm extends the standard NSGA-II with hybrid operators and multi-tier preservation mechanisms, solving the specific uncertainties of the ICLMF-MU. These enhancements are designed to provide high-quality solutions for large-scale problem instances by balancing convergence speed with solution diversity. The entire process is presented in [Algorithm 1](#) and [Fig. 6](#).

Algorithm 1: Bi-level hybrid NSGA-II: strategic-tactical decoupling.

Input: Network Data (Nodes, Costs, Demands), PopSize N , MaxGen $T_{\max}$

Decision Variables: Strategic $\mathbf{v}_{\text{strat}} = \{y, s'\}$; Tactical $\mathbf{v}_{\text{tact}} = \{x, \delta, \varphi\}$

Output: Pareto Optimal Set (PS) & Front (PF)

1. **Initialization** ($t = 0$): $P_0 \leftarrow \text{SmartInitialize}(N, \Omega)$ // Generate strategic genes $\mathbf{v}_{\text{strat}}$ and invoke heuristic tactical solver for initial $\mathbf{v}_{\text{tact}}$

foreach $p \in P_0$ **do**

 | Compute $\mathbf{v}_{\text{tact}}$, Objs via **CoreStrategy** (see [Algorithm 2](#))

2. **Main Evolutionary Loop:**

while $t < T_{\max}$ **do**

Step 2.1: Strategic Evolution (Upper Level)

 Select parents from P_t ; Generate offspring Q_t (N) by Crossover & Mutation **only on** $\mathbf{v}_{\text{strat}}$.

Step 2.2: Tactical Optimization (Lower Level)

foreach offspring $q \in Q_t$ **do** $q.\mathbf{v}_{\text{tact}}, \text{Objs} \leftarrow \text{CoreStrategy}(q.\mathbf{v}_{\text{strat}})$ ([Algorithm 2](#)) // Hybrid Mapping

Step 2.3: Boundary-Protected Selection

 Combine $R_t \leftarrow P_t \cup Q_t$ (Size $2N$); Identify **Boundary Elites** (Best Z_1, Z_2, Z_3).

 Rank R_t (Feasibility $\rightarrow$ Rank $\rightarrow$ Distance); Select top $N \rightarrow P_{t+1}$, **forcing** Elites.

Step 2.4: Adaptive Restart

if Diversity $< \Delta_{\min}$ **then** Replace bottom 70% of P_{t+1} with new random $\mathbf{v}_{\text{strat}}$

$t \leftarrow t + 1$

return Non-dominated solutions from P_t .

This algorithm incorporates six key improvements designed to prevent falling into local convergence and maximize coverage of the Pareto front: (1) Strategic-Tactical Decoupling employs a bi-level structure where genetic operators are applied exclusively to the

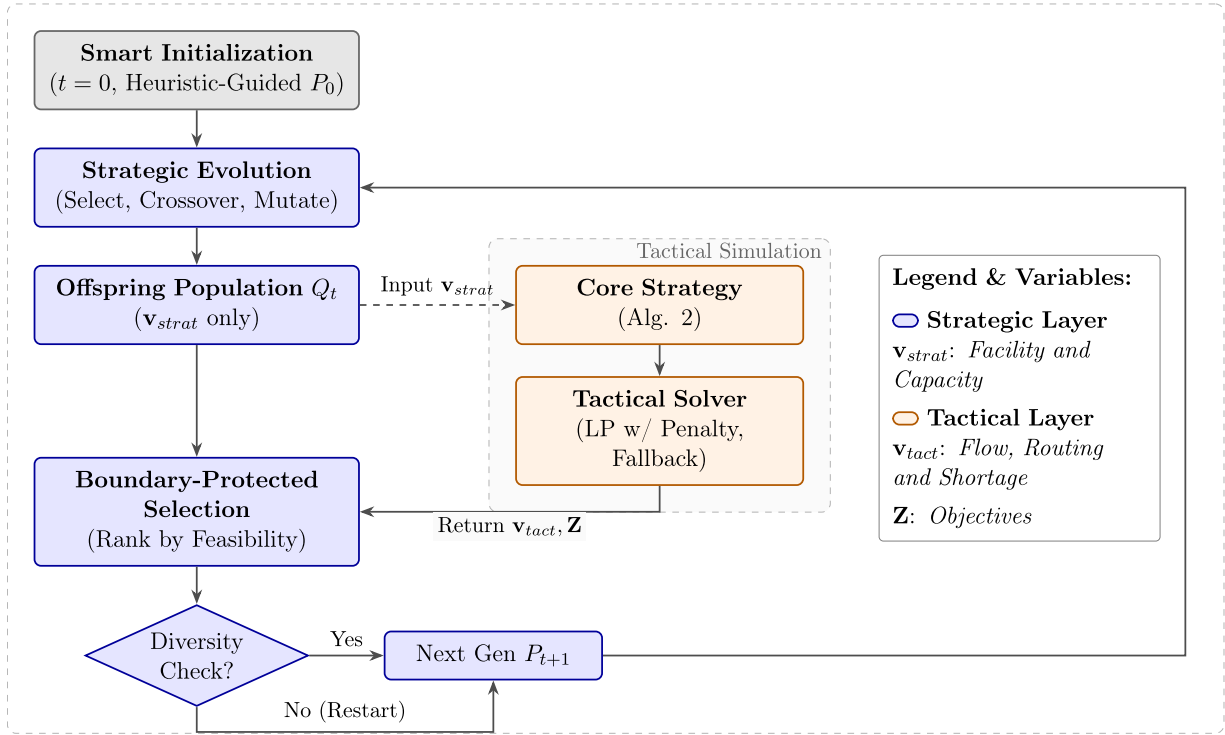


Fig. 6. The proposed bi-level framework.

strategic facility planning variables (v_{strat}), while the tactical network topology and flows (v_{tact}) are determined by specialized sub-solvers through a soft-constrained optimization procedure. (2) Heuristic-Guided Smart Initialization uses expert heuristics to generate strategic configurations (v_{strat}) and directly invokes the fallback heuristic to rapidly assign feasible tactical flows (v_{tact}) without the LP solver's overhead. (3) Soft-Constrained LP Mechanism incorporates a topology consistency penalty into the objective function, encouraging the use of existing strategic routes while allowing new routes to open when they reduce costs. The final topology δ is then reconstructed based on the optimal flows. (4) Boundary Protection Strategy utilizes an objective-specific elitism strategy to prevent the loss of extreme boundary solutions during non-dominated sorting. (5) Adaptive Strategic Restart manages population diversity by replacing the bottom 70% of individuals with new configurations upon diversity stagnation, retaining only the top 30% of high-performing solutions. (6) Hierarchical selection criterion prioritizes solutions based on feasibility first, followed by non-dominance rank and crowding distance. This ensures that constraint satisfaction is always prioritized over solution quality during the selection process.

Algorithm 2: Core Strategy. Algorithm 2 functions as the tactical support layer, which is called by Algorithm 1 and subsequently invokes Algorithm 3 or 7 depending on the feasibility of the flow balance. The algorithm includes a new hybrid bi-level evaluation and repair strategy, as detailed in Algorithm 2. And the corresponding logical flowchart is illustrated in Fig. 7. This strategy is specifically designed to handle complex flow balance constraints by enforcing feasibility through rigorous mathematical validation.

The approach combines the global search capability of GA with the local precision of Linear Programming (LP). When a strategic configuration is generated, the algorithm immediately triggers an operational LP solver (Algorithm 3) to derive optimal tactical flows. The LP acts as a tactical optimizer, computing the variables x and ϕ by minimizing total operational cost with an adaptive topology penalty. To ensure robustness, a Try-and-Fallback architecture is employed: if the LP cannot identify a feasible solution, a global path-based heuristic is automatically activated as a fallback mechanism to guarantee valid routing.

A key feature of this algorithm is the Reverse Mapping mechanism: the strategic topology variable δ is not predetermined. It is reconstructed after optimization based on the actual active flows ($x_{ij} > 0$). This approach ensures logical consistency between strategic decisions and tactical operations, effectively removing redundant ghost arcs that would increase costs without contributing to the solution. Furthermore, the service level requirement is treated as an optimization objective rather than a strict constraint, allowing the algorithm to explore the full Pareto front by retaining low-cost solutions with lower service levels, which is essential for exploring the full Pareto front.

Algorithm 3: Operational LP Solver.

Positioned as a lower-level optimization module, Algorithm 3 is called by the Core Strategy (Algorithm 2) to resolve operational variables within a relaxed topological space. This Operational LP Solver (Algorithm 3) serves as the tactical execution component,

Algorithm 2: Core strategy: bi-level evaluation and repair.

Input: Strategic Vector $\mathbf{v}_{strat} = \{y, s'\}$
Output: Tactical Vector $\mathbf{v}_{tact}$, Objectives $\mathbf{Z}$, Feasibility Status ν

1. Input Sanitization:
 Repair variable bounds and validate consistency of facility capacities (y, s') .

2. Tactical Solver Execution:
 // Attempt precise optimization using soft-constrained LP
 Run **Operational LP Solver with Adaptive Topology Penalty** (Algorithm 3) using fixed $\mathbf{v}_{strat}$ and topology hint δ .
if LP is successful ($\mathbf{X}_{opt}$ found) then
 Extract flows $\mathbf{x} \leftarrow \mathbf{X}_{opt}$.
 Numerical Cleaning: Set $x_{ij} \leftarrow 0$ if $x_{ij} < 10^{-5}$ (Prune ghost flows).
 Reverse Mapping: Reconstruct topology δ from active flows:
 $\delta_{ij} \leftarrow 1$ if $x_{ij} > 0$, else 0. // Synchronize tactical topology
else Run Global Path-Based Heuristic (Algorithm 7). // Fallback: Guarantee feasibility

3. Performance Evaluation:
 Compile a tactical solution $\mathbf{v}_{tact} = \{\mathbf{x}, \delta, \varphi\}$.
 Calculate Objectives $\mathbf{Z} = [Z_1(\text{Cost}), Z_2(\text{Utility}), Z_3(\text{Risk})]$.
 Calculate Constraint Violation $\nu \leftarrow \text{FlowResidual}(\mathbf{x})$.
 // Note: Service level β is optimized as objective, not hard constraint
return $\mathbf{v}_{tact}, \mathbf{Z}, \nu$.

Algorithm 3: Operational LP solver with adaptive topology penalty.

Input: Strategic Vector $\mathbf{v}_{strat} = \{y, s'\}$, Topology Hint δ_{hint}
Output: Optimal Flows $\mathbf{X}_{opt}$, Auxiliary Vars $\mathbf{Q}, \varphi$, Success Status

1. Adaptive Penalty Calibration:
 // Calculate penalty intensity based on scenario urgency
 Compute ratio $\rho \leftarrow \mathbf{u}_{avg} / \mathbf{c}_{avg}$.
Set Adaptive Factor α_{adapt} :

$$\alpha_{adapt} \leftarrow \begin{cases} 1.0 & \text{if } \rho > 50 \text{ (High Urgency Regime)} \\ 0.1 & \text{if } \rho \leq 50 \text{ (Cost Sensitive Regime)} \end{cases}$$
Construct Penalized Cost Vector $\mathbf{C}_{LP}$:
 $\mathbf{C}_{LP,ij} \leftarrow \mathbf{c}_{ij} + (\alpha_{adapt} \cdot \mathbf{c}_{avg})$ if $\delta_{hint,ij} = 0$, else $\mathbf{c}_{ij}$.
 // Penalize deviation from parent topology without forbidding exploration

2. LP Model Construction:
Objective Function:
 $\min Z_{ops} = \mathbf{C}_{LP}^\top \mathbf{x} + \mathbf{u}^\top \varphi$ // Minimize Operational Cost (Transport + Shortage Penalty)
Subject to:
 Node Balance: $\sum \text{Flow}_{in} - \sum \text{Flow}_{out} + \text{Supply} = \text{Demand} - \varphi$.
 Strategic Bounds: $q'_i \leq \gamma_i \cdot s'_i \cdot y_i$ // Upper-level decision constrains Lower-level supply
 Physical Capacity: $0 \leq x_{ij} \leq K_{ij}$. // Decoupled from δ_{hint} ; allows new routes

3. Dual-Simplex Optimization:
 Solve the linear program using the dual-simplex algorithm.
if Feasible Solution $\mathbf{X}^*$ found then
 Parse $\mathbf{X}^*$ into $\mathbf{X}_{opt}$ (flows), $\mathbf{Q}$ (supplies), and φ (shortages).
 return $\mathbf{X}_{opt}, \mathbf{Q}, \varphi$, Success = **true**.
else return $\emptyset, \emptyset, \emptyset$, Success = **false**.

implementing a Penalty-Guided Decoupling Strategy. Traditional formulations rigidly enforce flow constraints within a predetermined network structure ($x_{ij} \leq K_{ij} \cdot \delta_{ij}$). This approach relaxes topological bounds, allowing the solver to utilize any available physical arc ($x_{ij} \leq K_{ij}$), constrained only by upper level facility capacities ($\mathbf{v}_{strat}$). This formulation enables the LP solver to identify the global minimum operational cost (including both transportation and unmet demand penalty) for a given facility layout, avoiding the infeasibility issues common when GAs randomly generate disconnected topologies.

To balance operational efficiency with structural consistency, an Adaptive Topology Penalty mechanism is introduced. This mechanism addresses the inherent conflict between the continuous LP solver (which favors fragmented, low-volume routes) and the discrete GA objectives (which penalize arc maintenance costs). A penalty cost is applied when the solver uses arcs not included in the topology hint (δ_{hint}). The penalty intensity is adaptively calibrated based on scenario urgency-measured by the ratio (ρ) of the unmet demand

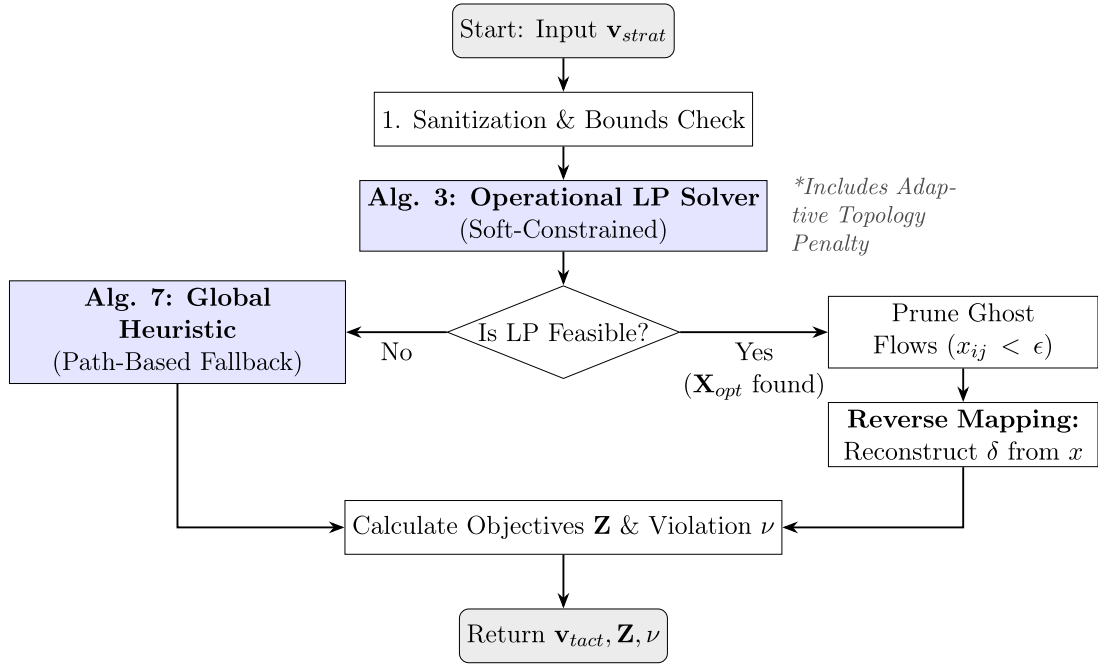


Fig. 7. Logic flow of tactical layer.

penalty to average transportation costs. In high-priority scenarios (e.g., Medical), a strong penalty factor ($\alpha = 1.0$) enforces strict adherence to the suggested network structure. In cost-sensitive scenarios, a weaker factor ($\alpha = 0.1$) permits greater exploration of alternative routes. This soft constraint ensures the solver prioritizes the existing network structure while retaining the flexibility to activate alternative routes when cost savings justify the penalty.

Algorithm 7: Path-Based Fallback Heuristic.

Algorithm 7 acts as an emergency feasibility mechanism, invoked by Algorithm 2 as a fallback when the LP solver detects structural infeasibility. When the LP solver fails to find a solution, a Global Path-Based Greedy Heuristic (Algorithm 7) is applied instead.

This method avoids the risk of short-sighted routing decisions by first identifying all valid complete routes ($S \rightarrow T \rightarrow D$ or $S \rightarrow D$). These routes are ranked by their total consolidated cost. Flow is assigned step by step to the lowest-cost routes until either capacity limits or demand requirements are met. This strategy effectively prevents local optima traps, ensuring that flow allocation is driven by system-wide cost efficiency rather than evaluating individual links in isolation. Detailed implementation steps are provided in Algorithm 7 of Appendix E.

3.2.3. Comparative analysis of improved results

To validate the enhanced NSGA-II (Algorithm 1), its approximate Pareto frontier is compared against the reference Pareto front (P_{ref}) generated by the exact method (Algorithm 3). Both algorithms were implemented in MATLAB R2023b.

Performance is evaluated using two widely adopted metrics: Hypervolume (HV) and Inverted Generational Distance (IGD). To ensure fair comparison across different objective scales, all objective values are normalized to a unified $[0, 1]^m$ space before metric calculation.

Hypervolume (HV) (Zitzler and Thiele, 1999) measures the volume of the objective space dominated by the solution set A relative to a reference point R . It indicates both how close solutions are to the reference Pareto front (convergence) and how well they spread across the front (diversity). A higher HV value indicates better performance. For a solution set $A = \{a_1, \dots, a_N\}$, HV is defined as:

$$HV(A, R) = \text{Volume} \left(\bigcup_{i=1}^N \text{hypercube}(a_i, R) \right) \quad (25)$$

In this study, the reference point is set to $R_{norm} = (1.1, 1.1, \dots, 1.1)$ in the normalized space for HV calculations.

Inverted Generational Distance (IGD) (Zitzler et al., 2003; Coello Coello, 1999) measures the average Euclidean distance from each point on the reference Pareto front P^* to the nearest point in the heuristic solution set A . This metric evaluates both convergence quality and solution coverage simultaneously. A lower IGD value indicates better algorithm performance. For a reference set $P^* = \{p_1^*, \dots, p_{|P^*|}^*\}$, IGD is calculated as follows:

$$IGD(A, P^*) = \frac{1}{|P^*|} \sum_{p^* \in P^*} \min_{a \in A} d(p^*, a) \quad (26)$$

Table 6
NSGA-II parameters for the benchmark comparison.

Parameter	Value
Network Structure	40 Nodes 8 Supply, 8 Potential, 16 Transit, 8 Demand
Population Size / Max Generations	200 / 300
Crossover Probability (p_c)	0.8
Mutation Probability (p_m)	0.2

Table 7
Algorithm performance comparison (20 runs).

Metric	NSGA-II (Heuristic)	Exact (P_{ref})
Hypervolume (HV)	0.8696 (Avg) $\pm$ 0.0148 (Std)	0.9883 (Fixed)
IGD (vs P_{ref})	0.076421 (Avg) $\pm$ 0.019610 (Std)	–

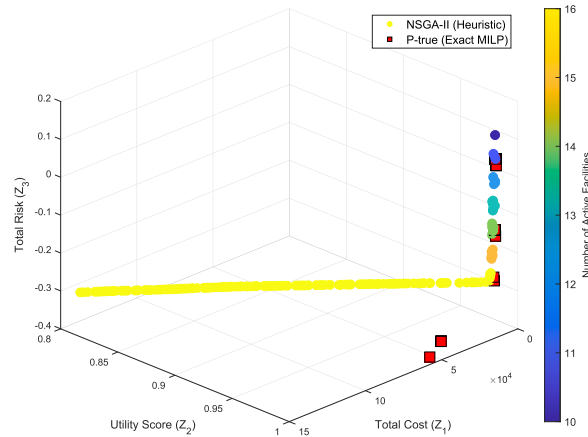


Fig. 8. 3D pareto front (best NSGA-II run vs P-ref).

where $d(p^*, a)$ represents the Euclidean distance between two points. Similar to the HV metric, IGD calculations are performed in the normalized $[0, 1]^m$ space to ensure consistent and comparable results across different problem scales.

Following the initial comparison of baseline algorithms, we extended the validation to a medium-scale instance (40 nodes). Table 6 presents the key parameters for this benchmark test, and Table 7 shows the optimization results comparison.

Distinct from the high-sensitivity stress test in the Section 3.1, this analysis uses a low-sensitivity parameter setting ($u \approx 4 \times$ transport cost) that reflects typical commercial conditions. This configuration creates significant trade-offs among the competing objectives (cost, utility, and risk), producing a well-developed Pareto front suitable for benchmarking. To ensure statistical reliability, all algorithms are run 20 independent times on the linearized benchmark problem. The optimization results are summarized in Table 7.

The enhanced NSGA-II demonstrates strong performance in approximating the reference Pareto Front (P_{ref}) obtained from the simplified linear model.

The algorithm achieves an average Hypervolume (HV) of 0.8696 with an extremely low standard deviation of (± 0.0148). Compared to the benchmark HV of 0.9883 from P_{ref} , this represents a performance gap that is expected for heuristic methods. It explores the solution space rather than guarantees global optimality. The minimal deviation demonstrates the validity of the heuristic approach of being highly stable and reliable.

For the Inverted Generational Distance (IGD) metric, the algorithm achieves an average value of 0.076421. This numerical result reflects the structural difference between the two solution sets.

Because the problem involves integer decision variables, the reference Pareto front P_{ref} consists of discrete, separated points (shown as red squares in Fig. 8). In contrast, the heuristic algorithm produces a smoother, continuous approximation (shown as the cyan curve). The IGD metric effectively measures the distance between this continuous heuristic curve and the discrete integer points distributed along the frontier. The low variance in IGD (± 0.019610) indicates that the enhanced NSGA-II consistently converges to the same high-quality solution front across all independent runs.

Figs. 8 and 9 show the optimization results for the three objectives: Cost (Z_1), Utility (Z_2), and Risk (Z_3).

The projection matrix (Fig. 9) demonstrates the alignment between the enhanced NSGA-II and the exact solver. In the Cost-Utility plane (top middle plot), the NSGA-II solutions (blue circles) closely follow the same trade-off curve as the exact solutions (red squares). This alignment confirms that the algorithm effectively captures the primary relationship between cost and utility. Both methods trace

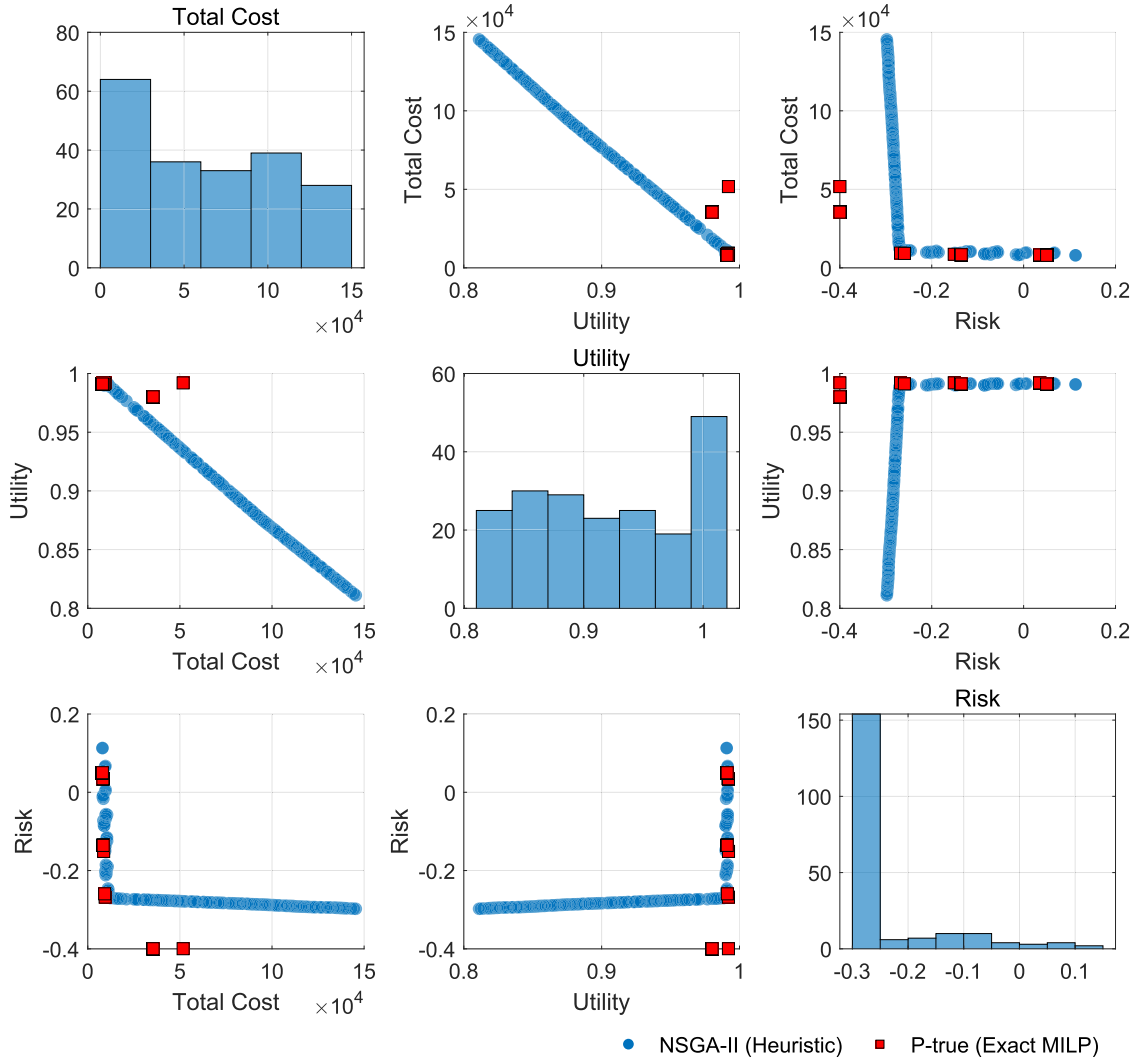


Fig. 9. Pareto front pairwise projection matrix.

the same steep trade-off pattern within the high-utility, low-cost region. The Exact Solver (P_{ref}) produces only a few sparse solutions concentrated at the extreme ends of the Pareto front, which naturally restricts its exploration of the full trade-off space.

A distinction is observed in the Risk dimension (Z_3). As shown by the overall trend in the 3D plot (Fig. 8), the Exact Solver identifies network structures with minimum risk values of approximately -0.4 . The enhanced NSGA-II stabilizes at a risk floor of approximately -0.3 . This gap reflects the distinct behavioral characteristics of each method. The Exact Solver excels at identifying the theoretical boundaries and pinpointing the absolute minimum risk values. But this focus results in limited sparse solution distribution. Conversely, the enhanced NSGA-II emphasizes a more comprehensive exploration of the trade-off space. As shown in Fig. 8, the algorithm generates a dense, continuous front that fills the gaps between the sparse exact solutions. The predominant yellow color of this surface reveals that the algorithm achieves this dense set of trade-off solutions by consistently activating a higher number of 16 facilities. Although it does not reach the lowest risk values of the exact method, this comprehensive coverage provides decision-makers with more flexibility when balancing conflicting objectives, rather than optimizing a single objective at the expense of others.

3.3. Phase III validation: impact of algorithmic components

To thoroughly evaluate the individual contributions of the proposed algorithmic enhancements and justify the added complexity, an ablation study is conducted on the original multi-objective non-linear optimization model (Section 2). This analysis focuses on a medium-scale instance (40 nodes) with parameter settings specified in Table 6, consistent with the scenarios utilized in Phase II. The Strategic-Tactical Decoupling (bi-level design) serves as the fundamental baseline. Building upon this architecture, we systematically isolate the remaining advanced modules. To ensure strict statistical reliability, all algorithm variants are executed 20 independent times.

Table 8

Configuration and performance of algorithm variants in the ablation study (20 runs).

Algorithm Variant	Algorithmic Components					Performance Metrics		
	Smart Init	Fallback	Penalty	Restart	Boundary	HV	IGD	Time (s)
(V1) Base Bi-level	–	–	–	–	–	1.7873	0.6788	126.1
(V2) Hybrid w/o Smart Init	–	✓	✓	✓	✓	1.1566	0.4217	81.4
(V3) Hybrid w/o Fallback	✓	–	✓	✓	✓	0.9890	0.5035	116.1
(V4) Hybrid w/o Penalty	✓	✓	–	✓	✓	1.0812	0.4134	156.9
(V5) Hybrid w/o Restart	✓	✓	✓	–	✓	0.9742	0.5039	217.5
(V6) Hybrid w/o Boundary	✓	✓	✓	✓	–	0.9668	0.5047	199.3
(V7) Proposed Hybrid	✓	✓	✓	✓	✓	0.9886	0.5047	202.1

As shown in Table 8, correlating these algorithmic configurations with their corresponding outcomes demonstrates that evaluating performance in highly constrained physical network problems requires a joint analysis of mathematical metrics and engineering feasibility.

The Base Bi-level NSGA-II (Variant 1) exhibits the worst Inverted Generational Distance (IGD) despite achieving the highest Hypervolume (HV). Without strict constraint handling mechanisms, Variant 1 tends to generate extreme solutions that artificially maximize the HV but fail to meet the essential engineering requirements of the ICLMF-MU model.

Variants 2 (w/o Smart Initialization) and 4 (w/o Penalty) highlight a fundamental trade-off between mathematical superiority and engineering consistency. Both variants achieve numerically better IGDs (0.4217 and 0.4134, respectively) and higher HVs (1.1566 and 1.0812) with faster computation time compared to the Proposed Hybrid V7. Variant 4 bypasses physical constraints by allocating flows to disconnected paths to minimize costs, while Variant 2 suffers from excessive early dispersion into mathematically viable but practically unusable solution spaces. These improvements are mathematical artifacts. The Proposed Hybrid V7 intentionally accepts these numerical compromises to strictly enforce topological consistency, ensuring all Pareto solutions represent realistically deployable networks.

Lacking Boundary Protection (Variant 6) maintains an identical IGD to the proposed method but loses elite solutions at the Pareto extremes, which negatively impacts the overall Hypervolume (HV). The Proposed Hybrid (Variant 7) resolves these issues by trading raw computational speed for engineering validity, confining the search to physically meaningful regions while maintaining a robust HV.

The Fallback (Variant 3) and Restart (Variant 5) mechanisms are designed for algorithmic robustness rather than only optimizing metrics. Without Restart (Variant 5), the HV decreases to 0.9742, proving the mechanism's necessity in preventing premature convergence. Although metrics of V3 are comparable to the proposed V7, the Fallback mechanism is required to ensure all solutions remain physically valid under extreme conditions.

In summary, the ablation study confirms that the added algorithmic complexity is not only justified but essential. By balancing evolutionary exploration with strict physical constraint satisfaction, the Proposed Hybrid algorithm (Variant 7) prevents the generation of mathematically optimal yet physically meaningless solutions, yielding a realistic, robust, and evenly distributed set of Pareto optimal decisions.

4. Large-scale case study: strategic network design in a trade war

Following verifying the accuracy and convergence of the Enhanced NSGA-II against an exact solver on the linearized benchmark (Section 3.2), we applied the algorithm to the original non-linear three-objective model (ICLMF-MU). This section demonstrates the scalability and effectiveness of the proposed method on a large-scale numerical instance. It is designed to capture the structural complexities and strategic trade-offs inherent in supply chains in the face of global trade instability.

4.1. Computational performance and model validation

4.1.1. Experimental setup

A large-scale illustrative example was constructed on a 100-node network. To reflect the complexity and hierarchical nature of global logistics networks, the network was organized as a multi-echelon system (You and Grossmann, 2010). The specific configuration parameters are summarized in Table 9.

Table 9

Parameter settings for the illustrative case study.

Category	Item	Parameter Configuration
A) Network	Nodes	$ S = 20$, $ S' = 20$, $ T = 40$, $ D = 20$.
	Topology	Multi-echelon ($S/S' \rightarrow T \leftrightarrow T \rightarrow D$ with direct bypass).
B) Algorithm	Parameters	PopSize: 500; MaxGen: 400; Crossover P_c : 0.8; Mutation P_m : 0.2.

Table 10
Parameters for multi-modal multi-echelon transportation.

Link Hierarchy	Connection	Capacity	Cost	Arc disruption (g_{ij})
1 (Direct)	$S \cup S' \rightarrow D$	50	20.0	0.001
2 (Backbone)	$T \leftrightarrow T$	800	1.0	0.005
3 (Feeder/Dist.)	$S \cup S' \rightarrow T, T \rightarrow D$	300	0.2	$\mathcal{U}(0.02, 0.12)$

*Note: To better reflect the real-world environment, a minor uniform noise of $\pm 10\%$ was applied to the distance-based transportation costs.

Transportation costs derive from Euclidean distances. To enforce meaningful strategic trade-offs, a hierarchical capacity structure was implemented. Depending on the topological connections, arcs in different link hierarchies are assigned distinct parameters (Table 10).

Inter-hub connections ($T \leftrightarrow T$) serve as high-capacity backbones to support consolidation, while direct connections ($S/S' \rightarrow D$) represent flexible but capacity-constrained express alternatives (e.g., emergency transportation to bypass blocked trade routes). The base arc disruption probabilities (g_{ij}) are dynamically scaled by their Euclidean distance ($dist_{ij}$). The effective disruption risk for each arc is formulated as $\min(0.5, g_{ij} \times (1 + dist_{ij}/200))$.

All computational experiments of this analysis were performed in MATLAB R2023b. Considering the stochastic nature of the heuristic algorithm and ensuring statistical reliability, each scenario was evaluated through 20 independent simulation runs so that the outcomes could be treated as consistently robust and reliable. The results presented in the following sections are from the run exhibiting the strongest convergence quality, measured by Hypervolume. This approach captures the algorithm's peak performance.

In order to more accurately reflect the diversity of logistics infrastructure in real-world scenarios, the potential facilities (S') in this study are classified into three tiers based on their strategic roles and investment scales (shown in Table 11). Tier I represents low-capacity and cost-efficient nodes designed for initial network coverage under budget constraints, while Tier III signifies large-scale hubs with large capacity for special risk situations. To account for spatial economic variations such as land prices and local accessibility, a stochastic geographic factor $\epsilon \in [0.8, 1.2]$ is incorporated into the fixed cost calculation, thereby enhancing the empirical validity of the strategic network design. Other cost factors and supply-demand parameters are detailed in Table 12.

Table 11
Strategic configuration and hierarchical parameters for potential facilities (S').

Tier	Facility Type	Prob.	Capacity	Cost	Operational Role
Tier I	Emergency nodes	0.3	40	150	Low-cost entry points
Tier II	Standard Warehouse	0.5	150	400	Primary network backbone
Tier III	Large-scale Hub	0.2	400	1000	High-capacity strategic hubs

*Note: A geographic factor $\epsilon \in [0.8, 1.2]$ is applied to f_i .

Table 12
Other cost factors and supply-demand parameters.

Parameter Category	Symbol / Range	Value / Calculation
Unsatisfied demand penalty	u_j	$\mathcal{U}(100\epsilon, 125\epsilon)$
Disruption penalty multiplier	M_{ij}/α	$50c_{ij}/2000$
Utility weights (Flow/Freshness)	λ_1/λ_2	0.5 / 0.5
Demand volume per node	d_j	$\mathcal{U}(100, 150)$ units
Supply-to-demand ratio	$\sum s / \sum d$	≈ 2.0
Node disruption probability	g_i^{node}	$\mathcal{U}(0.001, 0.025)$
Node availability ratio	γ_i	$\mathcal{U}(0.80, 0.95)$

4.1.2. Algorithmic performance

Before evaluating the optimization results, we verified the algorithm's stability and convergence through a residual metric, confirming that the constraints were satisfied with precision. Smaller residuals correspond to superior feasibility and accuracy. Throughout all generations, the flow balance residual remained consistently below the machine precision level of 10^{-8} . This demonstrates the robustness and accuracy of the embedded LP repair mechanism (Algorithm 3). This achieved mean residual fell four orders of magnitude below the set convergence tolerance of 10^{-4} . Occasional sharp spikes in the maximum residual were immediately corrected within a single generation by the LP solver. This further validates the efficiency of the enhanced hybrid approach and ensures that all Pareto solutions satisfy high feasibility standards.

Fig. 10 illustrates the convergence behavior of the algorithm. Owing to the considerable expense of calculating the exact Hypervolume (HV) in large-scale multi-objective problems, an efficient approximation was employed as a real-time proxy to track the evolutionary progress without more excessive computational overhead.

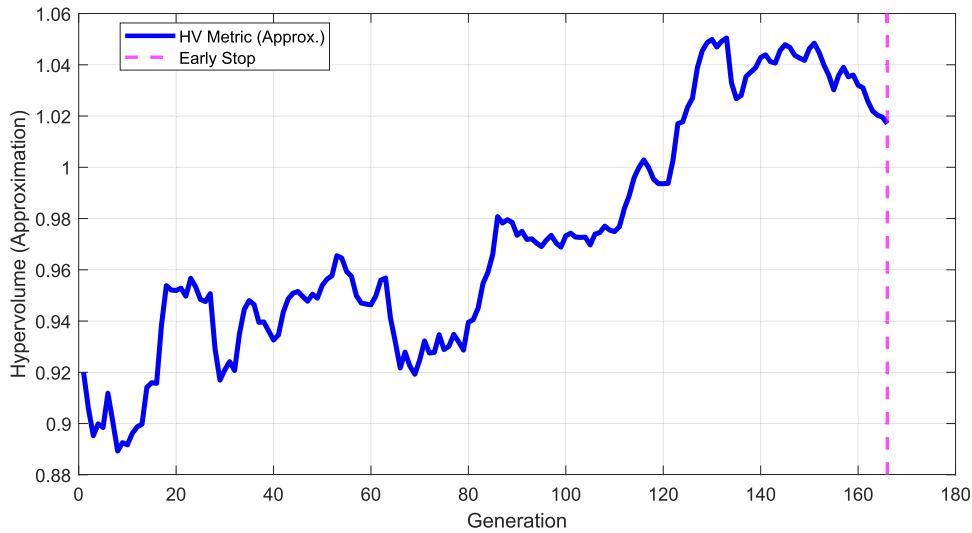


Fig. 10. Convergence analysis: hypervolume evolution.

The evolutionary process illustrated in Fig. 10 exhibits a highly dynamic search trajectory spanning approximately 165 generations. Initial iterations (Gen 0–20) exhibited sharp, rapid fluctuations that occurred as the population adjusted to the feasibility constraints. An upward trend followed, which was interrupted by a noticeable decline between Gen 50 and 70. The algorithm then showed a sharp ascent, approaching a plateau around 0.98 at Gen 90. During the final iteration phase (Gen 90–165), distinct fluctuations emerged and climbed to a global peak of 1.05 around approximately Gen 135. Such fluctuations indicate that the algorithm was refining the Pareto front. Search activity halted at Gen 165 upon maturation of the solution set. The Hypervolume metric employed here is an approximation. It serves as a relative quality indicator of solution quality rather than an absolute metric.

4.2. Strategic insights insights and and decision support

4.2.1. Comparative analysis of investment

To investigate the model's sensitivity to products of different categories under diverse global trade environments, two scenarios based on different supply chain priorities were defined (Table 13).

Scenario I represents market-driven sectors (e.g., Commercial scenario). It simulates low-value daily necessities or general consumer goods that are highly sensitive to tariff fluctuations and protectionist policies. These goods are price-sensitive, so the priority is to minimize logistics costs to maintain profits in the face of trade uncertainties. Therefore, we set a low penalty ($u \approx 4\bar{c}$), implying that using expensive emergency transport (or absorbing high tariffs) is not economical.

Scenario II represents strategic sectors (e.g., Medical scenarios). It simulates critical medical supplies or strategic resources that often become targets of export control and sanctions (such as vaccines, semiconductors, and critical raw materials). As these products prioritize speed and reliability over cost, shortages could have serious consequences for public safety or national security. Therefore, the penalty cost was set to be significantly higher ($u \approx 100\bar{c}$). This choice proves that key medical supplies (such as vaccines or organs) are of high strategic value relative to their weight. In real-world logistics, the transport costs for these items are small compared to the serious social and economic consequences of stockouts caused by trade disruptions. Therefore, a high penalty ratio is necessary to enforce a zero-tolerance policy for service failure.

To evaluate the model's adaptability, we compared the two distinct scenarios. The following comparative analysis focuses on two key managerial insights. To separate the cost of investment decisions from the cost of failures, the horizontal axis is defined as Investment (excluding the penalty cost for unsatisfied demand). This allows us to analyze the upfront investment needed to achieve a target service level, rather than the total cost after failures occur.

Table 13

Definition of comparative scenarios based on penalty costs.

Scenario	Product Type	Penalty (u)	Logic
Scenario I	market-driven sectors (e.g., Commercial scenario)	Low ($u \approx 4\bar{c}$)	$u < \text{High Transport Cost}$ (Cheaper to pay penalty than to transport)
Scenario II	strategic sectors (e.g., Medical scenarios)	High ($u \approx 100\bar{c}$)	$u > \text{High Transport Cost}$ (Cheaper to transport than to pay penalty)

*Note: $\bar{c}$ denotes the average transport cost.

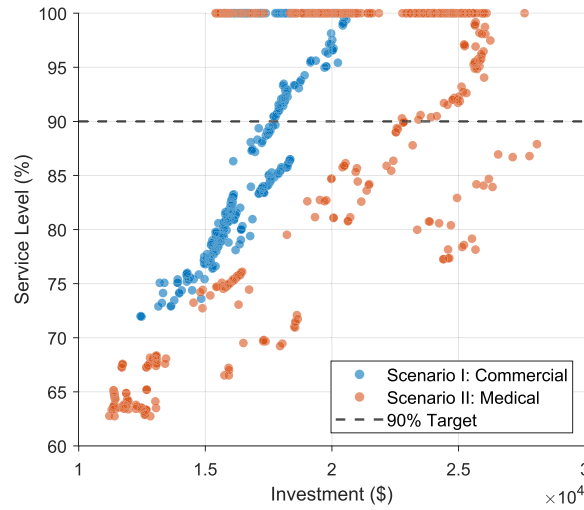


Fig. 11. Service level vs investment.

Investment vs Service level: Fig. 11 shows the trade-off between investment and service level for both scenarios. At a lower investment level, the trends of the two scenarios were similar, indicating comparable baseline efficiencies. When the service objectives increased, it showed an obvious difference. The Commercial scenario rose sharply, achieving high service levels with relatively low marginal investment. In contrast, the Medical scenario extended further to the right and requires more investment to achieve the same service level. Achieving 90% target service level required approximately 1.8×10^4 in the Commercial scenario, while in a medical scenario a higher baseline of 2.25×10^4 was needed. This difference arises because a low-penalty Commercial strategy prioritizes cost-effective demands to maximize return on investment. Meanwhile, driven by high failure penalties, the Medical scenario needs to meet expensive or remote demands even at high cost, thereby leading to a greater marginal cost for service improvement.

Investment vs Network Density: Fig. 12 illustrates a complex topological evolution. With rising investment, both scenarios exhibited branching patterns, yet they operated within distinct density ranges. In the Commercial scenario, a higher network density was achieved with a peak of roughly 1.45% around a relative low investment ($\approx 1.5 \times 10^4$). However, at higher investment levels (above 2.0×10^4), the Commercial density started to decline, whereas the Medical scenario maintained a stable high density ($\approx 1.3\% - 1.4\%$). Such stability suggests the Medical strategy prioritizes maintaining extensive connectivity to guarantee reliability. This high level of structural redundancy is deliberately deployed to reduce the risk of common node disruption in an unstable trade environment, serving as a clear physical manifestation of strategic redundancy. The Commercial scenario initially constructed a dense network to reduce transport costs before density consolidation for greater efficiency as investment grew. Consequently, the commercial network reached a higher density at lower investment levels (e.g., 1.5×10^4) than the medical network.

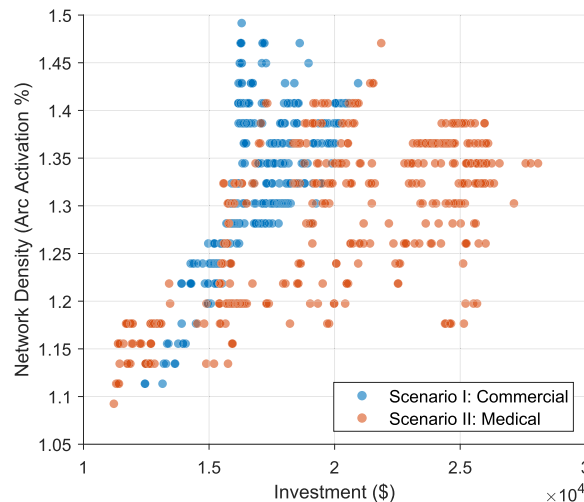


Fig. 12. Network density vs investment.

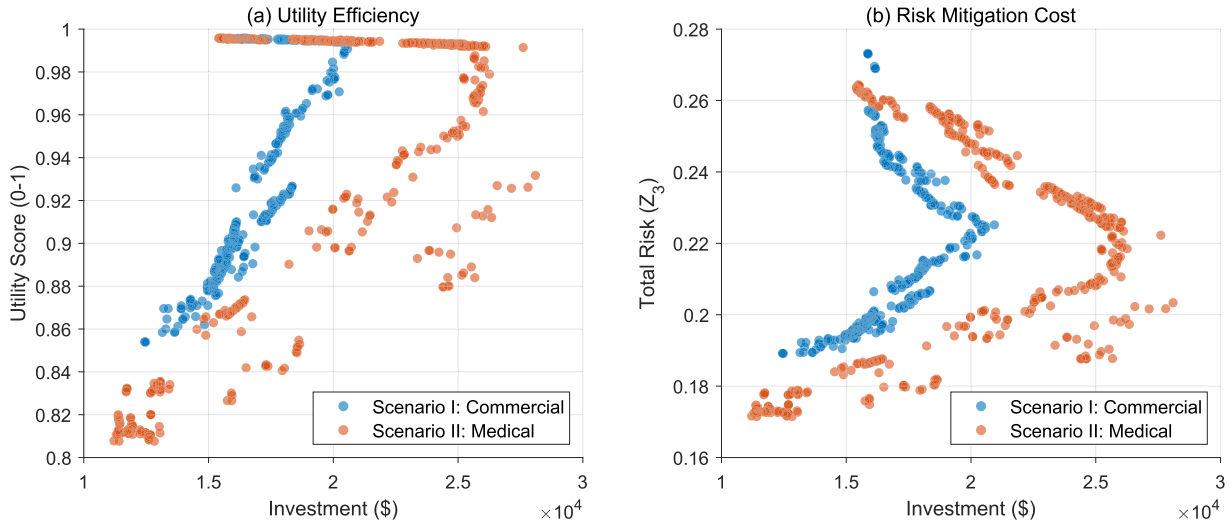


Fig. 13. Key trade-off projections.

Trade-off Projections: Fig. 13 provides a deeper analysis of these strategies. The left plot (Utility Efficiency) reveals a stronger positive relationship between investment and utility for the Commercial scenario, which climbed steadily with a tight cluster of solutions. The initial cluster of the Medical scenario solutions showed a lower utility score (≈ 0.81) than that of the Commercial one (≈ 0.85). To achieve similar levels of utility, the Medical scenario required higher investments compared to the Commercial one. In the meanwhile, the Medical scenario displayed considerable vertical scatter at lower and medium investment levels. While both scenarios ultimately reach a high utility of nearly 0.99, the Medical scenario forms a broad horizontal spread at this top level, as higher penalties force solutions to maintain consistently high service quality.

The right plot (Risk Mitigation) reveals how both scenarios eventually reduce risk, but at distinct investment thresholds. Commercial networks plateau at a final risk threshold of $Z_3 \approx 0.22$, whereas medical networks require extended investments (up to 2.6×10^4) to achieve further mitigation, with solutions scattering into a lower risk zone between 0.19 and 0.22. This indicates that while commercial networks hit a risk limit at around 0.22, medical networks get even lower risk with higher investments. A common phenomenon also exists in both scenarios: within the investment range starting from 1.2×10^4 , the figure shows a structural bifurcation where identical costs map to distinct risk tiers based on topological allocation.

Since our investment metric considers specific components of the objective Z_1 total cost (fixed facility construction, transportation, and route maintenance) while excluding the penalty cost for unsatisfied demand, the observed divergence represents the essential capital expenditure required to structurally reduce extreme risks. We define this as the Criticality Premium: distinct from a Risk Premium (compensating for bearing uncertainty; e.g., Azaron et al., 2008) or a Resilience Premium (enhancing resistance to disruptions or recovery speed; e.g., Kim et al., 2015), it is the proactive, structural marginal investment required to elevate a standard, cost-optimized commercial network into a highly reliable supply chain. This confirms that without the strict baseline requirements inherent to strategic or life-saving sectors, the optimization algorithm would not invest in the physical redundancy at this fundamental level.

3D Strategic: Fig. 14 displays how the two scenarios occupy distinct regions within the objective space. Pareto frontier points for the Commercial scenario formed a constrained trajectory, concentrated in low-investment areas with higher baseline risks. This reflects its greater emphasis on cost containment. The Medical scenario extended beyond this limit, generating a broad and scattered resilience frontier that reached into the regions of higher investment and moderated risk. The cost gap (dashed line) quantifies the Criticality Premium: the specific additional investment required to transform a cost-optimal commercial network into a reliable medical supply chain. This gap represents the necessary financial cost of guaranteeing reliability for emergency logistics. Furthermore, while real-world logistics managers primarily aim for service levels (e.g., $> 90\%$), the complete Pareto-optimal range presented in Section 4.2.1 illuminates the full spectrum of trade-offs between cost and risk across all efficiency levels.

4.2.2. Trade-off analysis and network topology in critical sectors Multi-objective Conflict and Strategic Selection.

To visualize the structural impact of ensuring strategic assets under trade conflicts, this section particularly focuses on the medical scenario. This case allows us to examine the necessary topological redundancy and the high-risk trade-offs required to maintain resilience in key sectors.

Fig. 15 effectively maps the high-dimensional relationships between conflicting objectives and structural variables across the entire Pareto frontier of the Medical scenario. It reveals how strategic decisions trigger chain reactions throughout the system.

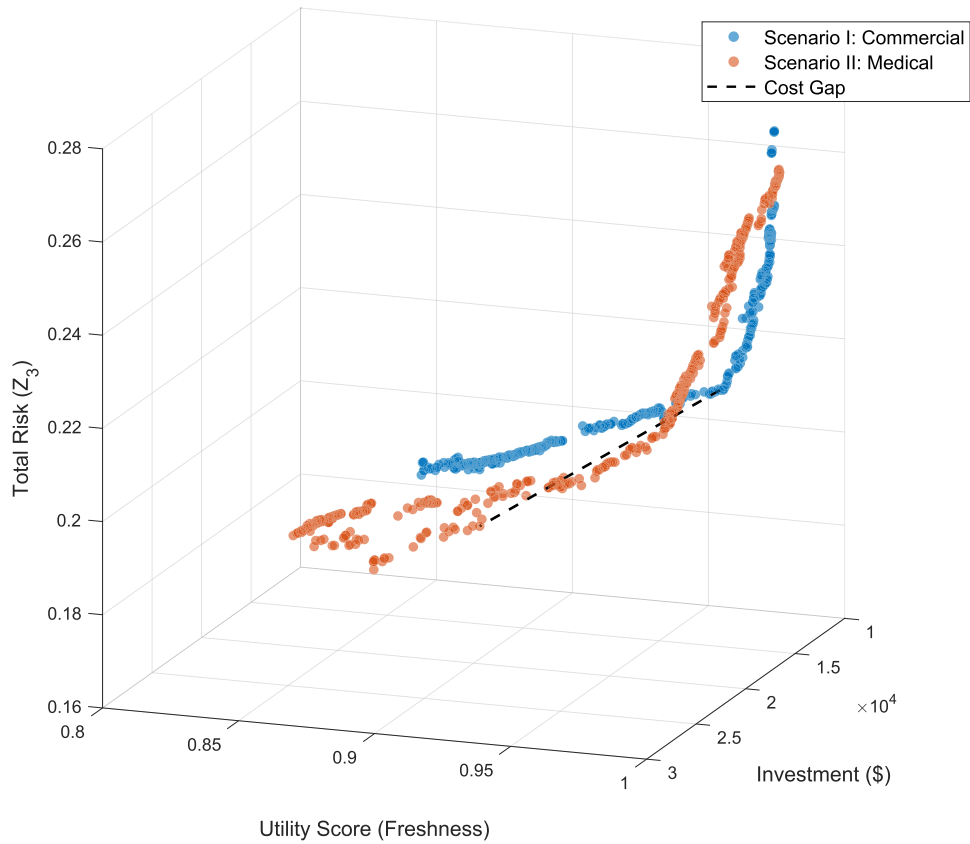


Fig. 14. 3D strategic comparison investment structure.

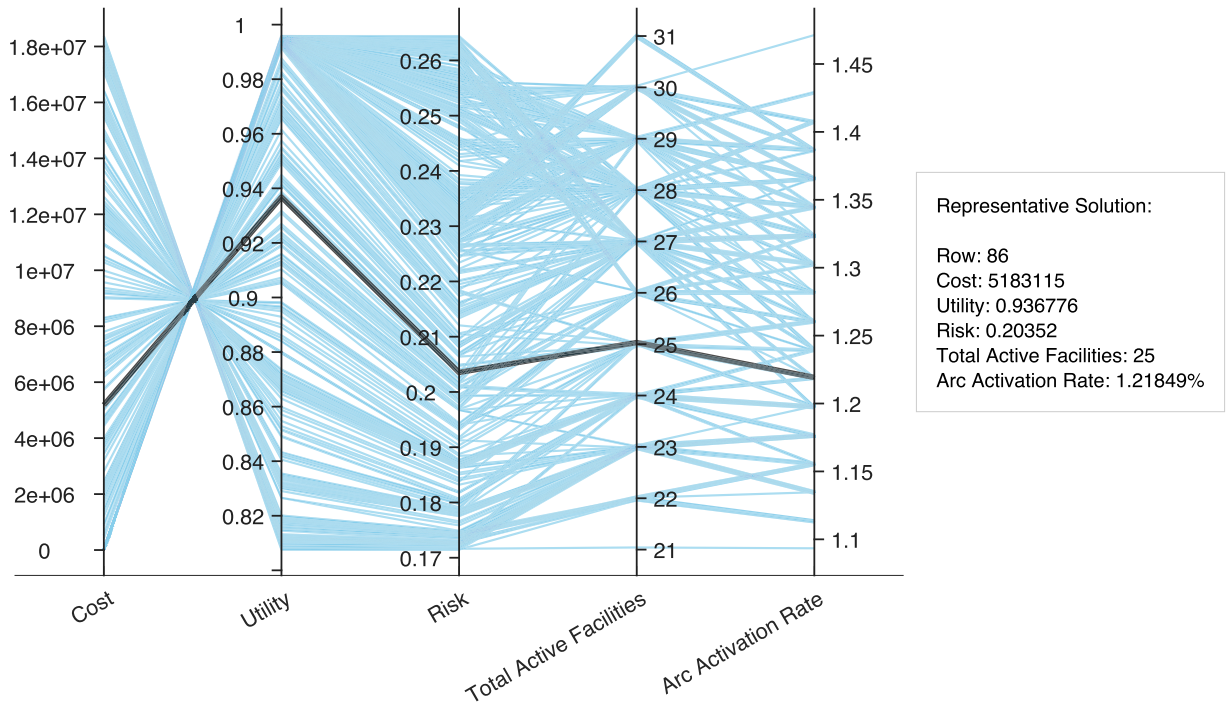


Fig. 15. Parallel coordinates plot of pareto solutions (scenario: medical).

Table 14

Comparison of key representative solutions (commercial vs. medical).

Scenario: Commercial					
Type	Index	Cost (Z_1)	Utility (Z_2)	Risk (Z_3)	Service (%)
Min Cost	1	1.59e+04	0.9955	0.2732	100.00%
Max Utility	2	1.64e+04	0.9957	0.2530	100.00%
Min Risk	14	2.12e+05	0.9463	0.2102	90.43%
Balanced	88	2.06e+04	0.9939	0.2247	100.00%
Scenario: Medical					
Type	Index	Cost (Z_1)	Utility (Z_2)	Risk (Z_3)	Service (%)
Min Cost	1	1.54e+04	0.9958	0.2637	100.00%
Max Utility	2	1.55e+04	0.9958	0.2644	100.00%
Min Risk	61	4.63e+06	0.9427	0.2064	90.17%
Balanced	53	2.76e+04	0.9914	0.2223	100.00%

*Note: For clarity, this table reports the actual non-negative utility (Z_2), even though the algorithm minimized $-Z_2$ during optimization.

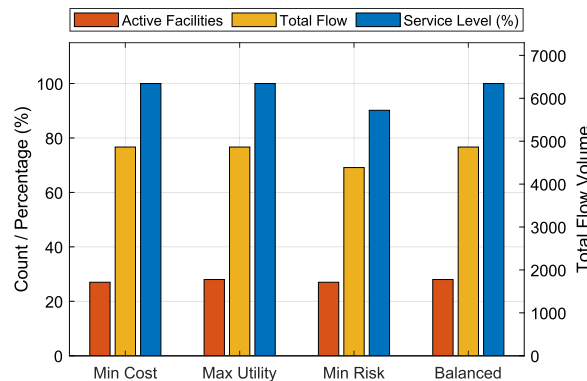
The figure highlights several typical decision-making scenarios. Its principal value lies in identifying balanced and compromise solutions; one such solution is traced by the black line. A representative solution from Row 86 demonstrates a well-balanced outcome across all objectives: it operates at a reasonable cost (5.18×10^6) and maintains a relatively high utility score (0.94) while maintaining a moderate risk level of 0.20. The plot reveals an apparent structural signature: high-performing solutions typically cluster around an Arc Activation Rate of approx. 1.22% and utilize approximately 25 active facilities. This regularity implies that optimizing network topology is more effective than merely maximizing facility count (which reaches up to 31). In a trade conflict scenario, maintaining active alternative paths is essential for structural immunity. Results indicate that a specific density threshold is adequate to preserve high utility and resilience without incurring diminishing returns on excessive investment.

Comprehensive Analysis of Representative Solutions.

For the subsequent detailed operational analysis (Figs. 16 and 17), we isolated four representative solutions (Min Cost, Max Utility, Min Risk, and Balanced). Only configurations with service levels exceeding 90% were considered, a criterion consistent with real-world practical operational requirements. This ensures that our comparison focuses only on practical, operationally feasible network designs rather than low-performing alternatives. The precise attributes of these solutions are shown in Table 14.

Fig. 16 presents the operational profiles of the four key strategies, each selected from the high-performance cluster (Service Level >90%). The Min Cost, Max Utility, and Balanced strategies demonstrate striking performance similarity. Despite their different optimization objectives, all three achieve near-perfect service levels (approaching 100%) and maximize total flow volume (approximately 4,900). Conversely, the Min Risk strategy displays different behavior. Although it meets the 90% service threshold, its total flow volume (approx. 4,450) is markedly lower compared to the other strategies.

This convergence indicates that in the Medical scenario, the high penalty for unsatisfied demand outweighs any incentive to reduce facility usage, effectively compelling the Min Cost solution to adopt a high-throughput, high-service configuration identical to the utility-focused strategies. The pattern of the Min Risk strategy suggests that to minimize risk while maintaining acceptable service levels, the strategy selectively fulfills demand through secure routes but avoids the additional exposure required to reach 100% service levels.

**Fig. 16.** Comprehensive analysis of representative solutions (medical).

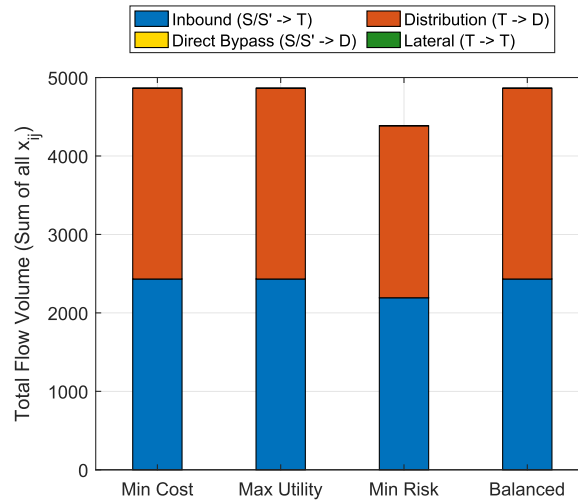


Fig. 17. Strategic flow composition for representative solutions (medical).

Fig. 17 analyzes the flow structure. A consistent pattern dominated by Distribution (T to D) and Inbound (S/S' to T) flows is observed across the Min Cost, Max Utility, and Balanced strategies, confirming a Multi-Echelon Distribution model. The Min Risk strategy follows the same multi-echelon structure but operates at a significantly reduced scale. Crucially, the universal absence of Direct Bypass flow (yellow component) across all high-performance strategies validates the model's structural design. In this network, direct links ($S/S' \rightarrow D$) were parameterized as high-cost, capacity-limited express lanes, whereas inter-hub links benefit from significant economies of scale.

The results validate that the model's cost structure effectively prohibits routine direct shipment, reserving it for purely theoretical edge cases. This parameterization effectively captures the prohibitive barriers often imposed on direct cross-border flows during trade conflicts. Therefore, the system naturally organizes into a tiered multi-echelon structure, leveraging regional hubs to simultaneously achieve transport efficiency and reduce the risk of cross-border friction.

Decision Space Configuration and Dynamic Evolution.

To visualize how these strategies change across the entire cost spectrum, Fig. 18 provides a detailed view of the Pareto-optimal solutions, visually demonstrating the fundamental cost-robustness trade-off. The plot displays the top 200 Pareto solutions, ordered

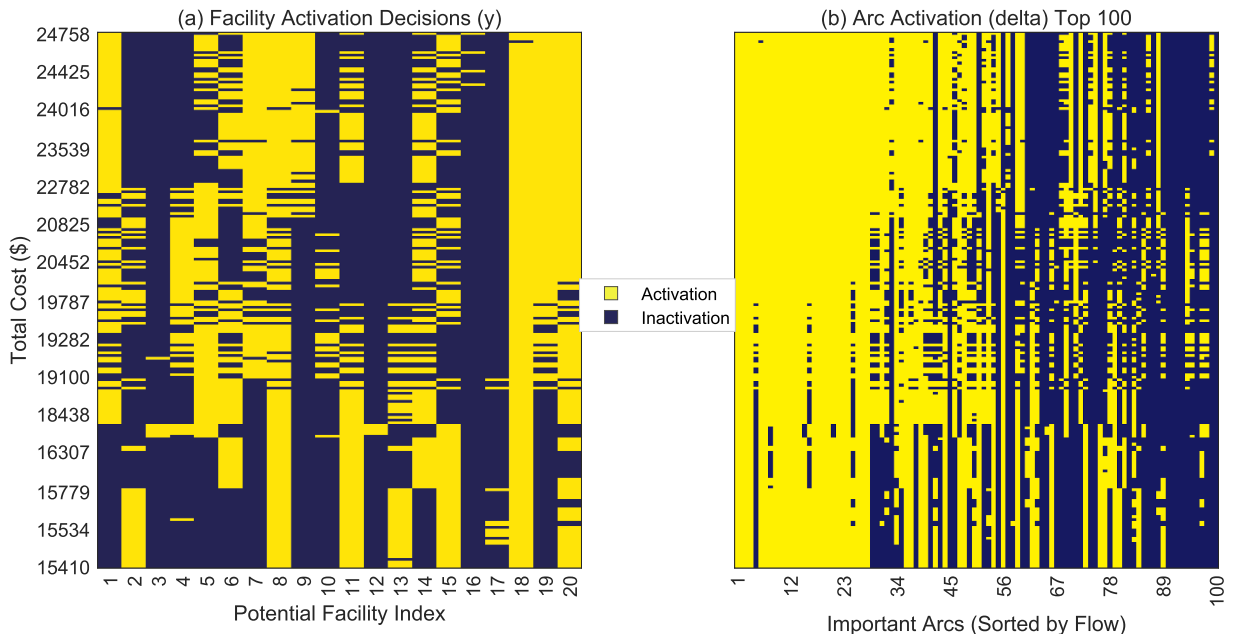


Fig. 18. Decision variable heatmap (scenario: medical).

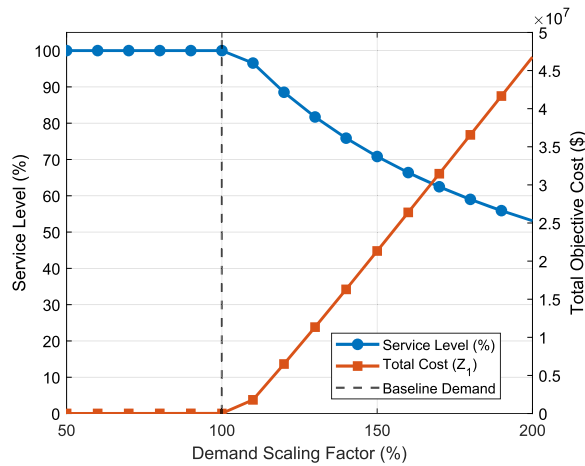


Fig. 19. Sensitivity analysis plot (solution 53: balanced strategy in medical scenario).

by increasing cost from bottom (low cost) to top (high cost) on the Y-axis. Activation is signaled by yellow and inactivation by dark blue.

The left panel (Facility Activation) illustrates a tiered infrastructure strategy. A core set of approximately 4 facilities (represented by solid vertical yellow lines) remains active across all cost levels. As costs increase (moving up the Y-axis), supplementary facilities are activated. This confirms that the algorithm identifies a core set of optimal facilities early on. High-reliability strategies are subsequently constructed by expanding the facility network to introduce redundancy.

The right panel (Arc Activation) concentrates on the top 100 important arcs to illustrate the densification of the network topology. A dense yellow block on the far left identifies the network backbone. Those critical routes are utilized in almost every scenario regardless of the cost level. Major network expansion accompanies increased cost, which is evident in the middle segment. In the low-cost regions, the network is sparse and fragmented. Moving to the high-cost region, it becomes denser. This visualization confirms that the transition from Min Cost to Balanced strategies relies on activating backup routes, providing the redundancy needed for robustness at higher cost levels. Furthermore, the lower-priority arcs on the right remain highly sparse across all cost levels. This highlights the efficiency of the algorithm. It only activates essential backup routes even at higher total cost levels to balance cost and reliability instead of full connectivity.

4.2.3. Resilience evaluation: regret analysis and sensitivity testing

Network Resilience and Stress Response.

We conducted sensitivity and regret analyses to evaluate the stability of the solutions under market uncertainty and supply chain disruptions.

Fig. 19 illustrates the resilience of the Balanced solution (Solution 53) under demand uncertainty in the medical scenario. The network exhibits a distinct phase transition at the 100% threshold. Below this point, the network maintains perfect service levels (100%) and incurs zero penalty costs, indicating sufficient capacity buffers. Beyond this point, service quality declines sharply in a non-linear pattern, and penalty costs of unsatisfied demand surge rapidly due to unmet demand. It simulates a scenario where supply chains collapse under the pressure of sanctions or sudden embargoes.

Fig. 20 compares these stress responses between scenarios. While both strategies begin to degrade at the same 100% demand level, the Medical Balanced strategy maintains slightly superior service levels during overload. At twice the baseline demand, service levels remain approximately 53% for the Medical network, exceeding the Commercial network's 50%. This reveals a critical insight: the medical strategy, driven by high penalty costs, constructs a network with superior structural redundancy. It maintains higher service levels even under extreme overload. However, while this conservative design provides stronger extreme-stress endurance, the Commercial strategy opts for slightly lower redundancy in favor of more operational flexibility.

Robustness Evaluation and Regret Analysis.

To evaluate the robustness of each strategy against unforeseen disruptions, regret analysis is used to reveal a clear and significant conclusion regarding different optimal strategies for the medical and commercial supply chains. As illustrated in Figs. 21 and 22, this regret analysis reveals a Robustness Paradox.

Across both scenarios, the Max Utility strategy consistently proved most robust, with minimal operational regret and the highest service resilience, 100% even under structural failures (node or arc failures). The Min Cost and Balanced strategies also demonstrated strong resilience against structural failures, but they exhibited divergent behaviors under a demand surge. The Balanced strategy in Medical incurred distinct financial regret ($\approx 4.5 \times 10^6$), and both strategies suffered moderate service deterioration ($\approx 77\%$ for Min

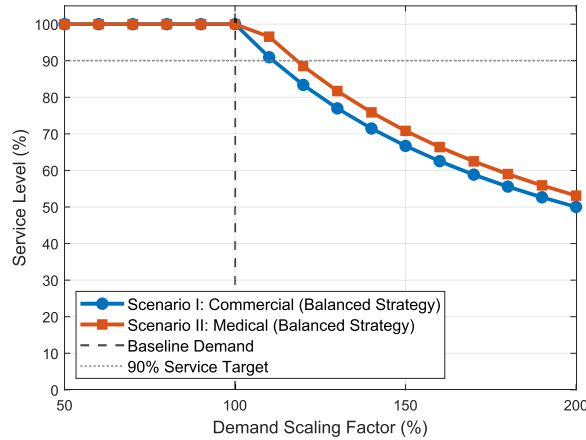


Fig. 20. Resilience stress test(scenario comparion).

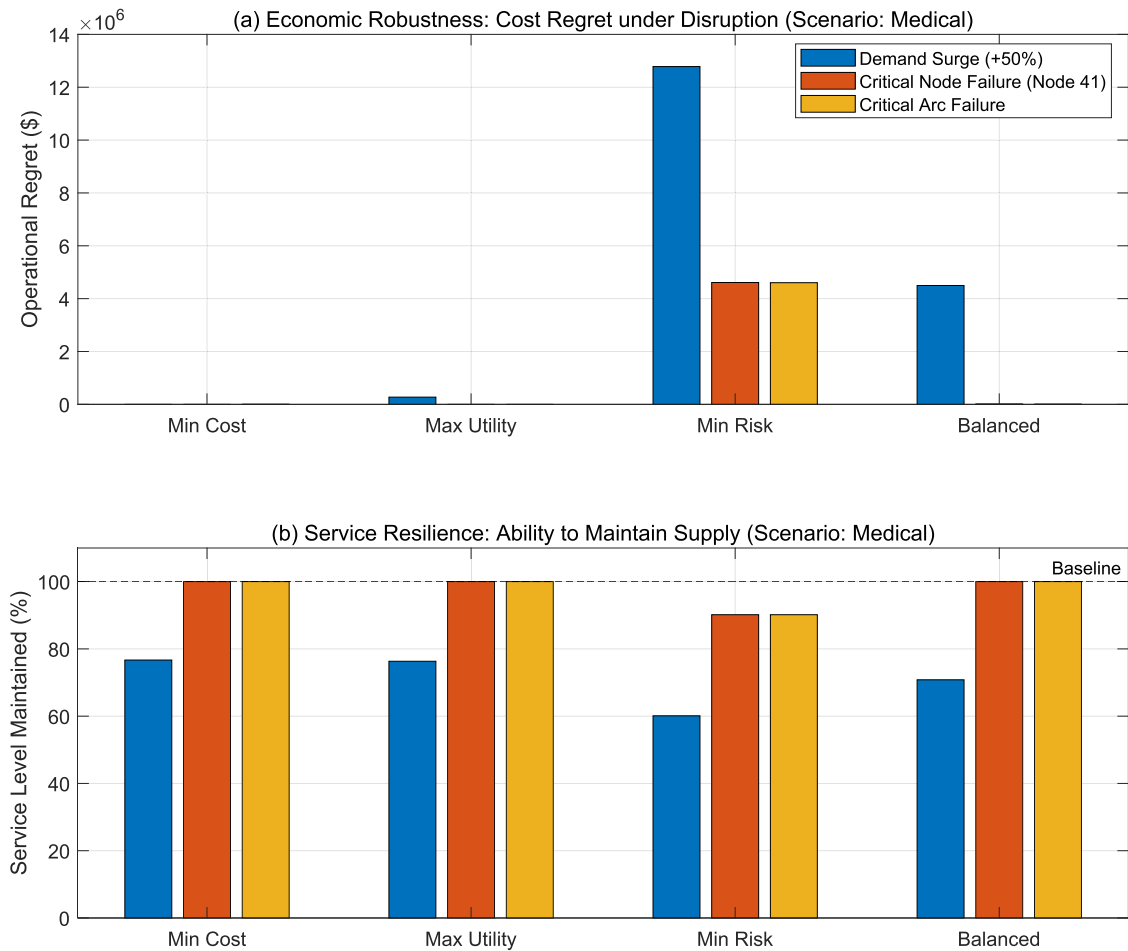


Fig. 21. Robustness regret plot (medical).

Cost and $\approx 72\%$ for Balanced) under the same demand stress. Conversely, the Min Risk strategy proved markedly fragile, with the highest regret ($\approx 12.8 \times 10^6$ for Medical under demand surge) and the poorest service resilience ($\approx 60\%$ under the same stress).

A cross-scenario comparison quantifies the demanding nature of critical supply chains. Though the relative performance ranking of the strategies stayed similar, the scale of regret differed dramatically, by two orders of magnitude. The maximum regret in the medical scenario, produced by the Min Risk strategy under demand surge ($\approx 12.8 \times 10^6$), was approximately 22 times higher than

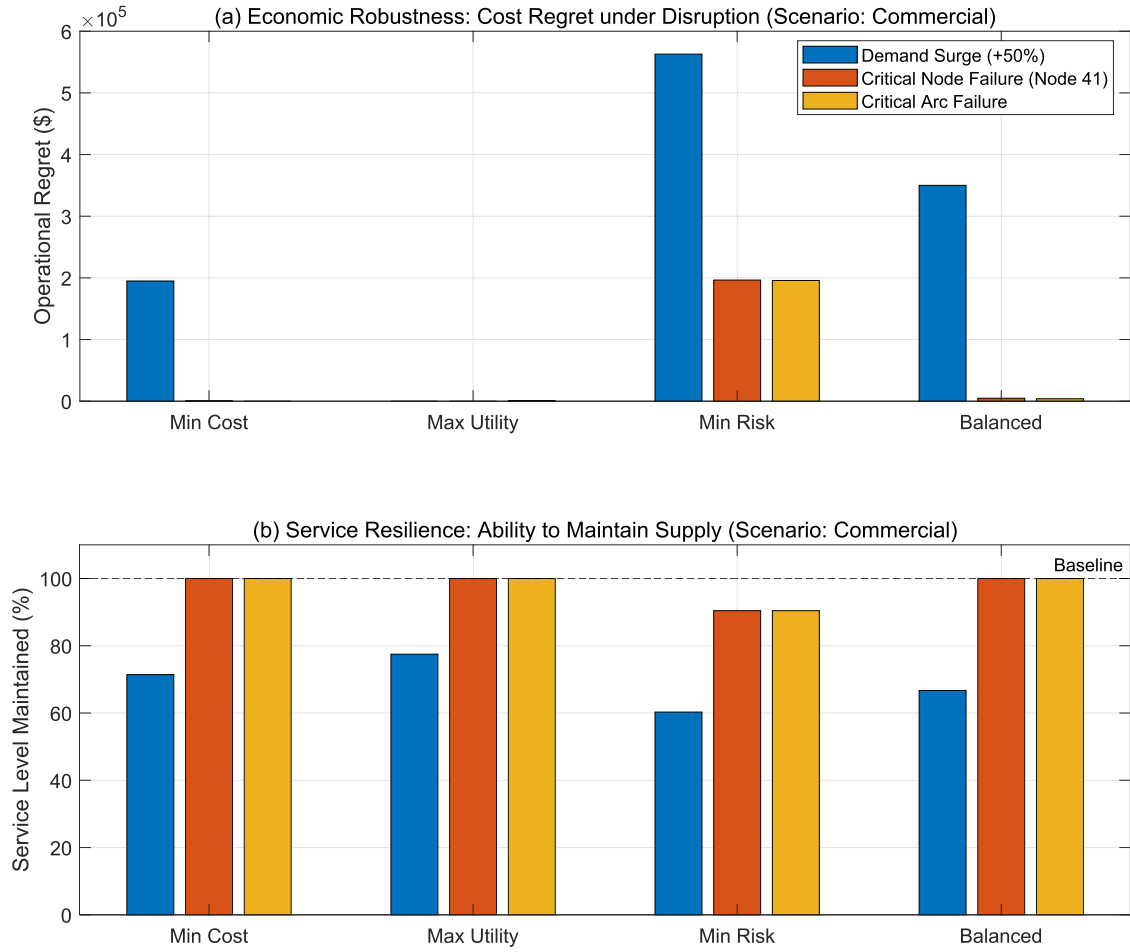


Fig. 22. Robustness regret plot (commercial).

in the commercial scenario ($\approx 5.7 \times 10^5$). The resilience requirements of the two scenarios differ fundamentally in their cost-service trade-offs. Most strategies maintain full service during structural failures in both scenarios. However, the steeper penalties for supply shortages in the Medical scenario drive different behaviors under demand surges. Cost-sensitive strategies such as Min Cost and Balanced are forced to maintain higher service levels in the medical context (77% and 72%) compared to the commercial one (71% and 67%).

This analysis provides a key insight about resilience-efficiency convergence. In critical supply chains, true operational resilience does not stem from minimizing theoretical risk metrics (Z_3) alone. Instead, it emerges from the capacity redundancy built into the Max Utility objective, and into Min Cost or Balanced depending on the uncertainty type. By naturally driving the algorithm to invest in high-quality redundant capacity, the objective of maximizing utility effectively insulates the system from financial exposure to sudden shocks. This confirms that under the constraint of high penalties, capacity buffering is not the result of inefficiency but a measure to resist external fluctuations. Consequently, in high-stakes environments where failure penalties are prohibitive, the supposed trade-off between efficiency and resilience collapses; robust infrastructure investment becomes a mathematical necessity for minimizing long-term total costs.

Structural Sensitivity and Topological Stability.

To verify whether the observed Robustness Paradox is a generalizable structural characteristic of resilient logistics networks rather than being a consequence of specific modeling assumptions, we conducted a comprehensive sensitivity analysis on the structural risk weights (μ_1 and μ_2).

An analysis of the Min Risk in Table 15 reveals consistent network structures across varying structural risk weights.

Table 15
Sensitivity analysis of structural risk parameters across different scenarios.

Scenario	Level	μ_1	μ_2	V_{active}	A_{active}	$\tilde{d}_{\text{active}}$	R_{topo}	R_{HHI}
Medical	S1	0.25	0.75	66	65	1.97	4.05	0.0216
	S2 (Base)	0.50	0.50	66	64	1.94	4.10	0.0213
	S3	0.75	0.25	67	66	1.97	4.05	0.0219
Commercial	S1	0.25	0.75	67	64	1.91	4.15	0.0216
	S2 (Base)	0.50	0.50	66	65	1.97	4.05	0.0212
	S3	0.75	0.25	67	65	1.94	4.10	0.0216

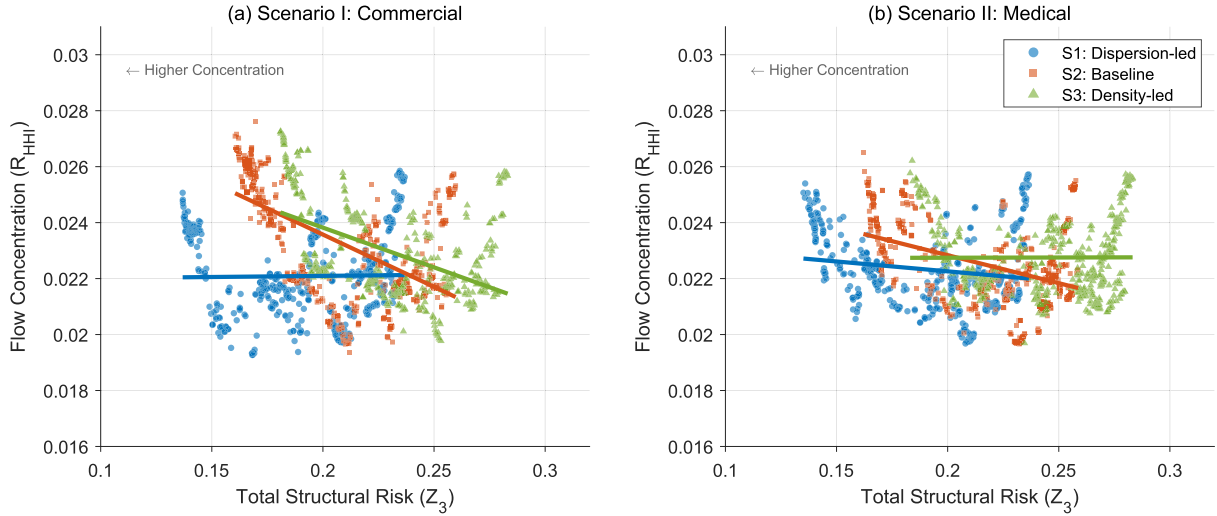


Fig. 23. Structural evolution sensitivity test.

The fluctuations in topological metrics are minimal, and the flow concentration index stabilizes near $R_{\text{HHI}} \approx 0.021$ signifying that the network traffic is distributed across many arcs. This implies that a highly dispersed and fragmented network is structurally superior with higher resilience.

Fig. 23 further supports this observation. Across different weight configurations (S1–S3), the vertical trendlines for R_{HHI} remains consistently flat, proving that low flow concentration is a strict requirement for network robustness regardless of structural risk weights. This confirms that the robustness paradox is a structural phenomenon of resilient supply chain design.

5. Conclusion

In the complex challenge of designing supply chain networks and locating facilities under geopolitical instability and operational uncertainties, this research demonstrates that supply chain resilience is a strategic balance between structural redundancy and operational efficiency.

We introduced a multi-objective optimization model under uncertainties (ICLMF-MU) and an Enhanced Hybrid NSGA-II algorithm to address these complexities. The extensive large-scale case study (100 nodes, 9900 arcs) further validates the applicability of the model in solving complex supply chains within a volatile global trade environment. The performance of the proposed enhanced hybrid heuristic algorithm confirms its consistent capacity to identify high-quality, mathematically feasible solutions in large-scale networks. Pareto solutions exhibit a clear topological bifurcation in Pareto solutions, which distinguishes the distinct structural transitions between sparse and dense network layouts. This efficiency is further validated by the Hypervolume curve, which exhibits a rapid early ascent toward the Pareto front, ensuring effective convergence before early termination.

A distinct non-linear correlation emerges between investment and network performance, defined by a distinct Investment Threshold. Beyond this saturation point, the marginal returns on additional investment diminish sharply. This finding indicates that simply increasing budget is inefficient for the market-driven sectors (e.g., Commercial scenario) once the baseline connectivity is established. In stark contrast, strategic sectors (e.g., Medical scenarios) require substantial investment through this high-cost region to achieve the necessary reliability levels. While the Commercial scenario achieves superior capital efficiency, reaching higher service levels with comparatively lower investment along a sharply rising efficiency frontier, the medical scenario incurs a Criticality Premium, requiring significantly higher investment to guarantee high reliability. To meet a high service target (e.g., 90%), the Medical scenario requires a substantially greater proportional investment than the Commercial scenario. This confirms that optimal strategies depend

fundamentally on product criticality and strategic importance. Extending commercial efficiency standards to strategic supply chains (e.g., medical or high-tech industries) leads to serious strategic errors and vulnerability to external sanctions.

In the Regret Analysis, a critical divergence is displayed between theoretical risk and operational resilience against geopolitical shocks. The Min Risk strategy reduces theoretical risks by reducing network scope, resulting in apparent operational fragility, placing the system within a Safety Trap. This is particularly dangerous when multiple trade routes are needed to bypass blockades. Across both scenarios, it consistently shows the greatest operational regret and weakest service resilience. In contrast, strategies optimized for cost and utility (Min Cost, Max Utility, and Balanced) show considerably stronger operational resilience. Among these strategies, the Max Utility deals with disruptions with significant effectiveness, exhibiting near-zero regret. While the Balanced strategy maintains high physical resilience, it incurs more significant financial regret during demand surges than the Max Utility alternative. Driven by high penalties, these robust strategies need to build networks with substantial redundancy. Furthermore, the penalty-driven redundancy creates a stronger physical buffer for absorbing geopolitical shocks. During extreme demand surges, the high penalty structure of the Medical scenario forces the system to maintain superior overall resilience compared to the Commercial scenario.

This research provides a practical decision-support tool, offering a comprehensive set of Pareto-optimal solutions. More importantly, this study delivers a critical warning for global supply chain managers: managers should avoid blindly pursuing theoretical risk indicators. Composite theoretical risk measures (such as normalized Z_3) are useful for network design, yet they cannot alone predict how well a network performs under real disruptions. True robustness is not achieved through avoiding risk (which leads to network contraction), but rather through combining efficiency with redundancy (driven by high penalty costs). This confirms that in a fragmented trade environment, structural redundancy (the physical presence of backup pathways) is no longer a sign of inefficiency, but a necessary condition for survival against instability. However, rather than blindly increasing network density, supply chains prefer to pursue strategic redundancy: the precise, optimized configuration of these structural backups to avoid the crippling costs of inefficient investments. These insights offer meaningful guidance for designing resilient global supply chains in an increasingly unstable trade environment.

Although the current model relies on proxy-based indices to maintain computational tractability, our future research will extend this framework into a scenario-based stochastic programming model. This will allow us to explicitly capture correlated disruptions and incorporate dynamic recourse decisions.

CRedit authorship contribution statement

Yi Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization; **Hari Nandan Nath:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization; **Stefan Nickel:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Yi Zhang reports financial support was provided by China Scholarship Council. If there are other authors, they 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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Data availability

Data will be made available on request.

Appendix A. Sensitivity analysis of the scaling parameter Θ

To clearly demonstrate the impact of the scaling parameter Θ on the decision-making process, we conducted a sensitivity analysis on a representative small-scale illustrative example. The model parameters are consistent with those in [Table 3](#). This approach allows us to transparently observe the topological changes in the supply chain network without the prohibitive computational time required by full-scale instances.

The primary objective of this analysis is to validate the magnitude alignment between the structural and operational risk dimensions. As shown in [Table A.1](#), $\Theta = 10$ provides the most balanced scaling, successfully mapping the topology risk into a range commensurate with the HHI-based concentration risk and the normalized operational risk. This ensures that the structural robustness of the network is adequately prioritized within the objective function Z_3 .

Table A.1Sensitivity analysis of risk components to the scaling parameter Θ .

Θ	R_{topo} (Scaled)	R_{HHH} (Natural)	R_{op} (Normalized)
0.1	0.0022	0.1898	0.3882
1.0	0.0222	0.1878	0.3909
10.0	0.2222	0.1895	0.3901
100.0	2.2222	0.1895	0.3901

Appendix B. Weighted sum method in phase I validation**Algorithm 4:** Weighted sum method (benchmark exact solver).**Input:** Linearized Model Ω , Weight Vector $\mathbf{w}$, Normalization Factors N_1, N_3 **Output:** Global Optimal Solution $\mathbf{X}^*$ **1. Objective Aggregation:**

// Construct single minimization objective from normalized components

Define $f(\mathbf{x}) \leftarrow w_1 \frac{Z_1(\mathbf{x})}{N_1} - w_2 Z_2(\mathbf{x}) + w_3 \frac{Z_3^{\text{lin}}(\mathbf{x})}{N_3}$.**2. Exact Solver Execution:****Solve MILP:** $\min_{\mathbf{x}} f(\mathbf{x})$ s.t. $\mathbf{x} \in \Omega$ (Flow Balance, Capacity, Logic Constraints).

// Using Branch-and-Cut solver (e.g., intlinprog/CPLEX)

3. Solution Extraction:if *Optimal Solution Found* then Extract variables $\mathbf{X}^* \leftarrow \{\mathbf{x}, \mathbf{y}, \mathbf{q}, \dots\}$; **return** $\mathbf{X}^*$ **Appendix C. Repair-based genetic algorithm in phase I validation****Algorithm 5:** Repair-based genetic algorithm (benchmark for linearized model).**Input:** Problem Instance, PopSize N , MaxGen T_{max} , Weight Vector $\mathbf{w}$ **Output:** Best Valid Solution $\mathbf{x}_{\text{best}}$ **1. Initialization** ($t = 0$):Generate random P_0 ; **Repair & Evaluate:** **foreach** $p \in P_0$ **do** Apply enforceFlowBalance (Heuristic + LP); Calc $W(p)$ **2. Main Evolutionary Loop:****while** $t < T_{\text{max}}$ **do****Step 2.1: Evolution (Selection & Reproduction)**Select parents (Binary Tournament); Generate offspring Q_t via **Mixed Operators**:Discr. y (Uniform Xover/Bit-flip) & Cont. q, ϕ (SBX Xover/Poly-Mutation).**Step 2.2: Hybrid Repair & Evaluation****foreach** offspring $q \in Q_t$ **do** Apply **Strong Repair** (Heuristic $\rightarrow$ LP); **if** *Valid* **then** Calc $W(q)$ **else** $W(q) \leftarrow \infty$ **Step 2.3: Elitist Survival**Combine $R_t \leftarrow P_t \cup Q_t$. Sort by **(1) Validity** $\rightarrow$ **(2) Weighted Fitness** W .Select top $N \rightarrow P_{t+1}$. Update global best $\mathbf{x}_{\text{best}}$. $t \leftarrow t + 1$ **return** $\mathbf{x}_{\text{best}}$

Appendix D. Epsilon-constraint exact method in phase II validation

Algorithm 6: Epsilon-constraint exact method (benchmark).

Input: Linearized Model Ω , Grid Density N_{grid}
Output: Exact Pareto Front P_{ref}

1. Initialization (Anchor Points):
 Calculate payoff ranges $[\underline{Z}_k, \overline{Z}_k]$ for $k \in \{2, 3\}$ by solving single-objective MILPs.
Grid Generation: Construct grid points $\mathcal{E} = \{(e_2^{(i)}, e_3^{(j)})\}$ based on ranges and N_{grid} .

2. Iterative Solving Loop:
foreach Constraint Vector $(e_2, e_3) \in \mathcal{E}$ **do**
 // Minimize Z_1 (Cost) subject to grid constraints on Z_2 and Z_3
 Solve MILP: $\min_{\mathbf{x}} Z_1(\mathbf{x})$ s.t. $Z_2(\mathbf{x}) \leq e_2, Z_3(\mathbf{x}) \leq e_3, \mathbf{x} \in \Omega$.
 if Feasible $\mathbf{x}^*$ **found** **then** Store outcome $\mathbf{z}^* = (Z_1(\mathbf{x}^*), Z_2(\mathbf{x}^*), Z_3(\mathbf{x}^*))$

3. Post-Processing:
 $P_{ref} \leftarrow \text{FilterDominatedPoints}(P_{raw}).$ // Keep only non-dominated solutions
return P_{ref} .

Appendix E. Path-based fallback heuristic

Algorithm 7: Global path-based heuristic (myopic-free fallback).

Input: Strategic Vector $\mathbf{v}_{strat} = \{y, s'\}$
Output: Feasible Tactical Vector $\mathbf{v}_{tact} = \{x, \delta, \phi\}$

1. Initialization:
 Reset Flows $\mathbf{x} \leftarrow \mathbf{0}$, Topology $\delta \leftarrow \mathbf{0}$, Path Registry $\mathcal{P}_{list} \leftarrow \emptyset$.
Initialize Remaining Resources: Initialize mutable copies $\mathbf{q}_{rem}, \mathbf{d}_{rem}, \mathbf{K}_{rem}$ based on $\mathbf{v}_{strat}$.

2. Exhaustive Path Enumeration:
 // Enumerate all valid routes from Fixed (S) and active Potential (S') sources
foreach Active Source i (where supply $\mathbf{q}_{rem,i} > 0$) **do**
 Mode A (Transshipment): Identify routes $i \rightarrow k \rightarrow j$ ($k \in T, j \in D$).
 if $\mathbf{K}_{rem}(i, k) > 0$ **and** $\mathbf{K}_{rem}(k, j) > 0$ **then** Add Path P to $\mathcal{P}_{list}$
 Mode B (Direct Express): Identify routes $i \rightarrow j$ (where $j \in D$).
 if $\mathbf{K}_{rem}(i, j) > 0$ **then** Add Path P to $\mathcal{P}_{list}$

3. Global Greedy Allocation:
Sort $\mathcal{P}_{list}$ by Total Cost C_P in **Ascending Order**. // Prioritize global cost efficiency
foreach Path $P \in \mathcal{P}_{list}$ **do**
 $f_{alloc} \leftarrow \min(\mathbf{q}_{rem}(\text{src}), \mathbf{d}_{rem}(\text{dst}), \min_{a \in P} \mathbf{K}_{rem}(a)).$
 if $f_{alloc} > 10^{-5}$ **then**
 Update Flows $\mathbf{x}$, Topology δ , and Residuals $(\mathbf{q}_{rem}, \mathbf{d}_{rem}, \mathbf{K}_{rem})$.
 if $\sum \mathbf{d}_{rem} \approx 0$ **then Break** (All demand satisfied)

4. Finalization:
 $\phi \leftarrow \mathbf{d}_{rem}$. Prune negligible flows. **return** $\mathbf{v}_{tact}$.

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