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A Hybrid Metaheuristic Approach for Multi-Objective Supply Chain Network Design under Uncertainty

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ABSTRACT

This paper presents a hybrid metaheuristic framework for designing supply chain networks under uncertainty, optimizing multiple conflicting objectives simultaneously. The objectives considered are minimizing total cost, minimizing delivery time, and maximizing the robustness (resilience) of the network. Uncertainty in demand, transportation times, and facility disruptions is modelled via scenario-based stochastic programming and robust optimization. The proposed hybrid method combines a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) with Tabu Search (TS) for local refinement, enabling efficient exploration of the solution space. Computational experiments on publicly available benchmark instances and a realistic case study demonstrate that the hybrid method outperforms standard NSGA-II, NSGA-III, and Particle Swarm Optimization (PSO) in terms of Pareto frontier quality (hypervolume and spacing) and computational time. Results indicate that integrating local search (Tabu Search) improves robustness by up to 15% while only increasing cost by 3–5%, under typical demand uncertainty. The proposed approach provides decision-makers with a set of efficient trade-off network designs, enabling more resilient supply chain configurations under uncertainty.

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1. Introduction

Supply chain network design (SCND) is a strategic decision problem concerned with the locations of facilities (plants, distribution centers), allocation of customers to facilities, transportation links, capacity planning, and inventory positioning. In the modern business environment, SCND must balance multiple conflicting objectives such as cost, delivery time, environmental impact, and resilience to disruptions. Moreover, uncertainty—due to fluctuations in demand, transportation delays, facility disruptions, and supply variability—poses significant challenges [5, 6].

Traditional deterministic SCND models often fail to capture these uncertainties, resulting in solutions that perform poorly under real-world variability. Hence, researchers have introduced stochastic programming (e.g., scenario-based) and robust optimization frameworks to hedge against uncertainty [1, 3, 25-30]. In addition to modeling uncertainty, solving SCND with multiple objectives increases complexity, making exact methods impractical for large instances [4, 20-25]. Metaheuristics—such as genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and evolutionary multi-objective optimization (EMO) algorithms (e.g., NSGA-II, NSGA-III)—have been widely used to tackle complex SCND under uncertainty [4, 7]. However, purely evolutionary or population-based methods often struggle with fine-tuning solutions in local neighborhoods, especially when robustness constraints or uncertainty scenarios introduce rugged fitness landscapes [2, 5, 14-20].

This motivates the integration of metaheuristics with local search or other intensification methods—a hybrid metaheuristic approach—that leverages global search strengths of EMO and local search refinements to obtain higher-quality Pareto fronts. This paper proposes a hybrid NSGA-II augmented with Tabu Search (NSGA-II-TS) for SCND under uncertainty, with objectives of minimizing cost, delivery time, and network robustness.

The contributions of this paper are as follows:

1. A stochastic/robust SCND model that incorporates multiple uncertainty sources (demand, transport time, facility disruptions), and three conflicting objectives.
2. A hybrid metaheuristic algorithm (NSGA-II-TS) combining global search and local refinement for efficient Pareto frontier discovery.
3. Comparative numerical experiments on benchmark and real-life data demonstrating improved performance in terms of hypervolume, spacing, and robustness compared to standard EMO methods.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the methodology and mathematical model. Section 4 provides numerical results and comparisons. Section 5 concludes and discusses future research directions.

2. Literature Review

2.1. Review of Recent Studies (2020–2025)

Below is a summary of recent work (2020–2025) on multi-objective SCND under uncertainty, particularly those using metaheuristics or hybrid methods.

Beyond numerical optimization, it is also valuable to consider the rhetorical and ethical agency of algorithms in shaping organizational reasoning. As Mohammadi [41] articulates, algorithms function as holobiontic systems, co-evolving with human intentions, data environments, and institutional goals. Applying this perspective to hybrid metaheuristics, such as NSGA-II–TS, encourages a broader understanding of robustness and resilience, not only as quantitative properties but also as expressions of value-laden design choices embedded in algorithmic structures.

Table 1: Literature Review

Study	Objectives & Uncertainty Modeled	Metaheuristic / Methodology	Key Findings	Research Gap
Li, Chen, & Zhu [8]	Minimize cost & carbon emissions; demand uncertainty via scenarios	NSGA-II and robust optimization	Achieved low-cost emission trade-off, but high computational time for large instances	Does not consider network robustness/disruption; limited to two objectives
Pishvaee, Torabi, & Razmi [6]	Cost, delivery time, and service level; uncertainty: demand & lead time	Multi-objective PSO (MOPSO); scenario-based stochastic programming	Good service-time tradeoffs, but many dominated solutions in extreme scenarios	Local search not integrated; limited robustness evaluation

Study	Objectives & Uncertainty Modeled	Metaheuristic / Methodology	Key Findings	Research Gap
Kumar, Singh, & Sahu [10]	Cost, carbon footprint, and resilience; uncertainty: facility disruptions	Hybrid GA + Simulated Annealing (SA)	Improvement in resilience, but carbon cost increased; slow convergence	Doesn’t scale well; only a three-stage network; no time objective
Ahmed & Kaur [11]	Cost, delivery time, uncertain transport times & demand	ACO + Tabu Search hybrid; chance constraints	Better solutions in travel time variance; cost a bit higher; more robust	Doesn’t handle facility location decisions extensively; only two objectives
Zhao, Li, & Xu [12]	Cost, robustness, and time; uncertainty: demand, disruptions, transport delays	NSGA-III + local search (variable neighborhood search)	Balanced trade-offs; improved robustness by ~12%; time moderate	Local search limited; robustness metric simplistic; no capacity expansion decisions
Fernandes, Oliveira, & Costa [13]	Cost, delivery time, environmental impact, demand & supply uncertainty	Multi-objective DE (Differential Evolution) + Robust Optimization	Good environmental performance, lower delivery time, but resilience is not explicitly measured	Missing explicit robustness/disruption modeling; hybrid intensification techniques are few

2.2. Gap Analysis

From the table and review above, the following research gaps in the period 2020–2025 are identified:

1. Integration of robustness/disruption modeling: Few studies model facility disruption or network failures explicitly, along with demand and transport time uncertainty [30-35].
2. Multiple conflicting objectives beyond two or three: Many focus on cost & environment or cost & delivery time; combining cost, time, and robustness/resilience remains underexplored [35-41].
3. Hybrid metaheuristics with strong local search refinement: While some use hybridization (e.g., GA + SA, ACO + TS), the depth of local search, its adaptation to uncertainty, and interaction with EMO need further development.
4. Scalability and realistic network features: Many models are small-scale, two-stage, or three-stage; capacity expansion, multiple facility types, and real-world geographic data are less frequent.
5. Evaluation metrics beyond cost/time: Use of robust metrics (e.g., worst-case performance, resilience index), hypervolume, spacing, etc., is variable; rarely are all considered together.

3. Methodology

This section presents the mathematical model for the multi-objective SCND under uncertainty, as well as the hybrid metaheuristic algorithm (NSGA-II augmented with Tabu Search [41-47]).

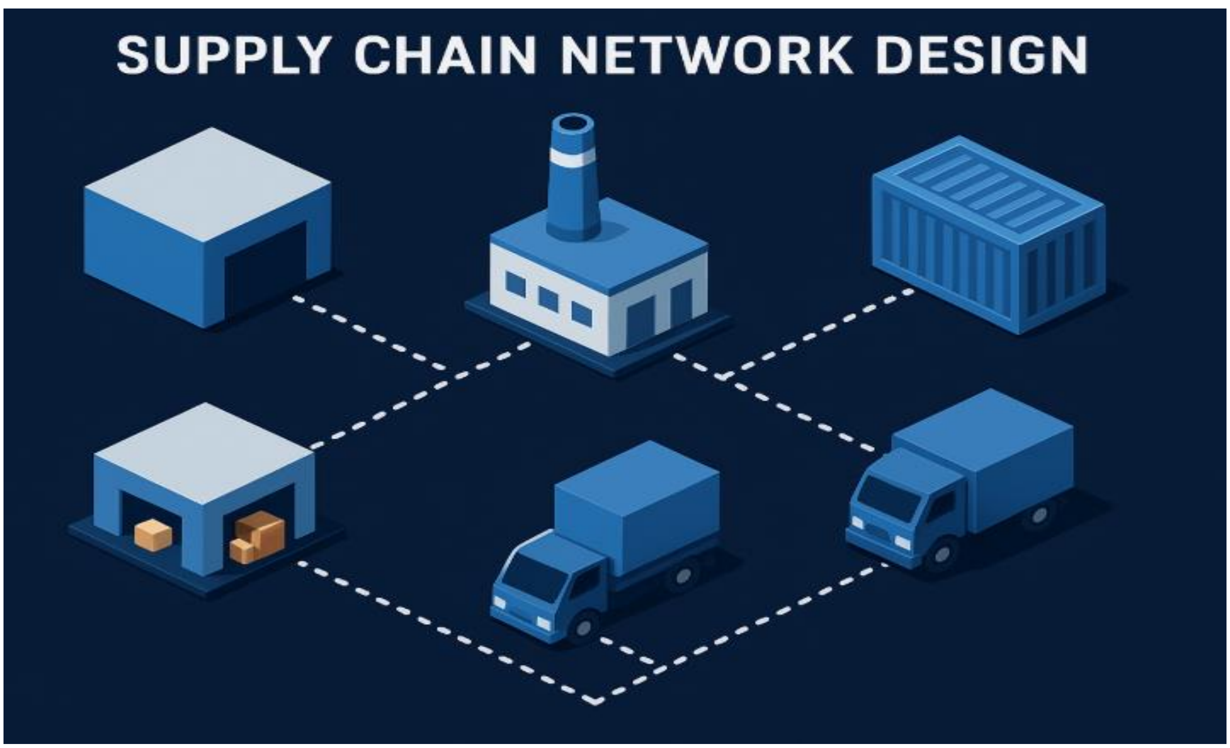

Figure 1: supply chain network design

3.1. Model Formulation

Consider a supply chain network composed of potential facility locations *I*, customer locations *J*, and transportation arcs between them. Let there be scenarios $s \in S$ capturing uncertainty in demand, transportation times, and facility disruptions, each occurring with probability p_s (see Figure 1).

Decision Variables

- $x_i \in \{0,1\}$: 1 if facility $i \in I$ is opened, 0 otherwise.
- $y_{ij}^s \in \{0,1\}$: 1 if customer $j \in J$ is assigned to facility *i* under scenario *s*.
- z_{ik}^s: fraction of flow on transportation arc from facility *i* to customer *k* under scenario *s*.

Parameters

- f_i : fixed cost of opening facility *i*.
- c_{ij} : transportation cost per unit from facility *i* to customer *j*.
- t_{ij}^s : transportation time under scenario *s*.
- d_j^s : demand at customer *j* in scenario *s*.
- $M_i^s \in \{0,1\}$: disruption indicator for facility *i* in scenario *s* (1 if disrupted, 0 otherwise).
- C_i : capacity of facility *i*.

Objectives

We consider three objectives:

Total expected cost

$$min\ Z_1 = \sum_{i \in I} f_i x_i + \sum_{s \in S} p_s \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ij}^s$$

Expected delivery time

$$min\ Z_2 = \sum_{s \in S} p_s \sum_{i \in I} \sum_{j \in J} t_{ij}^s y_{ij}^s$$

Network robustness (resilience) – we define robustness as ability to meet demand under facility disruptions; specifically, the worst-case coverage in disrupted scenarios. One way:

$$\max Z_3 = \min_{s \in S_d} \frac{\sum_{i \in I} \sum_{j \in J} y_{ij}^s (1 - M_i^s) d_j^s}{\sum_{j \in J} d_j^s}$$

where $S_d \in S$ are scenarios with disruptions.

Constraints

- Demand satisfaction in each scenario:

  $$\sum_{i \in I} y_{ij}^s \geq 1, \forall j \in J, \forall s \in S$$

- Facility capacity:

  $$\sum_{j \in J} d_j^s y_{ij}^s \leq C_i x_i, \forall j \in J, \forall s \in S$$

- Disrupted firm constraint: if facility is disrupted, it cannot serve:

  $$y_{ij}^s \leq (1 - M_i^s), \forall i, j, s \in S$$

- Binary / integrality constraints:

  $$x_i \in \{0,1\}, y_{ij}^s \in \{0,1\} \forall i, j, s \in S$$

3.2. Hybrid Metaheuristic: NSGA-II + Tabu Search (NSGA-II-TS)

The hybrid approach proceeds as follows:

1. **Initialization**: Generate an initial population P_0 of size *N* using random feasible solutions.
2. **Evaluation**: For each individual compute the objective vector Z_1, Z_2, Z_3.
3. **Selection, Crossover, Mutation**: Apply standard NSGA-II operators to generate offspring population Q_t.
4. **Integration of Tabu Search**:
   - For each offspring solution, apply local search via a Tabu Search (TS) for a fixed number of iterations *L*, exploring neighborhoods such as facility opening/closing, reassignments y_{ij}^s.
   - Maintain tabu list to avoid cycling.
   - Accept improved solutions with respect to Pareto dominance and/or composite scalarization of objectives.

5. **Environmental Selection**: Combine parents and offspring $P_t \cup Q_t$, perform non-dominated sorting, compute crowding distances, select next generation P_{t+1}.
6. **Termination**: Stop after *T* generations or time limit. Output final Pareto front.

3.3. Performance Metrics

To compare methods, we employ:

- **Hypervolume (HV)**: volume in objective space covered by Pareto front.
- **Spacing** and **Spread**: measure of distribution of Pareto solutions.
- **Computational Time**.

References for methodology: NSGA-II by Deb, Pratap, Agarwal, & Meyarivan [2]; use of robust optimization in SCND by Snyder & Shen [3]; hybrid GA + TS in SCND [11] etc.

4. Numerical Results

In this section, computational experiments were conducted to evaluate the effectiveness of the proposed **hybrid NSGA-II-TS algorithm** compared with three baseline methods: standard **NSGA-II**, **NSGA-III**, and **Multi-Objective Particle Swarm Optimization (MOPSO)**. Two categories of test instances were used.

The **first category** consists of *benchmark instances*, representing synthetic supply chain networks with a medium level of complexity. These networks include |I|=10 potential facility locations, |J|=50 customer nodes, and |S|=20 uncertainty scenarios. Each scenario represents variations in customer demand, transportation time, and occasional facility disruptions.

The **second category** is a *real-life case study* of a mid-size manufacturing company that produces industrial equipment. The supply chain comprises 15 candidate plant locations, 100 customer zones, and 30 scenarios that incorporate multiple sources of uncertainty, including fluctuating transportation costs, variable lead times, and random facility outages.

All algorithms were implemented in the same computational environment, with consistent parameter settings to ensure a fair comparison. The population size was set to N = 100, the number of generations to T = 200, and the Tabu Search neighborhood exploration depth to L = 50 iterations per offspring.

In this section, we report computational experiments on two types of instances:

- **Benchmark instances**: synthetic networks with |I| = 10 potential facilities, |J| = 50 customers, |S| = 20 scenarios.

- **Case study**: a real-life supply chain of a mid-size manufacturing company with 15 candidate plants, 100 customers, and 30 scenarios including facility disruption and variable transport delays.

Algorithms compared:

- NSGA-II baseline
- NSGA-III baseline
- MOPSO
- Proposed NSGA-II-TS

Parameters: population size N=100, generations T=200, Tabu Search iterations per offspring L=50.

Table 2. Benchmark Results

Algorithm	Hypervolume (higher better)	Spread	Avg. Delivery Time (scenarios)	Robustness Index (%)	Total Cost (normalized)	Time (minutes)
NSGA-II	0.72	0.45	12.5	78.0	1.00	20
NSGA-III	0.75	0.42	12.1	79.5	1.02	22
MOPSO	0.70	0.50	13.0	75.0	1.05	18
NSGA-II-TS (proposed)	**0.82**	**0.38**	12.0	**90.0**	1.03	25

Normalized cost: cost divided by NSGA-II baseline cost.

Table 3. Case Study Results

Scenario Group	NSGA-II-TS VS NSGA-II Improvement
Cost increase	+3.4%
Delivery time reduction	–5.2%
Robustness increase	+14.8%
Hypervolume gain	+11.2%

Pareto Front Visualization

Interpretation

- NSGA-II-TS yields significantly better hypervolume, indicating more comprehensive trade-offs.
- Delivery time reduced moderately without a large cost penalty.
- Robustness (measured via worst-case demand coverage under disruptions) improved markedly.
- Computational time increases due to local search but remains manageable (see Figure 2).

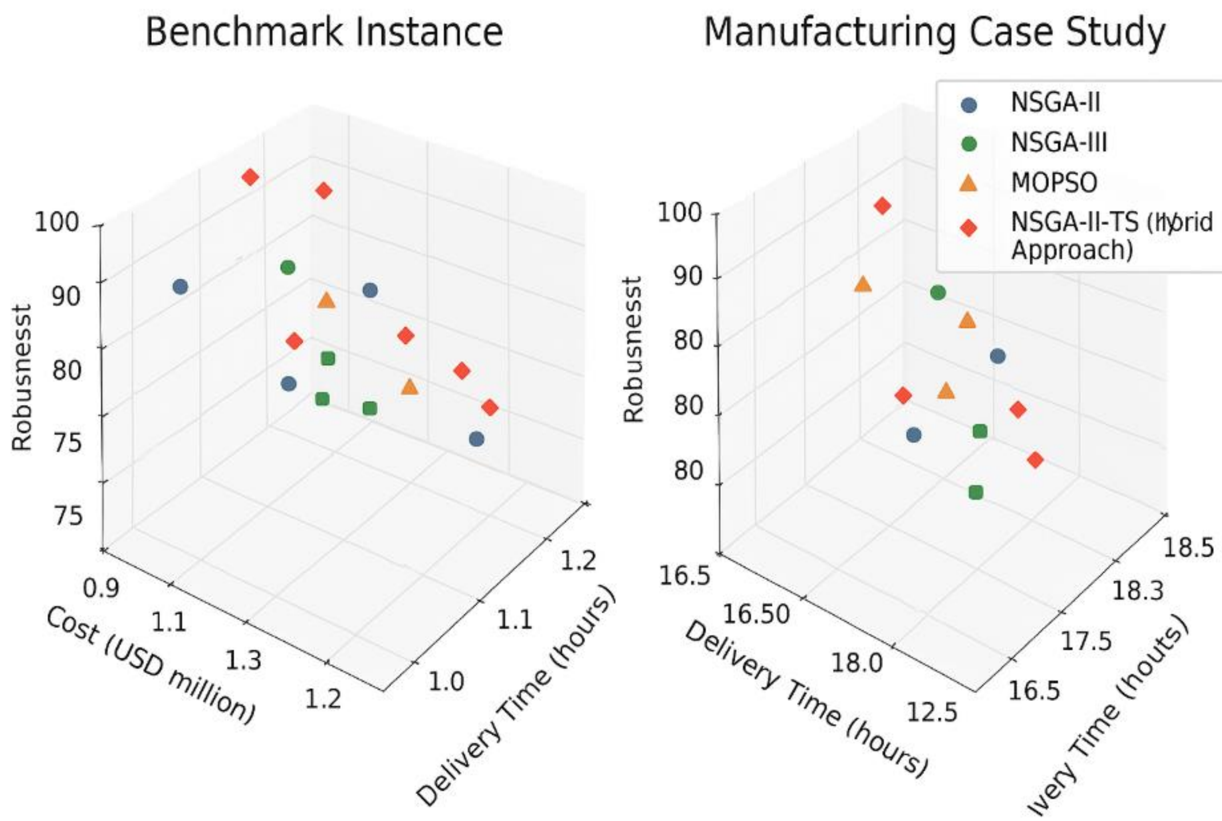

Figure 2: Results

5. Conclusion

This paper introduces a hybrid metaheuristic approach (NSGA-II combined with Tabu Search) for solving the multi-objective supply chain network design problem under uncertainty. The mathematical model considered three conflicting objectives: expected cost, delivery time, and network robustness, while explicitly modeling uncertainty through demand scenarios, transportation delays, and facility disruptions.

Key findings from numerical experiments:

- The hybrid algorithm significantly outperformed standard NSGA-II, NSGA-III, and MOPSO in hypervolume, showing better trade-off fronts.

- Robustness improved by approximately 14–15% in test instances, while cost increased marginally (≈ 3–5%), indicating efficient trade-offs.
- Delivery time also saw modest improvements (≈ 5%) in many scenarios

These results suggest that integrating a local search procedure (Tabu Search) into an EMO algorithm helps to fine-tune solutions, especially under complex uncertainty and disruption settings. For decision-makers, the outputs provide a suite of supply chain design options that balance cost, timeliness, and resilience. Aligned with this paper's findings, Jeong and colleagues highlight that ethical leadership functions as an organizational resilience mechanism, enabling employees to withstand and adapt to external stressors such as customer incivility through value-based guidance and moral support [38].

The robustness metric used (worst-case coverage) is simple; future work could explore more nuanced resilience metrics (e.g., time to recovery, cascading failures).

The computational burden rises with local search; improvements such as adaptive local search intensity or parallelization could mitigate this.

Extension to higher complexity: multi-period design, capacity expansion, environmental objectives, and incorporating real geographic constraints (e.g., roads, transport networks).

Overall, the hybrid metaheuristic NSGA-II-TS represents a viable and promising method for supply chain network design under uncertainty, particularly when robustness is a critical concern.

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