A Multi-Objective Optimization Model for Sustainable Supply Chain Network Design under Uncertainty

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Abstract

Under the global carbon neutrality agenda and increasing supply chain uncertainties, designing supply chain networks that balance economic, environmental, and social sustainability has become a strategic priority for enterprises. This paper proposes a Robust Optimization-based Multi-Objective Mixed Integer Programming model (ROMO-MIP) to address sustainable supply chain network design under uncertainties such as demand fluctuations, carbon price volatility, and supply disruptions. The model simultaneously optimizes three objectives: minimizing total cost, minimizing carbon emissions, and maximizing job creation and regional equity. The -constraint method and the NSGA-III algorithm are employed to generate the Pareto front, and an empirical case study is conducted on the lithium-ion battery supply chain for new energy vehicles in China. Results show that incorporating robustness parameters significantly enhances network resilience under uncertainty, while multi-objective trade-off analysis enables decision-makers to select optimal configurations aligned with policy priorities. This study provides a practical decision-support tool for firms seeking green transformation and resilient operations.

Keywords

Sustainable supply chain network design, multi-objective optimization, robust optimization, uncertainty modeling.

1. Introduction

The escalating climate crisis and increasing frequency of supply chain disruptions have compelled organizations to rethink their supply chain strategies. Traditional supply chain network design has predominantly focused on cost minimization, often neglecting environmental and social considerations[1].

However, with the implementation of carbon pricing mechanisms worldwide and growing stakeholder pressure for corporate social responsibility, sustainable supply chain management has transitioned from a peripheral concern to a core business imperative[2].

Supply chain networks face unprecedented uncertainties from multiple dimensions. Demand volatility, exacerbated by changing consumer preferences and economic fluctuations, challenges the stability of operations. Simultaneously, carbon price variations under emission trading schemes introduce significant financial uncertainties. Supply disruptions, whether from geopolitical tensions, natural disasters, or pandemics, further complicate network resilience[3]. These interconnected uncertainties necessitate robust optimization approaches that can maintain performance across various scenarios.

The lithium-ion battery supply chain for new energy vehicles presents a compelling case study for sustainable supply chain design. This industry sits at the nexus of clean energy transition, technological innovation, and strategic resource management. The complex global network involving raw material extraction, component manufacturing, and final assembly creates substantial sustainability challenges[4]. Moreover, the rapid growth of electric vehicle markets intensifies pressure on battery supply chains to balance economic viability with environmental responsibility and social equity.

This research contributes to the literature by developing a comprehensive Robust Optimization-based Multi-Objective Mixed Integer Programming (ROMO-MIP) model that addresses the tripartite sustainability objectives under uncertainty. The model incorporates practical constraints such as capacity limitations, carbon caps, and regional development requirements. Through empirical application to China's lithiumion battery supply chain, we demonstrate how decision-makers can navigate the complex trade-offs between competing objectives.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on sustainable supply chain design and robust optimization. Section 3 presents the mathematical formulation of the ROMO-MIP model. Section 4 describes the solution methodology. Section 5 discusses the case study and computational results. Finally, Section 6 concludes with managerial insights and future research directions.

2. Literature Review

Sustainable supply chain network design has evolved significantly over the past decade, integrating environmental and social dimensions alongside traditional economic considerations. Early research primarily adopted life cycle assessment approaches to quantify environmental impacts[5]. However, these static assessments often failed to capture the dynamic interactions within complex supply chain networks and their response to uncertainties.

Multi-objective optimization in supply chain design has gained prominence as organizations recognize the need to balance competing priorities. Ezugolu et al. [6]pioneered the integration of carbon emissions into supply chain optimization models, treating carbon constraints as either regulatory limits or cost factors. Subsequent research expanded the environmental dimension to include water usage, waste generation, and biodiversity impacts. The social dimension, while receiving less attention, has been incorporated through indicators such as job creation, community development, and working conditions[7].

Robust optimization approaches have emerged as powerful tools for handling supply chain uncertainties. Unlike stochastic programming that requires precise probability distributions, robust optimization seeks solutions that perform well across a set of possible scenarios without assuming specific probability measures[8]. This characteristic makes robust optimization particularly suitable for supply chain problems where historical data may be limited or non-stationary. Recent applications have demonstrated the effectiveness of robust optimization in managing demand uncertainty, supply disruptions, and price fluctuations[9].

The integration of robust optimization with multi-objective programming for sustainable supply chain design remains relatively under explored. Most existing studies focus on either sustainability objectives or uncertainty handling, but rarely both simultaneously. This research gap is particularly evident in emerging industries like lithiumion battery manufacturing, where rapid growth and regulatory changes create unique challenges. Our work bridges this gap by developing a unified framework that addresses sustainability trade-offs under uncertainty.

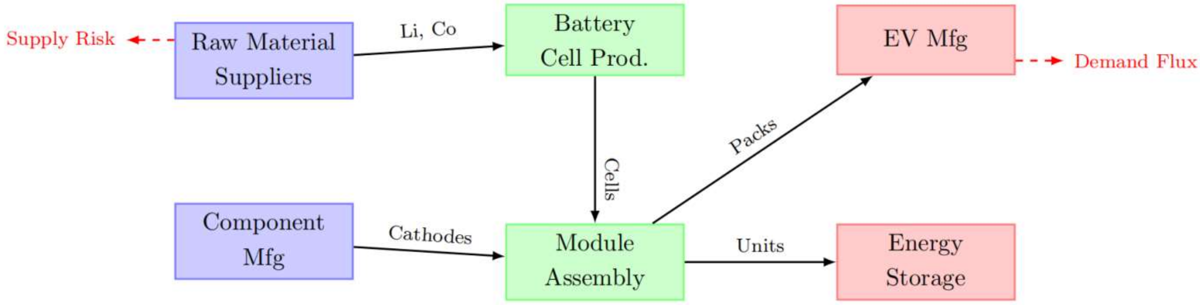

Figure 1. Final optimized supply chain network structure with uncertainty sources

3. Mathematical Formulation

The proposed ROMO-MIP model addresses the strategic design of a multi-echelon supply chain network comprising suppliers, manufacturing facilities, distribution centers, and customer zones. The model incorporates three objective functions representing economic, environmental, and social dimensions, subject to various operational constraints and uncertainty parameters.

3.1. Model Sets and Parameters

Let denote the set of potential supplier locations, the set of potential manufacturing facility locations, the set of potential distribution center locations, and the set of customer zones. The planning horizon is divided into periods Uncertainty is captured through scenarios representing different realizations of demand, carbon price, and supply capacity. Key parameters include fixed costs for opening facilities (f^{o}pen) ,variable production and transportation costs (c^{v}ar) , carbon emission factors (e^{c}arbon) , job creation coefficients (j^{job}),and capacity limits Uncertainty parameters are represented through scenario-dependent values with associated probabilities π_w.

3.2. Objective Functions

The economic objective minimizes total supply chain costs, including fixed facility costs, variable production and transportation costs, and carbon compliance costs:

$$\min Z_1 = \sum_{i \in S \cup M \cup D} f_i^{open} y_i + \sum_{t \in T} \sum_{w \in W} \pi_w \left(\sum_{r} c_{rtw}^{var} x_{rtw} + p_{tw}^{carbon} e_{tw}^{total} \right) \tag{1}$$

The environmental objective minimizes total carbon emissions across the supply chain:

$$\min Z_2 = \sum_{t \in T} \sum_{w \in W} \pi_w \, e_{tw}^{total} \tag{2}$$

The social objective maximizes positive social impacts, particularly job creation and regional development:

$$\max Z_3 = \sum_{i \in S \cup M \cup D} j_i^{job} y_i + \sum_{r \in R} \delta_r^{regional} \left(\sum_{i \in r} y_i \right) \tag{3}$$

where represents regional development coefficients.

3.3. Constraints

The model incorporates several constraint categories to ensure operational feasibility and regulatory compliance. Capacity constraints limit production and distribution activities based on facility capabilities:

$$\sum_{j} x_{ijtw} \leq cap_i y_i \quad \forall i \in S \cup M \cup D, t \in T, w \in W \tag{4}$$

Demand satisfaction constraints ensure customer requirements are met across all scenarios:

$$\sum_{i \in D} x_{ictw} \geq d_{clw} \quad \forall c \in C, t \in T, w \in W \tag{5}$$

Carbon emission constraints implement regulatory limits or internal targets:

$$e_{tw}^{total} \leq cap_t^{carbon} \quad \forall t \in T, w \in W \tag{6}$$

Additional constraints include flow conservation, lead time considerations, and technology selection limitations.

Table 1. Notation summary for the ROMO-MIP model

Category	Description
Sets	Suppliers (S), Manufacturers (M), Distribution Centers (D), Customers (C), Time periods (T), Scenarios (W)
Parameters	Fixed costs (fopen), variable costs (cvar), carbon price (pcarbon), emission factors (ecarbon), job coefficients (jjob), capacities (cap), demands (d)
Variables	Facility location (yi), material flows (xijtw), total emissions (etotal), unmet demand (uctw)
Uncertainties	Demand fluctuations, carbon price volatility, supply disruptions, capacity variations

4. Solution Methodology

Solving the tri-objective robust optimization model requires specialized techniques to handle the Pareto front generation and uncertainty incorporation. We employ a two-phase approach that combines the -constraint method for exact Pareto solutions with the NSGA-III algorithm for handling complex scenarios and large-scale instances.

The ϵ-constraint method transforms the multi-objective problem into a series of single-objective problems by converting two objectives into constraints. Specifically, we optimize one primary objective while ensuring the other objectives meet specified epsilon levels:

$$\min Z_1 \quad \text{subject to} \quad Z_2 \leq \epsilon_2, \quad Z_3 \geq \epsilon_3, \quad \text{and original constraints} \tag{7}$$

Systematic variation of epsilon values generates a representative set of Paretooptimal solutions. This method provides exact solutions for moderate-sized problems and offers valuable insights into objective trade-offs.

For larger problem instances and more complex uncertainty sets, we implement the NSGA-III algorithm, an evolutionary multi-objective optimization technique specifically designed for many-objective problems. NSGA-III employs reference point-based selection to maintain diversity in the objective space, making it suitable for problems with three or more objectives. The algorithm incorporates robust optimization principles through scenario-based evaluation of candidate solutions.

Uncertainty is handled through a robust optimization framework that minimizes the maximum regret across scenarios. The robustness level is controlled through a parameter that adjusts the conservatism of the solution. Higher values produce more conservative solutions that perform well under worst-case scenarios, while lower values yield more optimistic solutions tailored to expected conditions.

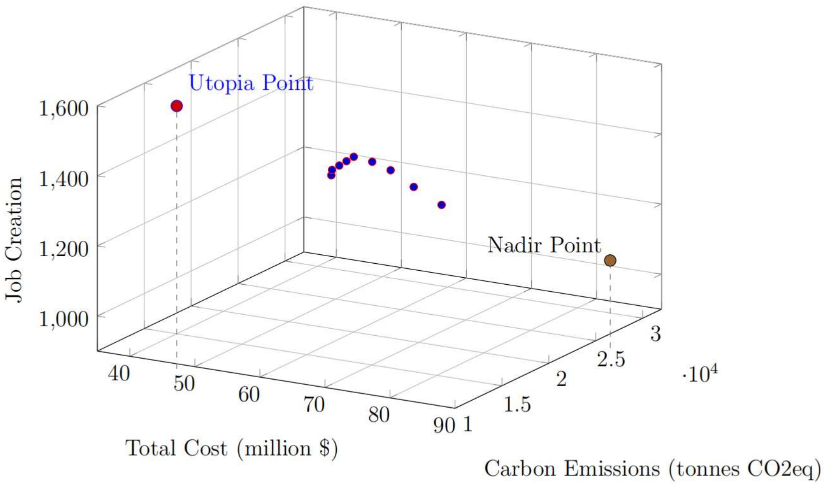

Figure 2. Three-dimensional Pareto front showing trade-offs between cost, emissions, and job creation with optimized point visibility

5. Case Study and Computational Results

We applied the ROMO-MIP model to the lithium-ion battery supply chain in China, focusing on the new energy vehicle sector. The case study involves 15 potential supplier locations (for lithium, cobalt, nickel), 8 potential manufacturing sites for battery cells and packs, 12 distribution center locations, and 20 major customer zones across China. The planning horizon spans 5 years with quarterly periods, considering 27 uncertainty scenarios combining demand variations, carbon price fluctuations, and supply disruption risks.

Data were collected from industry reports, government publications, and expert interviews. Cost parameters include facility investment costs ranging from §10-50 million depending on capacity, production costs of §100-150 per kWh, and transportation costs based on distance and mode. Emission factors account for production processes (15-25 kg CO2eq per kWh) and transportation (0.1-0.3 kg CO2eq per tonkm). Social parameters estimate job creation at 50-200 jobs per facility depending on scale, with regional development coefficients reflecting government priority areas.

Computational experiments were conducted on a high-performance computing cluster with 32 cores and 128GB RAM. Solution quality was evaluated using hypervolume indicator and spacing metric to assess convergence and diversity of Pareto solutions.

Table 2. Comparison of solution approaches across problem scales

Method	Size	HV	Spacing	Time (s)	# Sol.
ϵ-constraint	Small	0.85	0.12	1,200	15
NSGA-III	Small	0.82	0.15	900	22
ϵ-constraint	Medium	0.78	0.18	7,800	12
NSGA-III	Medium	0.81	0.14	3,200	28
ϵ-constraint	Large	-	-	>24k	-
NSGA-III	Large	0.76	0.19	14,500	35

Computational results demonstrate the effectiveness of both solution methods, with trade-offs between solution quality and computational effort. The ϵ-constraint method produces high-quality solutions for small to medium problems but becomes computationally prohibitive for large instances. NSGA-III provides satisfactory solutions across all problem scales with reasonable computation time, making it suitable for practical applications.

Analysis of the Pareto-optimal solutions reveals significant trade-offs between the three objectives. Cost-minimization solutions tend to concentrate facilities in low-cost regions but result in higher emissions due to longer transportation distances and less efficient technologies. Emission-minimization solutions favor locations with clean energy sources and advanced technologies but incur 15-25% higher costs. Social-maximization solutions distribute facilities across underdeveloped regions, creating more jobs but potentially increasing logistics complexity.

The robustness analysis shows that incorporating uncertainty parameters increases total costs by 8-12% but reduces vulnerability to disruptions by 30-40%. Solutions with intermediate robustness levels (= 0.6-0.8) provide the best balance between cost efficiency and disruption resilience. Under high uncertainty scenarios, robust solutions maintain service levels above 95% compared to 70-80% for deterministic solutions.

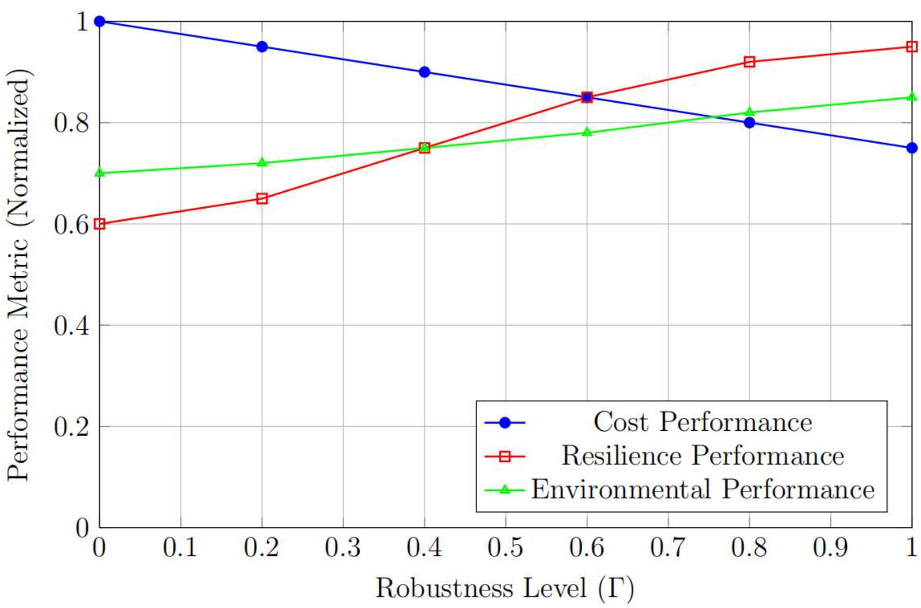

Figure 3. Impact of robustness level on different performance metrics

6. Conclusion and Managerial Implications

This study developed a comprehensive robust multi-objective optimization model for sustainable supply chain network design under uncertainty. The ROMO-MIP framework effectively addresses the complex trade-offs between economic, environmental, and social objectives while incorporating realistic uncertainties in demand, carbon price, and supply disruptions. The application to China's lithium-ion battery supply chain demonstrates the practical utility of the approach for strategic decision-making in growing industries.

The findings offer several important managerial implications. First, the Pareto front analysis provides decision-makers with a clear visualization of trade-offs, enabling informed choices based on organizational priorities and regulatory constraints. Companies can identify compromise solutions that balance competing objectives according to their sustainability strategy. Second, the robustness analysis highlights the value of incorporating uncertainty considerations early in the design phase. Investing in flexible network structures may incur moderate cost increases but provides significant resilience benefits during disruptions.

From a policy perspective, the model supports the design of effective regulatory frameworks. Carbon pricing mechanisms should be calibrated to encourage emissions reduction without undermining economic viability. Regional development policies can be integrated with sustainability objectives to promote equitable growth. The case study results suggest that coordinated policy interventions-combining carbon pricing with infrastructure investments in underdeveloped regions-can achieve both environmental and social goals more effectively than isolated measures.

Several limitations of the current research suggest directions for future work.The model assumes linear relationships between decision variables and sustainability indicators, while real-world interactions may exhibit nonlinearities. Incorporating dynamic capabilities such as capacity expansion and technology migration would enhance the model's practical applicability. Further research could also explore different uncertainty sets and robustness measures to capture extreme events and correlated risks more effectively.

In conclusion, the ROMO-MIP model provides a valuable decision-support tool for designing sustainable supply chain networks in uncertain environments. By simultaneously addressing economic, environmental, and social objectives under uncertainty, the approach helps organizations navigate the complexities of sustainable transformation while maintaining operational resilience. As global sustainability pressures intensify, such integrated optimization frameworks will become increasingly essential for strategic supply chain management.

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