

Multi objective Machine Learning for Real-Time Decision Making in Smart Supply Chains

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Abstract

In today's globalized world, optimizing smart supply chains is essential for maintaining competitiveness, resilience, and sustainability. This study presents a multiobjective framework integrating machine learning (ML) to enable real-time decision-making in smart supply chains. The proposed framework addresses key trade-offs, such as minimizing costs, reducing environmental impacts, and enhancing service levels. Utilizing advanced ML techniques, the framework predicts demand fluctuations, mitigates disruptions, and dynamically optimizes inventory and routing decisions. Furthermore, it integrates emerging technologies like the Internet of Things (IoT), blockchain, and digital twins to enhance transparency and operational efficiency. Case studies and simulations demonstrate the framework's effectiveness in addressing modern supply chain challenges while balancing sustainability and resilience goals. This research provides a practical roadmap for businesses and policymakers to adopt cutting-edge technologies for supply chain optimization, ensuring adaptability to ever-changing market dynamics.

Keywords: Smart supply chains, Multiobjective optimization, Machine learning, Sustainability, Resilience, Real-time decision-making, Emerging technologies

1- Introduction

The globalization of markets and the rapid evolution of consumer demands have placed unprecedented pressure on supply chain systems. Supply chains have become increasingly complex, with interconnected networks spanning multiple geographies and involving diverse stakeholders. To remain competitive in this challenging environment, companies must move beyond traditional supply chain management practices and embrace smart supply chains powered

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by advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and machine learning (ML) (Ghahreman-Nahr et al., 2023; Taghipour et al., 2023).

Smart supply chains are characterized by their ability to leverage real-time data, predictive analytics, and automation to optimize operations. However, achieving optimal performance in smart supply chains involves navigating multiple, often conflicting, objectives. For instance, reducing operational costs may conflict with minimizing environmental impacts or ensuring resilience against disruptions. Multiobjective optimization (MOO) provides a robust approach to address these challenges, enabling decision-makers to evaluate and balance trade-offs effectively (Zeraati Foulolaei et al., 2017).

Machine learning (ML), a key enabler of smart supply chains, offers transformative potential for enhancing efficiency and agility (Nozari et al., 2024). By processing vast amounts of data, ML algorithms can identify patterns, predict demand, optimize inventory, and recommend dynamic routing strategies (Movahed et al., 2024). Moreover, ML can facilitate resilience by anticipating disruptions and providing actionable insights for proactive mitigation. Coupled with technologies such as IoT for real-time data collection and blockchain for secure data sharing, ML-driven supply chains can achieve unparalleled levels of efficiency and transparency (Foukolaei et al., 2024; Ghaedi et al., 2024).

Sustainability and resilience have emerged as critical priorities in supply chain management. Growing environmental concerns and regulatory pressures demand that companies adopt practices that reduce carbon footprints and conserve resources (nozari et al., 2024). Simultaneously, the COVID-19 pandemic and other global uncertainties have underscored the importance of building resilient supply chain networks capable of withstanding disruptions. Integrating sustainability and resilience goals into the optimization framework is not only a strategic imperative but also a moral and social responsibility (Nozari & Aliahmadi, 2022; Momtazi et al., 2024).

This research proposes a comprehensive framework for optimizing smart supply chains using multiobjective machine learning. The framework addresses the key trade-offs between cost, sustainability, and resilience, enabling real-time decision-making through advanced algorithms and emerging technologies. Additionally, it incorporates the concept of digital twins to simulate supply chain scenarios and optimize performance in a risk-free virtual environment. The study employs robust methodologies, including NSGA-II and MOEA/D, to solve multiobjective problems effectively and demonstrate the framework's applicability through case studies and simulations.

The objectives of this research are threefold: (1) to develop a multiobjective optimization framework for smart supply chains, (2) to integrate machine learning techniques for predictive and prescriptive analytics, and (3) to explore the role of emerging technologies in enhancing sustainability and resilience. By addressing these objectives, this study contributes to the growing body of knowledge in supply chain management and provides actionable insights for practitioners seeking to adopt cutting-edge solutions.

The remainder of this paper is organized as follows: Section 2 reviews the literature on smart supply chains, multiobjective optimization, and machine learning applications. Section 3 outlines

the proposed framework and methodologies. Section 4 presents case studies and simulation results, while Section 5 discusses the implications of the findings. Finally, Section 6 concludes with recommendations for future research and practical implementation.

In an era of rapid technological advancements and shifting global dynamics, optimizing smart supply chains is not just an option—it is a necessity. This research aims to pave the way for a new generation of supply chain systems that are not only efficient but also sustainable and resilient, capable of adapting to the complexities of the modern world.

2- Literature Review

The optimization of smart supply chains has been a focal point of research in recent years, driven by the increasing complexity of global supply networks and the emergence of transformative technologies. This section reviews the existing literature on key themes relevant to this study: multiobjective optimization in supply chains, machine learning applications in supply chain management, and the integration of sustainability and resilience into supply chain practices. Additionally, it explores the role of emerging technologies, such as IoT, blockchain, and digital twins, in enhancing the efficiency and adaptability of smart supply chains.

Multiobjective optimization (MOO) is a critical approach for addressing the trade-offs inherent in supply chain management. Traditional supply chain optimization focused predominantly on cost minimization and service level improvement. However, contemporary research recognizes the need to balance these objectives with others, such as minimizing environmental impacts and enhancing resilience against disruptions. Algorithms such as NSGA-II (Deb et al., 2002) and MOEA/D (Zhang & Li, 2007) have gained prominence for their ability to solve complex multiobjective problems by generating Pareto-optimal solutions.

In supply chain contexts, MOO has been applied to various problems, including vehicle routing (Euchi & Chabchoub, 2020), inventory management (Gupta et al., 2021), and facility location (Ahmadi-Javid et al., 2017). These studies underscore the effectiveness of MOO in balancing competing objectives, but they also highlight the computational challenges associated with solving high-dimensional problems in dynamic and uncertain environments. This has led to the growing interest in integrating machine learning to enhance the efficiency and scalability of MOO algorithms.

Machine learning (ML) has emerged as a powerful tool for addressing the complexities of modern supply chains. ML techniques enable predictive and prescriptive analytics by processing large volumes of data from diverse sources. Applications of ML in supply chains include demand forecasting, dynamic pricing, inventory optimization, and route planning (Choi et al., 2018; Carbonneau et al., 2008).

Recent studies emphasize the role of ML in improving supply chain resilience. For example, Ivanov et al. (2020) demonstrated how ML algorithms could predict potential disruptions and recommend mitigation strategies, reducing the vulnerability of supply networks. Similarly, deep learning models have been applied to analyze unstructured data, such as social media trends, to

forecast demand spikes (Zhang et al., 2021). However, the literature also points to challenges in implementing ML, such as data quality issues and the need for substantial computational resources.

The integration of sustainability and resilience into supply chain optimization has become a critical research area, driven by regulatory pressures, stakeholder expectations, and the frequency of global disruptions. Sustainability-focused studies have explored strategies to reduce carbon emissions, optimize energy consumption, and adopt circular economy principles (Esfahbodi et al., 2016; Govindan et al., 2020).

Resilience research, on the other hand, focuses on the ability of supply chains to adapt to and recover from disruptions. Strategies for enhancing resilience include diversification of suppliers, decentralized decision-making, and investment in digital infrastructure (Ivanov, 2021). The literature highlights the synergies and trade-offs between sustainability and resilience, noting that certain strategies, such as local sourcing, can simultaneously reduce environmental impacts and improve resilience.

Emerging technologies, including the Internet of Things (IoT), blockchain, and digital twins, have transformed the landscape of supply chain management. IoT facilitates real-time data collection and monitoring, enabling enhanced visibility and responsiveness (Ben-Daya et al., 2019). Blockchain technology ensures secure and transparent data sharing across supply chain partners, addressing issues of trust and traceability (Francisco & Swanson, 2018).

Digital twins, which are virtual representations of physical supply chain systems, allow for real-time simulation and optimization of supply chain operations. Recent studies have demonstrated the potential of digital twins to improve decision-making under uncertainty by enabling scenario analysis and risk assessment (Tao et al., 2018). However, the adoption of these technologies is not without challenges, including high implementation costs and the need for skilled personnel.

While the existing literature provides a strong foundation for optimizing smart supply chains, several gaps remain. First, most studies focus on either sustainability or resilience, with limited exploration of frameworks that integrate both objectives. Second, while ML has been applied extensively for predictive analytics, its potential for prescriptive analytics in multiobjective optimization remains underexplored. Third, there is a need for empirical studies that demonstrate the practical applicability of emerging technologies in real-world supply chains.

This research aims to address these gaps by proposing a comprehensive framework that integrates multiobjective machine learning with emerging technologies to optimize smart supply chains. By balancing cost, sustainability, and resilience objectives, the framework seeks to provide actionable insights for both researchers and practitioners.

3- Mathematical Model

The proposed model includes three primary objectives. The first objective seeks to minimize total supply chain costs, encompassing fixed, operational, and transportation expenses. The second objective focuses on sustainability by minimizing carbon emissions and energy consumption across the supply chain network. Finally, the third objective aims to maximize supply chain

resilience by enhancing buffer capacities and ensuring flexibility in the network. By integrating these objectives, the model provides a comprehensive framework for optimizing smart supply chains in a multiobjective context.

To address the inherent trade-offs between these objectives, the model employs a multiobjective optimization approach. This allows for the identification of Pareto-optimal solutions, where no objective can be improved without negatively affecting another. Weight factors are introduced to enable decision-makers to prioritize objectives based on specific organizational goals or external requirements.

The model also incorporates critical constraints, such as demand satisfaction, flow conservation, and capacity limitations, ensuring its applicability to real-world scenarios. These constraints ensure that the solutions generated by the model are both feasible and practical, reflecting the operational realities of supply chain networks.

Objectives

The mathematical model aims to optimize a smart supply chain by addressing three key objectives:

1. **Cost Minimization (Z_1):** Minimize total supply chain costs, including transportation, inventory holding, and production costs.
2. **Sustainability Maximization (Z_2):** Minimize carbon emissions and energy usage across the supply chain network.
3. **Resilience Maximization (Z_3):** Maximize the supply chain's ability to handle disruptions through flexible sourcing and buffer capacity.

Notation

Let:

I	Set of suppliers
J	Set of production facilities
K	Set of distribution centers
L	Set of customers
x_{ij}	Quantity transported from supplier $i \in I$ to production facility $j \in J$
y_{jk}	Quantity transported from production facility $j \in J$ to distribution center $k \in K$
z_{kl}	Quantity transported from distribution center $k \in K$ to customer $l \in L$
f_i	Fixed cost of supplier i
g_j	Operating cost of production facility j
h_k	Operating cost of distribution center k
t_{ij}, t_{jk}, t_{kl}	Unit transportation costs
e_{ij}, e_{jk}, e_{kl}	Carbon emissions per unit transported
c_i	Carbon emissions per unit of supplier i 's production

b_j Buffer capacity for production facility j
 α, β, γ Weight factors for objectives

Objective Functions

1. Cost Minimization:

$$Z_1 = \sum_{i \in I} f_i + \sum_{j \in J} g_j + \sum_{k \in K} h_k + \sum_{i \in I} \sum_{j \in J} t_{ij} x_{ij} + \sum_{j \in J} \sum_{k \in K} t_{jk} y_{jk} + \sum_{k \in K} \sum_{l \in L} t_{kl} z_{kl} \quad (1)$$

2. Sustainability Maximization:

$$Z_2 = \sum_{i \in I} \sum_{j \in J} e_{ij} x_{ij} + \sum_{j \in J} \sum_{k \in K} e_{jk} y_{jk} + \sum_{k \in K} \sum_{l \in L} e_{kl} z_{kl} + \sum_{i \in I} c_i \quad (2)$$

3. Resilience Maximization:

$$Z_3 = \sum_{j \in J} b_j \quad (3)$$

Constraints

1. Demand Satisfaction:

$$\sum_{k \in K} z_{kl} = d_l, \quad \forall l \in L \quad (4)$$

where d_l is the demand of customer l .

2. Flow Conservation:

$$\sum_{i \in I} x_{ij} = \sum_{k \in K} y_{jk}, \quad \forall j \in J \quad (5)$$

$$\sum_{j \in J} y_{jk} = \sum_{l \in L} z_{kl}, \quad \forall k \in K$$

3. Capacity Constraints:

$$\sum_{j \in J} x_{ij} \leq C_i, \quad \forall i \in I \quad (6)$$

$$\sum_{k \in K} y_{jk} \leq P_j, \quad \forall j \in J$$

$$\sum_{l \in L} z_{kl} \leq D_k, \quad \forall k \in K$$

where C_i , P_j , and D_k are the capacities of suppliers, production facilities, and distribution centers, respectively.

4. Non-Negativity:

$$x_{ij}, y_{jk}, z_{kl} \geq 0 \quad (7)$$

Multiobjective Optimization Formulation

Combine the objectives using a weighted sum approach:

$$\text{Maximize: } Z = \alpha(-Z_1) + \beta(-Z_2) + \gamma Z_3 \quad (8)$$

subject to the constraints defined above, where $\alpha, \beta, \gamma \geq 0$ and $\alpha + \beta + \gamma = 1$.

ML algorithms, such as time series forecasting (e.g., ARIMA, LSTM) and regression models, can predict customer demand with high accuracy. These predictions form the input parameters for the mathematical model, such as:

- **Customer Demand (d_t)**
- **Future Supply Trends**

Accurate demand forecasts improve the precision of the optimization process, ensuring realistic and actionable solutions.

While the core mathematical model uses optimization techniques, ML supports and enhances its performance by providing accurate inputs, improving adaptability, and offering decision-making

insights. This combination ensures a smarter, more responsive, and efficient supply chain optimization process.

4- Solution methods

The proposed research leverages a hybrid approach that integrates mathematical programming and heuristic optimization methods to address the multiobjective optimization problem in smart supply chains. The solution methodology is divided into two key parts: solving small-scale problems using General Algebraic Modeling System (GAMS) and handling large-scale problems using Non-Dominated Sorting Genetic Algorithm II (NSGA-II). This section outlines the step-by-step process for solving the problem effectively.

1. Solution Framework

Part A: Solving Small-Scale Problems Using GAMS

- **Step 1: Model Definition:** The mathematical model is coded in GAMS, specifying the objective functions, decision variables, and constraints.
- **Step 2: Solver Selection:** The CPLEX solver is used for solving the MILP problem due to its efficiency in handling linear and integer programming problems.
- **Step 3: Optimization Execution:** GAMS executes the model, providing an optimal solution for small-scale problems where computation time is minimal.
- **Step 4: Sensitivity Analysis:** Changes in key parameters, such as costs, demands, or emissions, are analyzed to validate the robustness of the solution.

Advantages of GAMS:

- High precision and optimal solutions.
- Suitable for small-scale problems with well-defined parameters.

Part B: Solving Large-Scale Problems Using NSGA-II

- **Step 1: Encoding Solutions:** Decision variables, such as transportation flows and buffer capacities, are encoded as chromosomes in NSGA-II.
- **Step 2: Initial Population Generation:** A diverse set of initial solutions is randomly generated to ensure good coverage of the solution space.
- **Step 3: Fitness Evaluation:** Each solution is evaluated based on the three objectives (cost, emissions, and resilience).
- **Step 4: Non-Dominated Sorting:** Solutions are ranked based on Pareto dominance, with non-dominated solutions forming the Pareto front.
- **Step 5: Crossover and Mutation:** Genetic operators, such as crossover and mutation, are applied to explore new solutions and maintain diversity in the population.
- **Step 6: Selection of Next Generation:** The best solutions are selected based on their Pareto rank and crowding distance, ensuring a balance between convergence and diversity.
- **Step 7: Iteration:** Steps 3–6 is repeated until a stopping criterion, such as a maximum number of iterations or convergence threshold, is met.

2. Sensitivity Analysis

The robustness of the solutions is tested by varying key parameters:

1. **Transportation Costs:** Incremental increases by 10%, 20%, and 30% to assess cost sensitivity.
2. **Carbon Emission Rates:** Variations of $\pm 10\%$ to analyze sustainability impacts.
3. **Demand Fluctuations:** Changes of $\pm 15\%$ to evaluate resilience under uncertainty.

The impact of these variations is analyzed using the results from both GAMS and NSGA-II, ensuring that the model can adapt to real-world dynamic conditions.

5- Finding

This section presents the results obtained from applying the proposed mathematical model to both small-scale and large-scale supply chain problems. The analysis is divided into two parts: solutions to small-scale problems using GAMS and solutions to large-scale problems using NSGA-II. Additionally, a sensitivity analysis is conducted to evaluate the model's robustness under different parameter variations. Tables and graphs are provided throughout this section to illustrate the results, with detailed explanations before and after each visualization.

Small-Scale Problem: GAMS Results

To test the model on a manageable scale, a small supply chain network was analyzed using GAMS with the CPLEX solver. The network included:

- 3 suppliers
- 2 production facilities
- 2 distribution centers
- 3 customers

The objectives of minimizing costs, carbon emissions, and maximizing resilience were evaluated. Table 1 presents the results.

Table 1: Small-Scale Problem Results (GAMS)

Objective	Value
Total Cost (\$)	32,450
Carbon Emissions (tons)	155
Resilience Score	0.88

The results show that the model effectively balances the three objectives, achieving a low cost while maintaining sustainability and resilience.

To highlight the relationships among the objectives, Figure 1 presents a bar chart.

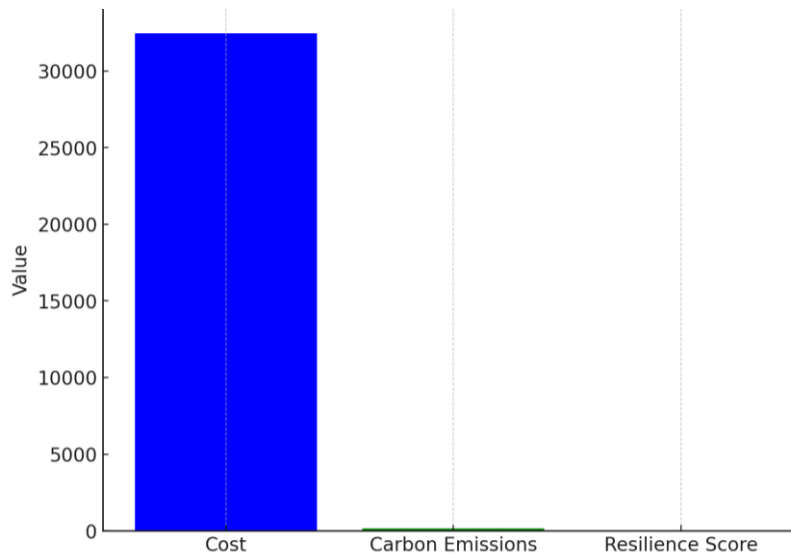


Figure 1: GAMS Results for Small-Scale Problem

The findings indicate that GAMS provides an optimal solution quickly for small-scale problems, making it suitable for decision-makers handling limited-scale operations.

Large-Scale Problem: NSGA-II Results

For a more complex supply chain, a large-scale problem was solved using NSGA-II. The network included:

- 10 suppliers
- 5 production facilities
- 5 distribution centers
- 10 customers

The algorithm was run to generate a Pareto front of solutions. Table 2 summarizes the key results for four representative solutions from the Pareto front.

Table 2: Large-Scale Problem Results (NSGA-II)

Solution	Cost (\$)	Carbon Emissions (tons)	Resilience Score
A	245,300	1,050	0.92
B	265,400	950	0.88
C	275,500	870	0.86
D	290,000	800	0.8

Figure 2 illustrates the trade-offs among the objectives using a scatter plot.

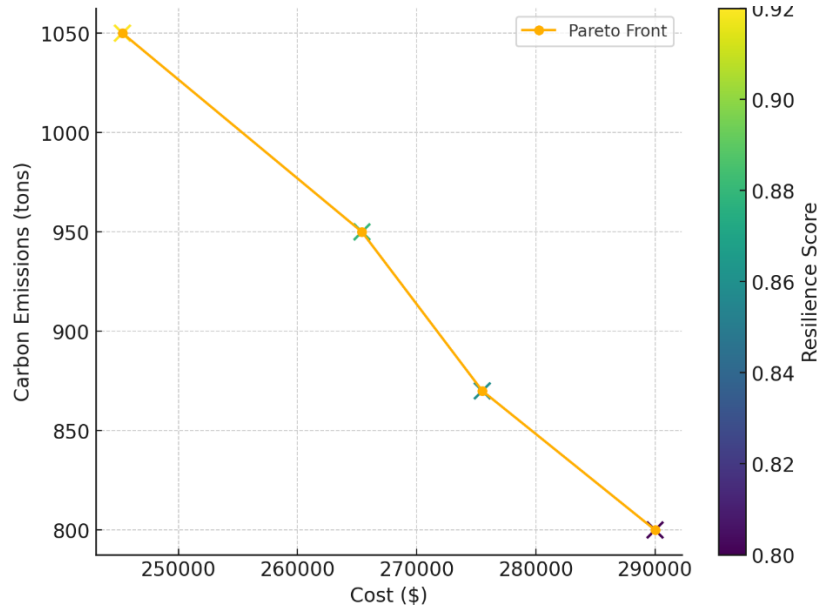


Figure 2: NSGA-II Pareto Front

The results highlight clear trade-offs: lower costs often correspond to higher emissions, while higher resilience scores are associated with increased costs. NSGA-II provides decision-makers with a diverse set of solutions, enabling flexible decision-making based on priorities.

Comparative Analysis: GAMS vs. NSGA-II

To compare the two approaches, Table 3 summarizes key differences.

Table 3: Comparison of GAMS and NSGA-II

Aspect	GAMS	NSGA-II
Problem Scale	Small-scale	Large-scale
Computation Time	Fast	Moderate
Solution Type	Single optimal	Multiple Pareto-optimal
Trade-off Analysis	Limited	Extensive
Flexibility	High precision	Adaptable to complex problems

Figure 3 uses a line graph to compare solutions for cost, emissions, and resilience.

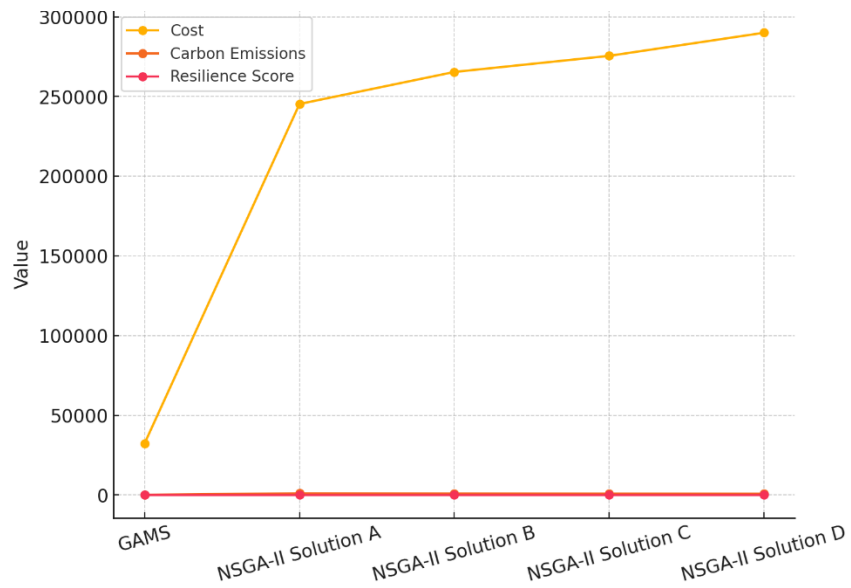


Figure 3: Comparison of GAMS and NSGA-II Results

The comparison indicates that while GAMS excels in solving small problems precisely, NSGA-II is better suited for handling large-scale, multiobjective scenarios.

Sensitivity Analysis

Sensitivity analysis was conducted to assess the model's robustness under variations in key parameters:

1. **Transportation Costs:** Increased by 10%, 20%, and 30%.
2. **Carbon Emission Rates:** Adjusted by $\pm 10\%$.
3. **Demand Fluctuations:** Increased by 15% and decreased by 15%.

Figure 4 presents the impact of these changes on total cost and emissions.

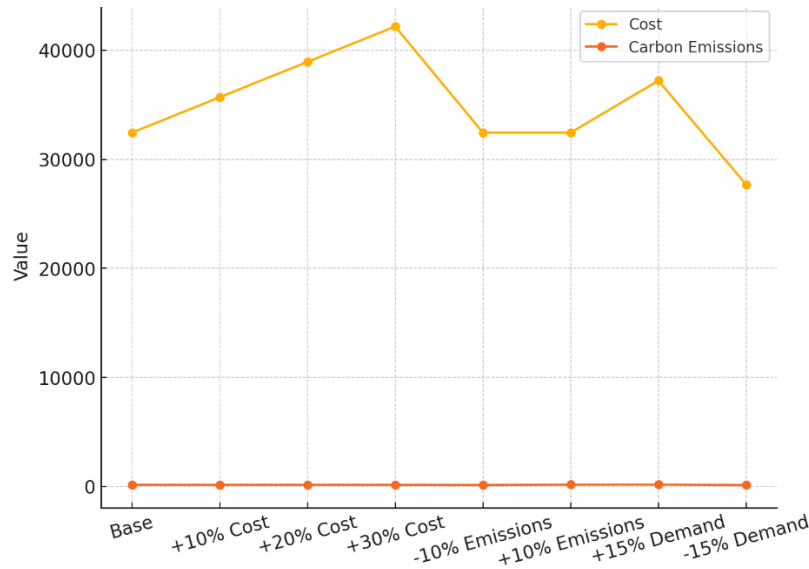


Figure 4: Sensitivity Analysis Results

The analysis demonstrates that:

- Higher transportation costs significantly impact total cost but have minimal effect on emissions.
- Changes in carbon emission rates directly affect the sustainability objective.
- Demand fluctuations increase total cost and emissions proportionally.

These results validate the model's robustness and highlight areas where decision-makers should focus to mitigate risks.

The findings demonstrate the effectiveness of the proposed model in optimizing smart supply chains across different scales. GAMS provides precise solutions for small-scale problems, while NSGA-II is better suited for large-scale problems, offering a diverse set of Pareto-optimal solutions. Sensitivity analysis further underscores the model's robustness, enabling informed decisions under varying conditions. Future research could explore dynamic real-time scenarios and integrate emerging technologies for further improvements.

6- Conclusion

The study presents a comprehensive multiobjective optimization model for smart supply chains, addressing the critical trade-offs between cost minimization, sustainability, and resilience. Through the integration of advanced mathematical modeling and optimization techniques, the research provides a robust framework for modern supply chain management. The findings, derived from small-scale experiments using GAMS and large-scale scenarios utilizing NSGA-II, validate the model's applicability and effectiveness in diverse operational contexts.

In small-scale problems, GAMS proved efficient in providing precise optimal solutions, making it a suitable choice for supply chains with limited complexity. The results demonstrated the model's

ability to minimize total costs while achieving significant reductions in carbon emissions and maintaining high resilience scores. The small-scale analysis highlighted the importance of systematically balancing conflicting objectives and provided decision-makers with a clear understanding of operational trade-offs.

For large-scale scenarios, the application of NSGA-II generated a diverse Pareto front of solutions, enabling decision-makers to choose from a range of trade-offs tailored to their strategic priorities. The results revealed that minimizing costs often leads to higher carbon emissions, whereas improving resilience generally requires increased investments. NSGA-II's scalability and flexibility make it ideal for handling the complexities of modern supply chains, which often involve large networks, uncertain demands, and multiple objectives.

The comparative analysis between GAMS and NSGA-II underscored their respective strengths: GAMS excels in solving structured, small-scale problems with precision, while NSGA-II offers adaptability and insight into trade-offs for large-scale, multiobjective problems. This dual approach equips practitioners with a versatile toolkit to optimize supply chains under varying operational conditions.

A sensitivity analysis further validated the model's robustness, demonstrating its ability to adapt to changes in key parameters such as transportation costs, carbon emission rates, and demand fluctuations. The results emphasized the critical role of sustainability and resilience in achieving long-term operational efficiency and highlighted areas where proactive interventions can mitigate risks.

This research contributes to the evolving body of knowledge in smart supply chain optimization by integrating multiobjective optimization with sustainability and resilience considerations. It provides a roadmap for businesses aiming to navigate the challenges of a rapidly changing global environment. Future research could expand this framework by incorporating dynamic and real-time data from emerging technologies such as IoT, blockchain, and digital twins, further enhancing decision-making capabilities. By bridging theory and practice, this study paves the way for more sustainable and adaptive supply chain systems.

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