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Research Article

An Intelligent Fuzzy Multi-Criteria Framework for Joint Procurement Allocation and Logistics Network Design under Sustainability and Risk Considerations

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ABSTRACT

This study proposes an integrated fuzzy multi-objective decision-support framework for the simultaneous optimization of procurement allocation and logistics network design in multi-echelon supply chains. The framework explicitly captures the interdependence between sourcing and transportation decisions while balancing four strategic objectives: minimization of total operational cost, minimization of supplier-related quality defects, maximization of supplier sustainability performance, and minimization of supply chain disruption risk. To address uncertainty in production capacities and operational conditions, the model incorporates fuzzy parameters and is solved using an Augmented Max–Min Fuzzy Multi-Objective Linear Programming (AMM-FMOLP) approach that generates balanced compromise solutions across conflicting objectives. The applicability of the proposed framework is demonstrated through a real-world case study involving a computer numerical control (CNC) machine-tool assembly supply chain consisting of 15 suppliers, 2 assembly facilities, 3 distribution centers, and 6 customer zones. The obtained compromise solution achieved utility values of 0.6667, 0.6820, 0.6747, and 0.6667 for cost, defect rate, sustainability performance, and disruption risk, respectively, resulting in a total operational cost of 26.586 million monetary units, a defect-rate index of 209.57, a sustainability score of 1,546.148, and a disruption-risk index of 214.223. Comparative scenario analyses revealed that single- and partial-objective optimization approaches yielded marginal improvements in individual objectives but produced less balanced overall performance. Sensitivity analyses further confirmed robustness of proposed framework under different conditions. Results demonstrate that proposed framework provides an effective mechanism for enhancing supply chain efficiency, sustainability, and resilience, making it a valuable decision-support tool for intelligent supply chain management in uncertain operating environments.

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1. Introduction

Modern supply chains operate in an increasingly complex environment characterized by globalization, volatile markets, and growing exposure to operational disruptions. In such conditions, effective supply chain management requires more than the efficient coordination of material and information flows; it demands integrated decision-making mechanisms capable of balancing economic performance, sustainability objectives, and operational resilience [1,2]. Organizations must simultaneously maintain service quality, control costs, ensure reliable supply, and respond rapidly to unexpected events. Consequently, strategic decisions related to procurement, logistics, and network design have become critical determinants of overall supply chain competitiveness [3-5]. The increasing interconnectedness of supply chain entities has also amplified network vulnerability. Disruptions occurring at a single supplier, facility, or transportation link can propagate throughout the network, causing delivery delays, inventory imbalances, service deterioration, and increased operating costs. These challenges highlight the importance of developing resilient supply chain structures capable of mitigating risks while maintaining efficient operations. As a result, resilience, sustainability, and risk management have emerged as key considerations in modern supply chain planning [6].

Among the most influential strategic decisions are procurement allocation and logistics network planning. Procurement allocation determines how purchasing volumes are distributed among available suppliers, while logistics planning governs the movement of materials and finished products across the network. These decisions are highly interdependent [7-9]. Supplier selection directly influences transportation requirements, delivery reliability, inventory levels, and operational flexibility, whereas logistics constraints affect the feasibility and effectiveness of sourcing strategies. Optimizing these decisions separately often results in locally efficient solutions that fail to maximize overall supply chain performance [10].

Although extensive research has been conducted on supply chain optimization, several important gaps remain. First, most studies address supplier allocation and transportation planning independently, despite their strong operational interactions. This limitation is particularly evident in manufacturing environments with multi -tier supplier structures and assembly operations, where coordinated decision-making is essential [11-15]. Second, many existing models focus primarily on cost minimization while providing limited consideration of other critical performance dimensions, such as product quality, supplier sustainability, and disruption risk [1,4-8,11,13]. Third, relatively few studies investigate the robustness of supply chain decisions under alternative operational scenarios, limiting managerial understanding of how different strategies perform under changing conditions [9-11,14,16].

To address these shortcomings, this study proposes an intelligent fuzzy multi-objective optimization framework that simultaneously considers procurement allocation and logistics network design within a unified decision-making environment. The proposed framework evaluates supply chain performance from four complementary perspectives: minimizing total operational cost, minimizing supplier defect rates, maximizing supplier sustainability performance, and minimizing disruption risk throughout the network. By integrating these objectives, the model supports balanced decision-making that reflects both economic and non-economic performance requirements. The proposed formulation incorporates practical operational constraints, including customer demand fulfillment, supplier capacity limitations, assembly and warehouse capacity restrictions, material flow balance, and system feasibility requirements. These considerations ensure that the generated solutions are not only theoretically optimal but also operationally implementable. Furthermore, the framework enables decision-makers to identify sourcing and transportation strategies that reduce costs while simultaneously enhancing quality, sustainability, and resilience. To solve the resulting multi-objective optimization problem, this study employs an Augmented Max–Min Fuzzy Multi-Objective Linear Programming (AMM-FMOLP) approach. The methodology transforms multiple conflicting objectives into a unified compromise solution using fuzzy membership functions and utility-based optimization. Unlike conventional optimization methods that may favor a single objective, the AMM-FMOLP approach seeks a balanced solution that maximizes overall satisfaction while preventing excessive deterioration in any individual performance dimension.

The applicability of the proposed framework is demonstrated through a real-world case study involving a multi-echelon CNC machine-tool manufacturing supply chain consisting of suppliers, assembly facilities, warehouses, and customer zones. Industrial data are utilized to capture realistic operational conditions and managerial requirements. In addition, several alternative decision scenarios are analyzed to evaluate the impact of different objective combinations on supply chain performance. Comparative experiments with other multi-objective decision-making approaches further demonstrate the effectiveness of the proposed methodology.

The results show that the AMM-FMOLP framework provides a well-balanced compromise among cost efficiency, product quality, supplier sustainability, and disruption resilience. Compared with traditional optimization approaches, the proposed model achieves superior overall performance by simultaneously addressing multiple strategic objectives rather than prioritizing a single performance criterion. These findings highlight the value of integrated procurement and logistics planning in supporting sustainable, resilient, and efficient supply chain operations. Consequently, this study contributes both a practical decision-support framework for industry and a methodological advancement for multi-objective supply chain optimization research.

The robustness of the proposed framework is also examined through a series of alternative operational scenarios and structural configurations. These experiments provide valuable managerial insights regarding the effects of network redesign, supplier performance variation, and disruption exposure on overall supply chain outcomes. The findings highlight the potential of the framework as a practical decision-support tool capable of assisting organizations in designing more adaptive, sustainable, and resilient supply chain systems under uncertain business environments.

The primary contributions of this research can be summarized as follows:

(i) A unified decision-support framework is developed to jointly optimize procurement allocation and logistics network design, enabling coordinated planning across interconnected supply chain activities.

(ii) The proposed optimization model simultaneously considers economic efficiency, supplier quality performance, sustainability achievement, and network disruption exposure, thereby providing a comprehensive evaluation of supply chain performance.

(iii) A fuzzy multi-objective optimization methodology is employed to address uncertainty and generate balanced solutions across multiple conflicting objectives.

(iv) Alternative supply chain configurations and operational scenarios are investigated to evaluate the impact of sustainability and resilience considerations on strategic decision-making.

(v) Managerial insights are derived from network restructuring experiments, including scenarios involving modifications to distribution infrastructure and logistics configurations.

(vi) The framework operates primarily on organizational data obtained from enterprise information systems, reducing dependence on subjective expert judgments and enhancing its suitability for intelligent, data-driven supply chain management applications.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature and identifies the theoretical foundations of the research. Section 3 describes the proposed optimization framework, including model assumptions, notation, objective functions, and operational constraints. Section 4 outlines the methodological procedure adopted to solve the problem and implement the fuzzy multi-objective decision-making approach. Section 5 introduces the industrial application, presents the case data, and reports the computational results. Section 6 provides an in-depth discussion of the findings, including scenario evaluations, sensitivity investigations, and comparisons with alternative multi-objective solution techniques. Finally, Section 7 summarizes the major conclusions, managerial implications, and potential directions for future research.

2. Literature Review

Supply chain network (SCN) decision-making has progressively evolved from isolated functional optimization toward integrated frameworks that coordinate procurement, production, transportation, distribution, sustainability, and resilience. This evolution reflects the increasing interdependence of supply chain decisions: supplier selection and order allocation determine the availability and quality of incoming components; production decisions influence downstream distribution requirements; transportation choices affect both cost and disruption exposure; and supplier characteristics increasingly influence environmental and social performance. Consequently, optimizing individual decision layers independently may produce locally efficient solutions while creating undesirable effects elsewhere in the network.

Recent studies have therefore increasingly employed multi-objective optimization, fuzzy programming, stochastic approaches, robust optimization, and metaheuristic techniques to address conflicting objectives and uncertain operating conditions [1-5]. However, the existing literature is not homogeneous. Different research streams tend to emphasize different dimensions of the supply chain problem [6-10]. Some studies focus on procurement–transportation integration, others emphasize sustainability, while another group concentrates on uncertainty or disruption resilience [11-15]. Although these streams have produced important advances, their simultaneous integration into a single operational decision framework remains comparatively less developed.

Accordingly, this review examines the literature from a critical rather than purely descriptive perspective. Four interconnected research streams are considered: (i) integrated procurement and transportation optimization, (ii) sustainability- and quality-oriented supplier decision-making, (iii) uncertainty and fuzzy multi-objective optimization, and (iv) disruption-aware and resilient supply chain design. The review then synthesizes the limitations of these streams and explains how they motivate the modeling architecture developed in this study.

2.1. Integrated Procurement and Transportation Optimization

The integration of procurement and transportation decisions has long been recognized as an important mechanism for improving supply chain coordination. Early optimization models demonstrated that supplier selection, order allocation, and transportation decisions can generate substantially different results when optimized jointly rather than sequentially [1,6]. Subsequent studies extended this concept to multi-echelon networks involving suppliers, manufacturing or assembly facilities, warehouses, and customers [7,11]. Such models recognize that procurement decisions determine upstream material flows and therefore directly affect production and downstream distribution requirements.

Lo et al. [1], for example, developed a fuzzy multi-objective framework integrating supplier order allocation and transportation planning under uncertainty. Similarly, Singh et al. [16] and Li et al. [17]considered integrated supply chain structures in which procurement and logistics decisions are coordinated under operational constraints. These studies demonstrate the importance of moving beyond sequential decision-making, particularly when supplier capacities, transportation costs, and network flows are strongly interdependent.

Nevertheless, integration of procurement and transportation does not necessarily imply comprehensive integration of supplier-performance dimensions. A substantial portion of the literature remains primarily oriented toward economic efficiency, capacity utilization, service performance, or network configuration [7,13,18]. Consequently, a supplier allocation that is optimal from a procurement-cost perspective may not necessarily be optimal when supplier quality, sustainability, or transportation disruption exposure are considered simultaneously.

This limitation is particularly important in multi-echelon manufacturing systems. Supplier order allocation determines not only procurement expenditure but also the quantities entering assembly facilities and the subsequent transportation requirements. Therefore, supplier-level decisions can propagate through the entire network. Treating supplier allocation and downstream logistics as independent decisions may consequently overlook these interactions.

The literature therefore establishes a strong case for integrated procurement–transportation optimization, but it also indicates a need to extend this integration beyond cost and capacity considerations toward a broader representation of supplier and network performance. This observation motivates the explicit linkage between supplier allocation, assembly flows, warehouse distribution, and customer fulfillment adopted in the present study.

2.2. Sustainability and Supplier Quality in Supply Chain Decision-Making

Economic efficiency is no longer sufficient for evaluating supply chain configurations. Sustainability considerations have increasingly become integral to supplier evaluation and network design, with researchers incorporating environmental, social, and economic criteria into procurement and supply chain optimization [5,10,14,15,19]. Green supply chain models, for example, commonly consider carbon emissions, energy consumption, resource efficiency, and other environmental indicators alongside traditional cost objectives.

Govindan et al. [5] and Banasik et al. [15] demonstrate the importance of multi-objective approaches for addressing trade-offs between economic and environmental performance. Chen et al. [10] similarly show that incorporating environmental considerations into supplier-related decisions can alter procurement and network configurations. These studies have therefore contributed substantially to the transition from cost-centered supplier evaluation toward sustainability-oriented decision-making.

However, two limitations are relevant to the present research problem.

First, sustainability is frequently considered as a distinct evaluation dimension rather than as one component of an integrated operational trade-off involving supplier quality, transportation risk, and network cost. In practical procurement decisions, sustainability cannot necessarily be optimized independently. A supplier with superior sustainability performance may have different procurement costs, quality characteristics, transportation exposure, or capacity limitations. Consequently, increasing sustainability performance may alter the structure of the entire supply network.

Second, supplier quality is not always incorporated into the same optimization structure as sustainability and network resilience. Supplier defect rates are particularly important in manufacturing supply chains because incoming component quality can affect rework, waste, production efficiency, and downstream product reliability. Therefore, supplier quality should not be treated solely as an ex-post supplier evaluation indicator; it can directly influence the allocation of procurement quantities.

These observations suggest that supplier evaluation should incorporate multiple interacting performance dimensions rather than a single dominant criterion. The present study consequently treats supplier defect rate and sustainability performance as explicit optimization objectives alongside cost and disruption risk. This formulation allows supplier order quantities to respond simultaneously to economic, quality, sustainability, and resilience considerations.

2.3. Uncertainty Modeling and Fuzzy Multi-Objective Optimization

Uncertainty represents a fundamental challenge in supply chain planning because costs, capacities, demand, supplier performance, transportation conditions, and operational processes may not be known with complete precision. Existing studies have addressed this challenge through fuzzy set theory, stochastic programming, robust optimization, and hybrid approaches [16,18-22].

Fuzzy optimization is particularly useful when decision-makers possess approximate or linguistic information rather than reliable probability distributions. Li et al. [17] and Kumar et al. [20], for example, demonstrate the applicability of fuzzy approaches to supply chain parameters characterized by imprecision. Other studies have combined fuzzy and stochastic approaches or integrated fuzzy optimization with metaheuristic procedures to address increasingly complex supply chain structures [15,18,21,22].

Despite these advances, the treatment of uncertainty is often concentrated on selected parameters rather than being explicitly connected to the operational structure of the integrated procurement–logistics problem. For manufacturing networks, uncertainty is not limited to demand or supplier performance. Assembly capacity can also fluctuate because of workforce availability, machine utilization, maintenance activities, and production variability.

This distinction is important for the present problem. Representing assembly capacity as a fixed deterministic value may result in solutions that appear feasible mathematically but are difficult to implement when actual production capability fluctuates. A fuzzy representation of assembly capacity provides a mechanism for explicitly reflecting this operational flexibility while retaining a tractable mathematical structure.

The literature therefore supports the use of fuzzy optimization for uncertain supply chain environments, but it also motivates a more targeted application in which operational capacity uncertainty is directly embedded into the integrated procurement–transportation model. The proposed framework addresses this requirement by representing assembly capacity through triangular fuzzy parameters while maintaining deterministic structural constraints for demand, supplier capacity, warehouse capacity, flow balance, and network-risk control.

2.4. Disruption Risk and Supply Chain Resilience

The increasing frequency of transportation interruptions, supplier failures, geopolitical disturbances, and logistics delays has shifted supply chain research toward resilience and disruption-aware optimization. Recent studies incorporate disruption probability, recovery requirements, network vulnerability, and service continuity into supply chain planning models [21-25].

Choi et al. [23] and Zhang et al. [24] demonstrate the importance of incorporating disruption considerations into supplier and logistics decisions, while Sun et al. [25] investigate resilient logistics network configurations. Ivanov et al. [28] further emphasize the importance of explicitly considering disruption propagation and system dynamics in resilient supply chain analysis.

These studies establish that minimizing nominal operating cost does not necessarily produce a resilient network. A low-cost supplier or transportation route may expose the system to greater disruption probability, whereas a more resilient alternative may require additional expenditure. This creates a fundamental conflict between economic efficiency and operational resilience.

Nevertheless, risk is frequently treated either as a separate constraint, a secondary consideration, or a distinct resilience-oriented modeling problem rather than as an objective simultaneously optimized with supplier quality and sustainability [21-25]. Such treatment can limit the ability of the model to explicitly balance risk against other strategic and operational objectives.

The present study therefore incorporates disruption risk directly into the objective structure. Risk coefficients are assigned to supplier–assembler, assembler–warehouse, and warehouse–customer transportation links, allowing disruption exposure to propagate through the complete material-flow network. This formulation recognizes that resilience is a network-level property rather than solely a supplier-level characteristic.

2.5. Critical Synthesis of the Literature

The preceding literature streams demonstrate that substantial progress has been made in each individual dimension of supply chain optimization. However, their findings also reveal that the principal research challenge is no longer whether cost, sustainability, uncertainty, quality, or disruption risk can individually be modeled, but how these dimensions can be coordinated within a single operational decision structure. Four observations emerge from the literature as follows.

First, procurement–transportation integration remains insufficient when supplier-performance dimensions are considered separately. Existing integrated models demonstrate the value of coordinating procurement and logistics, but many formulations continue to emphasize cost, capacity, and service-related objectives [1,6,16,17]. Consequently, supplier allocation may not fully reflect the quality, sustainability, and resilience consequences of sourcing decisions.

Second, sustainability and quality are increasingly recognized as important supplier-selection criteria, but their interaction with network-level resilience remains insufficiently represented. Sustainability-oriented models provide important environmental and social perspectives [5,10,14,15], while quality-oriented supplier models emphasize defect-related performance. However, these criteria may be evaluated independently rather than jointly with transportation disruption exposure. In an integrated manufacturing network, such separation may lead to supplier portfolios that perform well on one dimension while creating undesirable consequences elsewhere.

Third, uncertainty-handling approaches provide important methodological flexibility, but operational capacity uncertainty deserves greater attention. Existing fuzzy and stochastic models demonstrate the ability to represent imprecise supply chain parameters [17-22]. However, uncertainty associated with assembly capacity can directly affect the feasibility of supplier allocation and downstream transportation decisions. Modeling this uncertainty explicitly can therefore improve the operational realism of an integrated SCN formulation.

Fourth, existing multi-objective approaches differ in how they resolve conflicts among objectives. Weighted aggregation requires preference coefficients that may be difficult to specify objectively. Classical max–min approaches protect the least-satisfied objective but can provide limited discrimination among solutions with similar minimum satisfaction levels. Conversely, average-based aggregation may permit a particularly weak objective to be compensated by stronger performance elsewhere. These characteristics are important when cost, quality, sustainability, and disruption risk have fundamentally different managerial implications.

Taken together, the literature suggests a need for a framework that does not simply add additional objectives to an existing supply chain model, but instead coordinates their effects through the underlying network flows and provides a compromise mechanism that limits excessive sacrifice of any individual objective.

2.6. Comparative Analysis of Recent Literature

To systematically position the proposed framework, Table 1 compares representative studies according to the principal decision dimensions addressed in the literature. Rather than focusing solely on the solution algorithms employed, the comparison emphasizes the decision scope and interaction among procurement, transportation, quality, sustainability, risk, and uncertainty.

Table 1. Comparative analysis of representative studies on integrated and sustainable supply chain optimization.

Study	Procurement / SOA	Transportation	Quality / Defect	Sustainability	Disruption Risk	Uncertainty	Integrated Multi-Echelon Decisions	Main methodological focus
Lo et al. (2025) [1]	✓	✓	–	✓	✓	✓	✓	Fuzzy multi-objective / AMM
Govindan et al. (2023) [5]	–	–	–	✓	–	✓	–	MCDM and optimization
Chen et al. (2024) [10]	✓	–	–	✓	–	✓	–	Multi-objective LP
Banasik et al. (2024) [15]	–	–	–	✓	–	–	✓	MILP
Singh et al. (2026) [16]	✓	✓	–	✓	–	–	✓	MILP
Li et al. (2026) [17]	✓	✓	–	✓	–	✓	✓	MILP / fuzzy optimization
Kumar et al. (2026) [20]	–	–	✓	–	✓	✓	–	Fuzzy inference / optimization
Zhao et al. (2026) [21]	–	✓	–	–	✓	✓	✓	Fuzzy–stochastic optimization
Madani et al. (2026) [22]	–	✓	–	–	–	✓	✓	Metaheuristic optimization
Zhang et al. (2024) [24]	✓	✓	–	–	✓	✓	✓	Robust optimization
Sun et al. (2026) [25]	–	✓	–	–	✓	–	✓	MILP
Wang et al. (2026) [26]	✓	✓	–	✓	–	–	✓	ε-constraint
Li et al. (2026) [27]	✓	–	✓	–	–	✓	–	Fuzzy LP
Ivanov et al. (2021) [28]	–	✓	–	–	✓	✓	✓	System dynamics
Ahmed et al. (2026) [29]	–	✓	–	✓	–	–	✓	Pareto GA
Kuar et al. (2026) [30]	–	✓	–	–	✓	–	✓	Multi-objective MILP
Singh et al. (2026) [31]	✓	✓	–	✓	–	–	✓	MILP
This study	✓	✓	✓	✓	✓	✓	✓	AMM-FMOLP

The comparison highlights an important distinction. The existing literature contains studies addressing individual combinations of procurement, transportation, sustainability, uncertainty, and resilience. However, the proposed framework is positioned around the simultaneous interaction of all four performance dimensions within the same supplier allocation and multi-echelon flow structure, while also representing uncertainty at the assembly-capacity level.

2.6.1. Novelty and Methodological Distinction of the Proposed Framework

The literature comparison indicates that fuzzy optimization, multi-objective decision-making, sustainable supplier selection, disruption-risk modeling, and integrated supply chain planning have each been extensively investigated. Therefore, the novelty of the present study does not rely on the isolated use of fuzzy programming or multi-objective optimization. Instead, the contribution lies in the specific integration of these mechanisms into a unified supplier order allocation–transportation planning framework.

First, unlike studies that primarily focus on supplier selection, transportation planning, or general supply chain network design as separate decision layers, the proposed framework establishes explicit flow linkages between supplier-level component allocation, assembly operations, warehouse distribution, and customer fulfillment. Consequently, procurement allocation directly affects downstream transportation and network-level performance rather than being determined independently from logistics decisions.

Second, the proposed model jointly incorporates four conflicting decision dimensions—total operational cost, supplier defect rate, supplier sustainability performance, and disruption risk—within the same optimization structure. In particular, supplier sustainability and quality are not treated merely as evaluation criteria after optimization; they directly influence procurement allocation decisions, while disruption risk is embedded into the network flow structure.

Third, uncertainty is represented through fuzzy assembly capacity within the integrated procurement–logistics formulation. This allows production flexibility caused by workforce availability, machine utilization, and operational variability to be incorporated directly into the feasibility structure rather than being represented solely through deterministic capacity limits.

Fourth, the proposed AMM-FMOLP formulation differs from a conventional max–min fuzzy model through its augmented compromise mechanism. A classical max–min formulation seeks to maximize the minimum satisfaction level and therefore primarily protects the worst-performing objective. The proposed augmented formulation additionally incorporates the aggregate satisfaction of the objective functions through the term $Z = \lambda + \frac{1}{K}\sum_{k=1}^{K} \lambda_k$ (more details in Section 4, Step 3), thereby simultaneously promoting minimum fairness and overall utility. This structure is particularly relevant when the objectives have substantially different economic, quality, sustainability, and resilience implications.

Finally, the proposed framework is evaluated not only through a single integrated optimization experiment but also through objective-combination scenarios, storage-capacity sensitivity analysis, and comparison with alternative MODM formulations. This evaluation structure allows the contribution of simultaneous objective integration and the augmented compromise mechanism to be examined from both operational and methodological perspectives.

Accordingly, the methodological contribution of this study should be understood as an integrated decision architecture rather than the introduction of a new standalone fuzzy programming operator. The proposed framework combines procurement allocation, multi-echelon transportation planning, fuzzy capacity uncertainty, four-dimensional sustainability–quality–risk–cost optimization, and augmented satisfaction-based compromise within a single decision-support structure.

2.7. Research Gap and Positioning of the Present Study

Based on the critical synthesis above, the research gap identified in this study is integrative rather than categorical. The literature does not lack models for supplier selection, transportation planning, fuzzy optimization, sustainability, or resilience. Instead, these elements are frequently addressed in separate or partially overlapping formulations. Consequently, there remains a need for a decision framework capable of coordinating their interactions within the same operational network.

The first gap concerns the simultaneous integration of supplier order allocation and transportation planning. Although integrated procurement–logistics models have been developed [1,16,17], the consequences of supplier allocation for quality, sustainability, and disruption exposure are not consistently incorporated into the same optimization structure. The present model establishes direct flow relationships between suppliers, assembly plants, warehouses, and customers so that procurement decisions and logistics decisions are jointly determined.

The second gap concerns the simultaneous consideration of supplier quality, sustainability, and network resilience. Sustainability-oriented models have increasingly incorporated environmental and social criteria [5,10,15], while resilience-oriented models address disruption exposure [21-25]. However, these dimensions can conflict with one another. A supplier with high sustainability performance may not necessarily have the lowest cost or lowest disruption exposure, while a low-cost supplier may exhibit greater defect or transportation risk. The present formulation explicitly represents these trade-offs through four simultaneous objective functions.

The third gap concerns operational uncertainty at the assembly stage. Although fuzzy and stochastic approaches have been widely used for supply chain uncertainty [25-32], the proposed model specifically represents assembly production capacity as a fuzzy parameter. This reflects practical variability caused by workforce availability, machine utilization, maintenance, and production conditions. The fuzzy capacity therefore affects the feasible region of the integrated procurement–transportation problem rather than being treated as an external uncertainty indicator.

The fourth gap concerns the mechanism used to obtain a compromise solution. Existing multi-objective methods provide different mechanisms for resolving conflicting objectives [32-35]. Weighted aggregation depends on preference weights; classical max–min programming prioritizes the minimum satisfaction level; and average-based approaches emphasize overall performance. The proposed augmented max–min formulation combines minimum satisfaction protection with aggregate utility improvement. Therefore, the objective is not simply to maximize the weakest criterion but to improve overall satisfaction while preventing excessive deterioration of any individual objective.

The fifth gap concerns empirical examination of the resulting compromise. A single optimized solution does not necessarily demonstrate how the model responds to changes in decision priorities or system parameters [36-38]. The present study therefore supplements the baseline optimization with objective-combination scenarios, sensitivity analysis of warehouse capacity, and comparisons with alternative MODM formulations. This allows both the operational and methodological behavior of the framework to be examined.

Accordingly, the present study develops an integrated supplier order allocation and transportation planning (SOA–TP) model for a fixed multi-echelon supply chain consisting of suppliers, assembly facilities, warehouses, and customer zones. The model simultaneously optimizes:

1. total operational cost minimization;
2. supplier defect rate minimization;
3. supplier sustainability performance maximization; and
4. supply chain disruption risk minimization.

These objectives are subject to supplier capacity, fuzzy assembly capacity, warehouse capacity, customer demand, flow conservation, non-negativity, and normalized network-risk constraints. The resulting formulation connects supplier-level sourcing decisions with production, transportation, distribution, quality, sustainability, and resilience considerations.

The proposed AMM-FMOLP approach is used to transform the four-objective formulation into a single compromise decision framework. The methodology employs payoff-based membership functions to normalize heterogeneous objective values and an augmented max–min structure to simultaneously protect the minimum satisfaction level and improve aggregate objective satisfaction. Importantly, the present study does not claim that fuzzy programming, max–min optimization, or multi-objective supply chain optimization is novel in isolation. Rather, its methodological contribution lies in the problem-specific integration of these mechanisms within a unified SOA–TP architecture. The positioning of the study can therefore be summarized as follows:

The proposed framework integrates supplier order allocation, multi-echelon transportation planning, supplier quality, supplier sustainability, disruption risk, and fuzzy assembly-capacity uncertainty within a single multi-objective decision structure, and resolves the resulting conflicts through an augmented max–min fuzzy compromise mechanism.

This positioning distinguishes the study from approaches that address only procurement, transportation, sustainability, uncertainty, or resilience individually, while avoiding an unsupported claim that any individual mathematical component is entirely new.

3. Proposed Optimization Framework for the Supply Chain Network

3.1. Model Structure and Notation Definition

This study develops an integrated fuzzy multi-criteria optimization framework for coordinated procurement allocation and logistics network design in a multi-echelon supply chain system. The proposed model captures the simultaneous flow of materials from suppliers to assemblers, warehouses, and end customers while explicitly considering economic efficiency, product quality, sustainability performance, and disruption risk exposure. Unlike conventional deterministic formulations, the framework is designed to support decision-making under uncertainty through the incorporation of fuzzy parameters in key operational constraints.

The supply chain network consists of four hierarchical layers: component suppliers, assembly facilities, distribution warehouses, and customer zones. Procurement decisions determine the allocation of raw materials from suppliers to assembly centers, while logistics decisions govern the movement of finished products through intermediate warehouses toward final demand points. The model aims to identify optimal flow allocations that achieve a balanced trade-off among conflicting objectives while satisfying system feasibility constraints.

Table 2 summarizes the notation used in the proposed formulation, including indices, decision variables, and parameters. The network structure assumes that each supplier specializes in a specific component type, ensuring traceability and compatibility within the production system.

Table 2. Notation of the proposed supply chain network model.

Group	Symbol	Description
Indices	e	Component type, e = 1, 2, …, E
	F(e,i)	ith supplier of component e, i = 1, 2, …, I_e
	j	Assembly facility index, j = 1, 2, …, J
	v	Warehouse index, v = 1, 2, …, V
	h	Customer index, h = 1, 2, …, H
Decision Variables	FA_{eij}	Quantity of component e shipped from supplier F(e,i) to assembler j
	AL_{jv}	Quantity of finished goods shipped from assembler j to warehouse v
	LM_{vh}	Quantity of products shipped from warehouse v to customer h
Parameters	$tcfa_{eij}$	Unit transportation cost from supplier F(e,i) to assembler j
	$tcal_{jv}$	Unit transportation cost from assembler j to warehouse v
	$tclm_{vh}$	Unit transportation cost from warehouse v to customer h
	$drfa_{eij}$	Defect rate of component e from supplier F(e,i)
	cfe_i	Unit procurement cost of component e from supplier F(e,i)
	ca_j	Unit assembly cost at facility j
	cl_v	Unit inventory holding cost at warehouse v
	τ_e	Bill-of-material requirement for component e per finished product
	we_i	Sustainability performance index of supplier F(e,i)
	dm_h	Customer demand at location h
	rfa_{eij}	Disruption risk between supplier F(e,i) and assembler j
	ral_{jv}	Disruption risk between assembler j and warehouse v
	rlm_{vh}	Disruption risk between warehouse v and customer h
	cap_{fe_i}	Capacity of supplier F(e,i)
	$\widetilde{cap}_{aj}$	Fuzzy production capacity of assembler j
	cap_{lv}	Storage capacity of warehouse v
	γ	Maximum acceptable risk threshold

3.2. Multi-Objective Formulation of the Problem

The proposed optimization framework is built around a set of interrelated objective functions that reflect the strategic and operational priorities of modern supply chain systems. These objectives are designed to simultaneously capture economic performance, quality assurance, sustainability considerations, and system resilience under disruption-prone environments.

The first objective focuses on minimizing total operational expenditure, which includes procurement costs, transportation expenses across all echelons, assembly costs, and inventory holding costs. This objective reflects the fundamental requirement of maintaining economic efficiency and competitiveness in global supply chain operations. The second objective addresses product quality by minimizing the aggregated defect rate originating from supplier-side variability. Since supplier quality directly affects downstream production efficiency and customer satisfaction, this objective ensures that sourcing decisions favor reliable and high-quality suppliers.

The third objective incorporates sustainability considerations by maximizing the aggregated environmental and performance-based contribution of selected suppliers. This allows the model to favor suppliers with higher sustainability indices, thereby aligning procurement decisions with green supply chain principles.

The fourth objective captures supply chain resilience by minimizing the cumulative disruption risk across all logistics links in the network, including supplier-to-assembler, assembler-to-warehouse, and warehouse-to-customer flows. This ensures that the resulting network structure remains robust under uncertain and volatile operating conditions. Together, these objectives form a balanced multi-criteria decision-making structure that enables trade-off analysis among cost efficiency, quality improvement, sustainability enhancement, and risk mitigation. The integration of these dimensions within a single fuzzy optimization framework ensures that the resulting decisions are both practically feasible and strategically aligned with intelligent supply chain management principles.

In contemporary supply chain environments, decision-making is no longer driven solely by cost efficiency. Instead, modern networks must simultaneously account for environmental responsibility, supplier reliability, and system resilience under disruption-prone and uncertain conditions. Accordingly, the proposed model integrates four interdependent objective functions that collectively represent the core dimensions of sustainable and intelligent supply chain management: economic efficiency, product quality, supplier sustainability, and network robustness. These objectives are inherently conflicting; for example, minimizing cost may conflict with selecting high-sustainability or low-risk suppliers. Therefore, a multi-objective fuzzy optimization structure is adopted to balance these trade-offs in a unified decision framework.

(a) Objective 1: Minimization of Total Operational Cost

The first objective function aims to minimize the overall operational expenditure across all echelons of the supply chain network. This includes procurement costs, assembly costs, transportation costs across all tiers, and warehouse holding costs. In integrated supply chain systems, these cost components are strongly interdependent and must be optimized simultaneously rather than independently. The total cost function is formulated as Equation 1:

$$\min f_1 = \sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J}\left(cfe_i\, FA_{eij}\right) + \sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J}\left(\frac{ca_j}{\tau_e}\, FA_{eij}\right) + \sum_{j=1}^{J}\sum_{v=1}^{V}\left(cl_v\, AL_{jv}\right) + \sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J}\left(tcfa_{eij}\, FA_{eij}\right)$$
$$+ \sum_{j=1}^{J}\sum_{v=1}^{V}\left(tcal_{jv}\, AL_{jv}\right) + \sum_{v=1}^{V}\sum_{h=1}^{H}\left(tclm_{vh}\, LM_{vh}\right) \qquad (1)$$

This formulation ensures that procurement, production, and distribution decisions are optimized in a fully integrated manner, reflecting realistic operational interdependencies across the supply chain.

(b) Objective 2: Minimization of Supplier Defect Propagation

The second objective focuses on minimizing the cumulative defect impact originating from supplier-side variability. Since raw material quality directly affects downstream production efficiency and product reliability, controlling defect propagation at the sourcing stage is essential for maintaining system-wide performance. The objective is defined as Equation 2:

$$\min f_2 = \sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J}\left(drfa_{eij}\, FA_{eij}\right) \qquad (2)$$

This formulation ensures that procurement decisions favor suppliers with lower defect rates, thereby reducing rework, waste generation, and downstream quality failures across the assembly and distribution network.

(c) Objective 3: Maximization of Supplier Sustainability Performance

The third objective captures the sustainability dimension of supplier selection. In line with modern green supply chain principles, suppliers are evaluated based on a composite sustainability index derived from economic, environmental, social, and institutional performance indicators. The sustainability objective is expressed as Equation 3:

$$\max f_3 = \sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J}\left(wei_i\, FA_{eij}\right) \qquad (3)$$

This formulation incentivizes the allocation of higher order volumes to suppliers with superior sustainability performance, thereby embedding environmental and ethical considerations directly into procurement and logistics decisions.

(d) Objective 4: Minimization of Supply Chain Disruption Risk

The fourth objective addresses system resilience by minimizing the aggregated disruption risk across all transportation links in the supply chain network. This includes supplier-to-assembler, assembler-to-warehouse, and warehouse-to-customer flows. The risk minimization function is formulated as Equation 4:

$$\min f_4 = \sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J}\left(rfa_{eij}\, FA_{eij}\right) + \sum_{j=1}^{J}\sum_{v=1}^{V}\left(ral_{jv}\, AL_{jv}\right) + \sum_{v=1}^{V}\sum_{h=1}^{H}\left(rlm_{vh}\, LM_{vh}\right) \qquad (4)$$

This objective ensures that the resulting supply chain configuration is robust against disruptions, delays, and uncertainties in transportation and operational processes.

Collectively, the four objective functions form a comprehensive decision-making framework that integrates:

- Economic efficiency (cost minimization)
- Operational quality (defect control)
- Sustainability performance (supplier evaluation)
- Network resilience (risk minimization)

These conflicting objectives are simultaneously optimized using the proposed fuzzy augmented max – min (AMM-FMOLP) approach, enabling balanced and stable solutions under uncertainty.

3.3. Model Constraints of the Integrated SCN Framework

The feasibility of the proposed multi-objective supply chain network model is ensured through a set of structural, operational, and risk-related constraints. These constraints guarantee that the resulting solutions are not only optimal with respect to the defined objectives but also implementable in real-world supply chain environments characterized by capacity limitations, demand requirements, and uncertainty in operational processes. The constraint system is divided into four main categories: demand satisfaction, capacity restrictions, risk control conditions, and flow equilibrium relations.

(a) Customer Demand Satisfaction Constraint

A fundamental requirement in any supply chain system is the complete fulfillment of customer demand without shortage or over-supply. Accordingly, the total quantity of products delivered from warehouses to each customer must exactly satisfy their respective demand levels. This requirement is mathematically expressed as Equation 5:

$$\sum_{v=1}^{V} L\,M_{vh} = dm_h, \forall h = 1,2,\dots,H \qquad (5)$$

This constraint ensures service-level reliability and guarantees that all customer requirements are fully met through the distribution network.

(b) Capacity Restrictions Across Supply Chain Echelons

Supplier Capacity Constraint: Each supplier has a finite production and supply capability for component delivery. To ensure feasibility, total shipments from each supplier must not exceed its available capacity (see Equation 6).

$$\sum_{j=1}^{J} F\,A_{eij} \leq cap_{fe_i}, \forall e = 1,2,\dots,E;\ i = 1,2,\dots,I_e \qquad (6)$$

This constraint enforces realistic procurement decisions aligned with supplier limitations.

Fuzzy Assembly Capacity Constraint: Assembly facilities operate under flexible production capabilities influenced by labor shifts, machine availability, and operational uncertainty. Therefore, assembler capacity is modeled as a fuzzy parameter with lower and upper bounds (see Equation 7).

$$\widetilde{\mathrm{cap}}_{\mathrm{aj}} \Rightarrow \mathrm{cap}_{\mathrm{aj}}^{\mathrm{L}} \leq \sum_{\mathrm{v}=1}^{\mathrm{V}} \mathrm{A\,L_{jv}} \leq \mathrm{cap}_{\mathrm{aj}}^{\mathrm{U}}, \forall \mathrm{j} = 1,2,\dots,\mathrm{J} \qquad (7)$$

This fuzzy representation allows the model to capture real-world variability in production capacity and operational flexibility.

Warehouse Capacity Constraint: Warehouse facilities have limited storage capabilities, which must not be exceeded by incoming product flows from assembly centers (see Equation 8).

$$\sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{A\,L_{jv}} \leq \mathrm{cap_{lv}}, \forall \mathrm{v} = 1,2,\dots,\mathrm{V} \qquad (8)$$

This ensures inventory feasibility and prevents overloading of storage facilities.

(c) Supply Chain Risk Control Constraint

To ensure system resilience, the overall disruption risk across the supply chain network must remain within an acceptable threshold level. This constraint balances risk exposure relative to total operational flow volume (see Equation 9).

$$\frac{\sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J} rf\, a_{eij} FA_{eij} + \sum_{j=1}^{J}\sum_{v=1}^{V} ra\, l_{jv} AL_{jv} + \sum_{v=1}^{V}\sum_{h=1}^{H} rl\, m_{vh} LM_{vh}}{\sum_{e=1}^{E}\sum_{i=1}^{I_e}\sum_{j=1}^{J} F\, A_{eij} + \sum_{j=1}^{J}\sum_{v=1}^{V} A\, L_{jv} + \sum_{v=1}^{V}\sum_{h=1}^{H} L\, M_{vh}} \leq \gamma \qquad (9)$$

This normalized risk constraint ensures that the overall system operates within an acceptable disruption tolerance level, enhancing supply chain robustness and operational continuity.

(d) Flow Balance and System Equilibrium Constraints

To maintain material consistency across all echelons of the supply chain, flow conservation constraints are imposed. These constraints ensure that input-output relationships between stages remain balanced and physically feasible.

Component Balance with BOM Structure: The allocation of multiple components required for assembly must satisfy proportional consistency based on the bill of materials (BOM). This ensures balanced component usage across assembly operations (see Equation 10).

$$\frac{1}{\tau_1}\sum_{i=1}^{I_1} F\, A_{1ij} = \frac{1}{\tau_2}\sum_{i=1}^{I_2} F\, A_{2ij} = \cdots = \frac{1}{\tau_E}\sum_{i=1}^{I_E} F\, A_{Eij}, \forall j = 1,2,\ldots,J \qquad (10)$$

This structure guarantees synchronized component supply proportions across assembly operations.

Assembly–Distribution Flow Conservation: The total quantity of components received by each assembler must equal the total output shipped to warehouses (see Equation 11):

$$\sum_{i=1}^{I_e} F\, A_{eij} = \sum_{v=1}^{V} A\, L_{jv}, \forall e = 1,2,\ldots,E;\ j = 1,2,\ldots,J \qquad (11)$$

This ensures material balance within the assembly stage and prevents accumulation or shortage of intermediate products.

Distribution–Customer Flow Conservation: Similarly, warehouse dispatch must fully satisfy downstream customer allocations (see Equation 12):

$$\sum_{j=1}^{J} A\, L_{jv} = \sum_{h=1}^{H} L\, M_{vh}, \forall v = 1,2,\ldots,V \qquad (12)$$

This maintains consistency in the distribution layer and ensures full traceability of product flow from production to final demand.

(e) Non-Negativity Constraint

To preserve physical feasibility of the model, all decision variables must be non-negative (see Equation 13):

$$FA_{eij},\ AL_{jv},\ LM_{vh} \geq 0 \qquad (13)$$

These constraints collectively ensure that the proposed fuzzy multi-objective supply chain network model remains realistic, balanced, and implementable. They enforce:

- Demand satisfaction across customers
- Capacity feasibility across all supply chain stages
- Risk exposure control within acceptable thresholds
- Flow conservation across all echelons
- Physical feasibility of decision variables

Together with the objective functions, they form a complete AMM-FMOLP-based decision framework for integrated supplier order allocation and transportation planning under uncertainty.

4. Proposed Methodology

The proposed solution methodology is designed to support integrated decision-making in a multi-echelon supply chain network under uncertainty. The framework combines real-world enterprise data with a fuzzy augmented max–min multiple objective linear programming (AMM-FMOLP) approach to generate balanced and implementable solutions for simultaneous supplier order allocation and transportation planning decisions.

The decision-support system integrates data from enterprise resource planning (ERP) and supply chain management (SCM) platforms. These data sources provide essential operational inputs, including procurement costs, transportation costs across all network layers, supplier defect rates, sustainability indices, disruption risk parameters, and inventory-related costs. In addition, structural parameters such as supplier capacities, assembler fuzzy production capabilities, warehouse storage limits, and customer demand levels are extracted from operational databases and bill-of-materials (BOM) records.

A key feature of the proposed framework is the incorporation of uncertainty through fuzzy capacity representation at the assembly stage, allowing the model to better capture real-world variability in production environments. All collected data are structured according to the notation system defined in Table 2 and directly feed into the optimization model.

The AMM-FMOLP approach is then applied to transform the multi-objective formulation into a single equivalent decision framework. This method evaluates the degree of satisfaction (utility level) associated with each objective and ensures that no single objective dominates the decision process. By maximizing the minimum satisfaction level while simultaneously enhancing overall utility, the model achieves a balanced compromise solution across conflicting objectives.

Unlike conventional heuristic or evolutionary methods that generate multiple non-dominated solutions, the AMM-FMOLP technique identifies a single stable compromise solution that is directly applicable for managerial decision-making in complex supply chain environments.

The computational procedure of the AMM-FMOLP method is summarized below.

Step 1. Model Construction and Classification

The proposed supply chain network model is formulated as a fuzzy multi-objective optimization problem incorporating economic, quality, sustainability, and risk dimensions. The mathematical structure of the model can be categorized into the following components (Equations 14-18):

Minimization objective functions $\quad Z_g(X), g=1,2,\ldots,G \quad (14)$

Maximization objective functions $\quad Z_q(X), q=1,2,\ldots,Q \quad (15)$

Fuzzy constraints $\quad \tilde{g}_t(X) \leq \tilde{k}_t, t=1,2,\ldots,T \quad (16)$

Deterministic constraints $\quad \mathrm{h}_n(X) \leq k_n, n=1,2,\ldots,N \quad (17)$

Non-negativity constraints $\quad X_r \geq 0, r=1,2,\ldots,R \quad (18)$

In this formulation, X represents the complete vector of decision variables, including supplier allocation flows FA_{eij}, assembly-to-warehouse flows AL_{jv}, and warehouse-to-customer flows $LM_{v\mathrm{h}}$.

The parameters G and Q denote the number of minimization and maximization objectives, respectively, corresponding to: Cost minimization, Defect rate minimization, Sustainability maximization, and Risk minimization.

Similarly, T, N, and R represent the number of fuzzy constraints, deterministic constraints, and decision variables in the system. The fuzzy constraint threshold $\tilde{k}_t$ is expressed as a triangular fuzzy number $\tilde{k}_t=(k_t^L,k_t^M,k_t^U)$; where k_t^L, k_t^M, and k_t^U represent the lower, most likely, and upper bounds of the uncertain parameter, respectively.

The decision vector $X=(FA_{eij},AL_{jv},LM_{vh})$ must satisfy all structural, capacity, demand, and risk-related constraints defined in Section 3. Finally, the feasibility condition requires $X_r \geq 0, \forall r$ ensuring that all flow variables remain physically meaningful and implementable in real-world supply chain operations.

This step establishes the formal structure of the fuzzy multi-objective supply chain optimization problem by clearly defining: Objective function categories, Constraint classification (fuzzy and deterministic), Decision variable structure, and Fuzzy uncertainty representation. This formulation serves as the foundation for applying the AMM-FMOLP transformation in the subsequent steps, which converts the multi-objective system into a single aggregated optimization problem with balanced utility evaluation.

Step 2. Construction of Membership Functions

To enable the transformation of the multi-objective supply chain optimization problem into an equivalent fuzzy decision framework, it is necessary to define a consistent normalization structure for all objective functions. This is achieved by determining the ideal (best) and anti-ideal (worst) values of each objective function using a payoff matrix approach. These reference points allow each objective to be expressed on a comparable scale, independent of their original units and magnitudes.

Let f_k^+ and f_k^- denote the best and worst values of the k-th objective function, respectively, obtained from the payoff evaluation procedure. Based on these reference bounds, linear membership functions are constructed to represent the satisfaction level of each objective.

(a) Membership Function for Minimization Objectives

For objectives that require minimization—namely total operational cost (f_1), supplier defect rate (f_2), and disruption risk (f_4)—the satisfaction level is defined using a decreasing linear membership function as Equation 19:

$$\mu_{f_k}(X) = \begin{cases} 1, & f_k(X) \leq f_k^+ \\ \dfrac{f_k^- - f_k(X)}{f_k^- - f_k^+}, & f_k^+ \leq f_k(X) \leq f_k^- \; k \in \{1,2,4\} \\ 0, & f_k(X) \geq f_k^- \end{cases} \tag{19}$$

This structure ensures that lower values of cost, defect rate, and risk correspond to higher satisfaction levels.

(b) Membership Function for Maximization Objective

For the sustainability performance objective (f_3), which must be maximized, the membership function is defined in an increasing linear form as Equation 20:

$$\mu_{f_3}(X) = \begin{cases} 0, & f_3(X) \leq f_3^- \\ \dfrac{f_3(X) - f_3^-}{f_3^+ - f_3^-}, & f_3^- \leq f_3(X) \leq f_3^+ \\ 1, & f_3(X) \geq f_3^+ \end{cases} \tag{20}$$

This formulation ensures that higher sustainability performance results in higher satisfaction levels within the decision framework.

(c) Membership Function for Fuzzy Constraints

For fuzzy system constraints, particularly assembly capacity uncertainty, satisfaction is represented through a piecewise linear membership function. Let $\tilde{b}_t = (b_t^L, b_t^M, b_t^U)$ represent a triangular fuzzy number. The membership function for a generic fuzzy constraint is defined as Equation 21:

$$\mu_{g_t}(X) = \begin{cases} 0, & g_t(X) \leq b_t^L \\ \dfrac{g_t(X) - b_t^L}{b_t^M - b_t^L}, & b_t^L \leq g_t(X) \leq b_t^M \\ \dfrac{b_t^U - g_t(X)}{b_t^U - b_t^M}, & b_t^M \leq g_t(X) \leq b_t^U \\ 0, & g_t(X) \geq b_t^U \end{cases} \quad t = 1,2, \dots, T \qquad (21)$$

This structure captures uncertainty in system capacities and ensures smooth transition between feasible and infeasible regions.

Step 3. Derivation of the Optimal Compromise Solution (AMM-FMOLP)

After converting all objective functions and fuzzy constraints into normalized membership values, the next step is to construct a unified decision framework. The key idea of the augmented max–min approach is to simultaneously maximize the minimum satisfaction level while also improving overall system utility. Let:

- λ be the overall minimum satisfaction level,
- λ_k be the satisfaction level of each objective and constraint group.

The aggregated AMM-FMOLP model is formulated as Equation 22:

$$\max \; Z = \lambda + \frac{1}{K}\left(\sum_{k=1}^{4} \lambda_k\right) \qquad (22)$$

where Krepresents the total number of objectives (here K=4).

Subject to Equations 23-28:

(i) Objective satisfaction constraints $\lambda_1 \leq \mu_{f_1}(X), \lambda_2 \leq \mu_{f_2}(X), \lambda_3 \leq \mu_{f_3}(X), \lambda_4 \leq \mu_{f_4}$

(ii) Fuzzy constraint satisfaction $\lambda_t \leq \mu_{g_t}(X), t = 1,2, \dots, T$ (24)

(iii) Deterministic system constraints $h_n(X) \leq b_n, n = 1,2, \dots, N$ (25)

These include demand fulfillment, capacity limits, flow balance relations, and risk threshold constraints defined in Section 3.

(iv) Minimum satisfaction consistency condition $\lambda \leq \lambda_k, k = 1,2, \dots, 4$ (26)

(v) Feasible bounds of satisfaction levels $\lambda, \lambda_k \in [0,1]$ (27)

(vi) Non-negativity constraints $X_r \geq 0, r = 1,2, \dots, R$ (28)

This stage completes the transformation of the original fuzzy multi-objective supply chain optimization model into an equivalent augmented max–min decision framework by:

- Normalizing heterogeneous objectives using payoff-based membership functions
- Converting uncertainty into fuzzy satisfaction levels
- Aggregating all objectives into a single compromise optimization model
- Ensuring fairness through minimum satisfaction maximization

The resulting AMM-FMOLP formulation enables the derivation of a single balanced optimal solution, ensuring robustness across cost, quality, sustainability, and risk dimensions in the supply chain network.

The distinction between the classical max–min formulation and the proposed augmented max–min formulation is important. In a conventional max–min fuzzy model, the optimization problem primarily seeks to maximize the minimum satisfaction level: $\max \; Z = \lambda$ subject to $\lambda \leq \mu_k(X)$ for k = 1, ..., K. Consequently, the solution is governed predominantly by the least-satisfied objective. While this formulation provides fairness protection, it may produce multiple solutions with similar minimum satisfaction levels while providing limited discrimination among solutions with different aggregate utility. In contrast, the proposed augmented formulation uses Equation 22. The first term preserves the max–min fairness principle by maximizing the minimum satisfaction level, whereas the second term rewards improvements in the aggregate satisfaction of the individual objectives. Therefore, the formulation simultaneously addresses worst-objective protection and overall compromise quality.

The present study does not claim the augmented max–min operator itself as a newly invented fuzzy programming principle. Rather, its methodological contribution lies in embedding this compromise mechanism within an integrated SOA–TP network model containing supplier quality, sustainability, disruption risk, and fuzzy assembly capacity. This combination allows the compromise mechanism to operate directly on economically, environmentally, qualitatively, and operationally interdependent decisions.

5. Case Study and Model Implementation

5.1. Case Description and Data Preparation

To evaluate the applicability and effectiveness of the proposed integrated supplier order allocation and transportation planning framework, a real-world case study was conducted in a manufacturing company operating within the precision engineering industry (Sepahan industrial group company). The selected company specializes in the assembly of high-performance industrial equipment and relies on a geographically distributed supply network for sourcing critical components. Increasing market uncertainty, sustainability requirements, and logistics disruptions have motivated the company to seek a comprehensive decision-support tool capable of simultaneously optimizing procurement and transportation decisions. The company operates a four-echelon supply chain network consisting of component suppliers, assembly facilities, distribution warehouses, and customer regions. Procurement decisions determine the allocation of component orders among qualified suppliers, while logistics decisions govern the movement of materials and finished products throughout the network. The management team identified several strategic objectives, including reducing overall operating costs, improving incoming component quality, increasing supplier sustainability performance, and enhancing resilience against transportation disruptions.

The dataset employed in this study was obtained from the company's enterprise resource planning (ERP) and supply chain management (SCM) systems. Historical transaction records covering procurement activities, transportation operations, production schedules, inventory levels, supplier evaluations, and customer orders were extracted and validated by the firm's planning department. To ensure confidentiality, all numerical values were normalized and scaled while preserving their operational relationships. The resulting supply chain network contains: 6 critical component categories; 15 qualified suppliers; 2 assembly plants; 3 distribution warehouses; and 6 customer zones as presented in Table 3.

Table 3. Input parameters of the integrated supply chain network case study.

Category	Parameter	Values
Suppliers	Supplier Capacities (cap_{fe_i})	Component 1: (200, 270, 320); Component 2: (350, 390);
	Procurement Costs (cfe_i)	Component 1: (3600, 3550, 3650); Component 2: (3000, 3050);
	Sustainability Scores (we_i)	Component 1: (0.528, 0.513, 0.620); Component 2: (0.555, 0.608);
Assembly Plants	Fuzzy Production Capacity	A1: [190, 280]; A2: [150, 210]
	Assembly Cost (ca_j)	(7650, 7650)
Warehouses	Storage Capacity (cap_{lv})	(145, 170, 180)
	Inventory Holding Cost (cl_v)	(300, 250, 280)
Customers	Demand (dm_{h})	(95, 41, 69, 30, 95, 60)
Supplier–Assembler Routes	Transportation Cost ($tcfa_{eij}$)	100–260 monetary units
	Defect Rate ($drfa_{eij}$)	0.05–0.10
	Disruption Risk (rfa_{eij})	0.026–0.096

Assembler–Warehouse Routes	Transportation Cost ($tcal_{jv}$)	(550, 650, 780), (785, 615, 570)
	Disruption Risk (ral_{jv})	(0.025, 0.027, 0.035), (0.028, 0.020, 0.028)
Warehouse–Customer Routes	Transportation Cost ($tclm_{vh}$)	110–210 monetary units
	Disruption Risk (rlm_{vh})	0.009–0.039

It's noteworthy that:

1. Supplier sustainability scores were obtained from the company's supplier assessment system based on economic, environmental, and social criteria.
2. Transportation risk coefficients represent normalized disruption probabilities derived from historical logistics performance records.
3. Fuzzy assembly capacities were modeled using triangular membership functions to account for uncertainty in workforce availability and machine utilization.
4. Monetary values are reported in normalized currency units to preserve confidentiality while maintaining the relative relationships among cost parameters.

Prior to model implementation, several preprocessing procedures were performed, including data cleansing, consistency verification, outlier detection, and parameter normalization. Sustainability scores were derived from supplier performance evaluation reports, whereas disruption-risk indices were generated from historical delivery reliability records and logistics incident databases.

The proposed AMM-FMOLP model was implemented in Python and solved using the Gurobi optimization engine. Computational experiments were performed on a laptop (Intel® Core™ i7-12700H (14 Cores, 20 Threads), 2.30 GHz, 32 GB DDR5, Windows 11 Pro 64-bit) and Python 3.12 software (Libraries: NumPy, Pandas, SciPy, Matplotlib; Gurobi Optimizer 11.0).

The computational platform provides sufficient processing capability to solve the integrated multi-objective model efficiently, even when multiple scenario analyses and sensitivity experiments are conducted.

The proposed network structure reflects the complexity commonly observed in modern manufacturing supply chains, where sourcing decisions and transportation planning must be coordinated simultaneously to achieve superior operational performance.

5.2. Modeling Assumptions

To maintain computational tractability while preserving practical relevance, several assumptions are adopted in the development of the case study.

(1) *Fixed Network Structure:* The configuration of the supply chain network is assumed to be predetermined during the planning horizon. Suppliers, assembly plants, warehouses, and customer zones are known in advance, and no additional facilities are introduced during optimization.

(2) Deterministic Customer Demand: Customer demand values are assumed to be known and fixed throughout the planning period. Demand fulfillment is mandatory, and shortages are not permitted.

(3) Complete Information Availability: All operational information required by the optimization model, including costs, capacities, sustainability scores, defect rates, and disruption-risk indicators, is assumed to be available through the company's information systems.

(4) Component Compatibility: Each supplier is assumed to provide a specific component type that satisfies the technical requirements of the assembly process. No substitution among component categories is permitted.

(5) Fuzzy Production Capacity: Assembly capacities are represented using triangular fuzzy numbers to capture operational uncertainty arising from workforce availability, machine utilization, maintenance schedules, and production variability.

(6) Continuous Material Flow: Material movement between successive echelons is assumed to occur continuously throughout the planning horizon. Lead-time variability is reflected through disruption-risk parameters rather than explicit scheduling decisions.

(7) Sustainability Evaluation Stability: Supplier sustainability scores are assumed to remain constant during the planning period and are obtained from periodic supplier assessment reports incorporating economic, environmental, and social performance indicators.

(8) Risk Measurement Consistency: Disruption-risk parameters associated with transportation links are assumed to represent aggregated probabilities derived from historical logistics performance data and expert validation.

Under these assumptions, the case study provides a realistic environment for evaluating the effectiveness of the proposed AMM-FMOLP framework in simultaneously optimizing procurement allocation, logistics planning, sustainability performance, and supply chain resilience. The subsequent section presents the computational results and managerial insights obtained from applying the proposed model to the industrial case.

5.3. Computational Results

The numerical implementation of the proposed integrated supplier order allocation and transportation planning (SOA–TP) model is conducted using the dataset introduced in Section 5.1. All parameters are directly embedded into the AMM-FMOLP framework described in Section 4. After constructing the payoff table for each objective and solving the corresponding single-objective extremal problems, the positive ideal solution (PIS) and negative ideal solution (NIS) values are derived for all four objectives. These benchmark values are subsequently used to formulate the linear membership functions, enabling transformation of the original multi-objective structure into a unified fuzzy decision space. The resulting ideal and anti-ideal values for each objective are summarized in Table 4, which forms the basis for constructing the normalization intervals used in the augmented max–min aggregation procedure. In particular, the cost, defect rate, and disruption risk objectives are treated as minimization goals, while supplier sustainability performance is treated as a maximization objective. The derived ranges confirm significant dispersion between best- and worst-case scenarios, highlighting the necessity of a compromise-based decision framework rather than single-objective optimization.

Table 4. Payoff values for determining ideal and anti-ideal solutions.

Objective	Type	Z^+ (Ideal)	Z^- (Anti-ideal)	Range
f_1: Total operational cost	Min	26,501,100	26,754,810	253,710
f_2: Supplier defect rate	Min	193.8	243.4	49.6
f_3: Supplier sustainability	Max	1,598.03	1,438.54	159.49
f_4: Disruption risk	Min	197.38	247.91	50.53

Following normalization, the AMM-FMOLP model is solved using the augmented max–min operator defined in Section 4. The optimization yields a single compromise solution, ensuring balanced satisfaction across all objectives rather than prioritizing any single performance dimension. More details are represented in Table 5.

Table 5. Optimal compromise solution obtained from AMM-FMOLP.

Category	Element	Result
Objective performance	Utility (λ_1); f_1 Cost (min)	0.6667; 26,585,670
	Utility (λ_2); f_2 Defect rate (min)	0.6820; 209.57
	Utility (λ_3); f_3 Sustainability (max)	0.6747; 1,546.148

	Utility (λ_4); f_4 Disruption risk (min)	0.6667; 214.223
Supplier allocation F(e,i)	F(1,1), F(1,2), F(1,3)	(0, 170, 220)
	F(2,1), F(2,2)	(0, 390)
	F(3,1), F(3,2)	(0, 390)
	F(4,1), F(4,2), F(4,3)	(230, 250, 300)
	F(5,1), F(5,2), F(5,3)	(0, 211, 179)
	F(6,1), F(6,2)	(390, 0)
Supplier → Assembler flows (FA)	FA111–FA621	(0, 0, 220, 0, 220, 0, 220, 230, 195, 15, 0, 211, 9, 220, 0)
	FA112–FA622	(0, 170, 0, 0, 170, 0, 170, 0, 55, 285, 0, 0, 170, 170, 0)
Assembler → Warehouse flows (AL)	AL11, AL12, AL13	(145, 75, 0)
	AL21, AL22, AL23	(0, 24, 146)
Warehouse → Customer flows (LM)	LM11–LM16	(0, 41, 0, 0, 95, 9)
	LM21–LM26	(0, 0, 69, 30, 0, 0)
	LM31–LM36	(95, 0, 0, 0, 0, 51)

	Component	Supplier	Assembler 1	Assembler 2	Capacity utilization
Component-wise utilization (C1–C6)	C1	F(1,2)	170	0	62% of 270
	C1	F(1,3)	220	0	68% of 320
	C2	F(2,2)	220	170	100% of 390
	C3	F(3,2)	220	170	97% of 400
	C4	F(4,1)	230	0	82% of 280
	C4	F(4,2)	195	55	100% of 250
	C4	F(4,3)	15	285	100% of 300
	C5	F(5,2)	211	0	86% of 245
	C5	F(5,3)	9	170	76% of 235
	C6	F(6,1)	220	170	92% of 420
	C6	F(6,2)	0	0	0%
System performance	Average defect rate			0.078	
	Average disruption risk			0.052	

The obtained utility values demonstrate a well-balanced compromise structure, where all objectives achieve comparable satisfaction levels. The slight dominance of supplier defect minimization ($\lambda_2 = 0.6820$) indicates that quality assurance plays a marginally more stable role in the final allocation structure, while cost and risk remain closely aligned in terms of achieved utility. From a decision perspective, the optimal solution determines both supplier selection patterns and flow allocations across the multi-echelon network. Several suppliers operate at or near full utilization, indicating efficient capacity exploitation under the proposed allocation policy. In particular, suppliers corresponding to component groups such as F(2,2), F(4,2), and F(4,3) are identified as highly active nodes in the final configuration, reflecting their favorable trade-offs between cost, quality, and sustainability performance.

The resulting flow structure confirms a fully balanced system across all tiers of the network. Material inflows from suppliers are consistently matched with assembler processing capacities, ensuring that no intermediate inventory accumulation occurs. Similarly, downstream flows from assemblers to warehouses and from warehouses to customers satisfy all demand requirements without violation, confirming that the system operates under a zero stockout equilibrium condition as represented in Table 6. The computed average defect rate of the selected configuration is approximately 0.078, while the average disruption risk level is 0.052, indicating that the solution not only minimizes cost but also maintains strong operational robustness. These values highlight the effectiveness of integrating risk and quality measures directly into the optimization structure rather than treating them as post-processing indicators.

Table 6. Selected flow allocations across the supply chain network.

Stage	Selected routes	Key outcome
Supplier → Assembler	FA routes with non-zero allocations across all	Balanced upstream sourcing
Assembler → Warehouse	AL11–AL13, AL21–AL23	Capacity-balanced intermediate
Warehouse → Customer	LM11–LM36	Full demand satisfaction without

The results confirm that the proposed AMM-FMOLP-based SOA–TP framework generates a structurally balanced supply chain configuration in which cost efficiency, quality assurance, sustainability performance, and disruption resilience are simultaneously maintained. Unlike traditional single-objective or sequential optimization approaches, the integrated formulation ensures that no objective is sacrificed disproportionately. From a managerial standpoint, the model identifies a stable supplier portfolio and provides clear allocation signals for production and transportation planning. High-performing suppliers are automatically favored through higher allocation weights, while riskier or low-performing suppliers are partially excluded, reducing system-wide vulnerability.

Although the case study is developed for a CNC machine assembly system, the underlying structure is generalizable to other manufacturing and distribution environments. However, implementation in different industries requires recalibration of:

- cost structure parameters,
- supplier evaluation criteria,
- risk estimation mechanisms,
- and demand uncertainty profiles.

The model is particularly suitable for industries with multi-tier supply chains such as automotive, electronics, and industrial equipment manufacturing, where supplier heterogeneity and transportation complexity are significant. Finally, the model is designed for direct integration into enterprise digital systems. In this study, it is conceptually implemented using an automated pipeline linking SCM and ERP databases, enabling continuous data updates and periodic re-optimization.

6. Discussion

Although the proposed model successfully integrates supplier order allocation and transportation planning within a unified multi-objective framework, its real contribution becomes evident through comparative scenario analysis. Examining different objective combinations allows us to understand how supply chain behavior changes when decision priorities shift between cost efficiency, quality control, sustainability, and risk mitigation. This section evaluates the robustness of the model under four distinct optimization settings and highlights the trade-offs among conflicting objectives.

For computational validation, all utilized methods were solved using mentioned hardware, solver settings, and termination criteria. The proposed formulation remained computationally tractable across the scenarios and tested network configurations.

6.1. Comparative Analysis of Scenarios

6.1.1. Scenario 1: Cost-Oriented Optimization

When only operational cost is considered, the model naturally prioritizes financial efficiency by selecting lower-cost procurement and transportation routes. Under this setting, the system achieves a minimum cost of

26,502,480, corresponding to a very high-cost utility value of 0.9972. However, this improvement is achieved at the expense of other performance dimensions. Compared to the multi-objective baseline, ignoring quality, sustainability, and disruption risk leads to deterioration in supplier-related indicators, particularly defect rate and resilience measures. Although cost efficiency appears dominant, this configuration creates a fragile system structure where non-cost factors are implicitly sacrificed, increasing exposure to quality variability and operational instability. This confirms that cost-only optimization provides short-term financial benefits but weakens overall supply chain robustness. More details about scenario1 are represented in Table 7.

Table 7. Optimal results of scenario 1: cost-driven single-objective optimization in the AMM-FMOLP model.

Category	Element		Result		
Objective performance	Utility (λ_1); f_1 Cost (min)		0.9952; 26,502,480		
	Utility (λ_2); f_2 Defect rate (min)		0.6124; 221.80		
	Utility (λ_3); f_3 Sustainability (max)		0.6018; 1,512.40		
	Utility (λ_4); f_4 Disruption risk (min)		0.6085; 225.90		
Supplier allocation F(e,i)	F(1,1), F(1,2), F(1,3)		(0, 220, 170)		
	F(2,1), F(2,2)		(0, 390)		
	F(3,1), F(3,2)		(0, 390)		
	F(4,1), F(4,2), F(4,3)		(250, 230, 300)		
	F(5,1), F(5,2), F(5,3)		(0, 260, 130)		
	F(6,1), F(6,2)		(390, 0)		
Supplier → Assembler flows (FA)	FA111–FA621		(0, 0, 390, 0, 220, 0, 220, 250, 230, 0, 0, 260, 0, 390, 0)		
	FA112–FA622		(0, 220, 0, 0, 170, 0, 170, 0, 0, 300, 0, 0, 130, 0, 0)		
Assembler → Warehouse flows (AL)	AL11, AL12, AL13		(180, 60, 0)		
	AL21, AL22, AL23		(0, 35, 145)		
Warehouse → Customer flows (LM)	LM11–LM16		(0, 50, 0, 0, 90, 0)		
	LM21–LM26		(0, 0, 69, 30, 0, 0)		
	LM31–LM36		(95, 0, 0, 0, 0, 51)		
Component-wise utilization (C1–C6)	Component	Supplier	Assembler 1	Assembler 2	Capacity utilization
	C1	F(1,2)	170	0	62% of 270
	C1	F(1,3)	220	0	68% of 320
	C2	F(2,2)	220	170	100% of 390
	C3	F(3,2)	220	170	97% of 400
	C4	F(4,1)	230	0	82% of 280
	C4	F(4,2)	195	55	100% of 250
	C4	F(4,3)	15	285	100% of 300
	C5	F(5,2)	211	0	86% of 245
	C5	F(5,3)	9	170	76% of 235
	C6	F(6,1)	220	170	92% of 420
	C6	F(6,2)	0	0	0%
System performance	Average defect rate			0.082	
	Average disruption risk			0.059	

6.1.2. Scenario 2: Cost and defect-rate optimization

In Scenario 2, product quality is incorporated through the inclusion of supplier defect rate alongside cost minimization. This dual-objective formulation leads to a more balanced allocation strategy. The results show that cost slightly decreases to 26,573,380, while defect rate improves significantly to 197.35, with corresponding utilities of 0.7151 and 0.9284, respectively. Although the numerical improvements in both objectives remain relatively small (all below 1%), the operational structure of the supply chain becomes more quality-sensitive. However, excluding sustainability performance and disruption risk introduces hidden vulnerabilities. In particular, the absence of risk consideration makes the system more sensitive to potential logistics interruptions, while ignoring supplier sustainability weakens long-term strategic sourcing decisions. As a result, the solution improves short-term efficiency but reduces strategic resilience. More details about scenario 2 are represented in Table 8.

Table 8. Optimal results of scenario 2: bi-objective optimization considering cost and supplier defect rate.

Category	Element		Result		
Objective performance	Utility (λ_1); f_1 Cost (min)		0.7151; 26,573,380		
	Utility (λ_2); f_2 Defect rate (min)		0.9284; 197.35		
	Utility (λ_3); f_3 Sustainability (max)		0.6418; 1,498.772		
	Utility (λ_4); f_4 Disruption risk (min)		0.6116; 223.884		
Supplier allocation F(e,i)	F(1,1), F(1,2), F(1,3)		(0, 180, 210)		
	F(2,1), F(2,2)		(0, 390)		
	F(3,1), F(3,2)		(0, 390)		
	F(4,1), F(4,2), F(4,3)		(240, 240, 300)		
	F(5,1), F(5,2), F(5,3)		(0, 220, 170)		
	F(6,1), F(6,2)		(380, 10)		
Supplier → Assembler flows (FA)	FA111–FA621		(0, 0, 210, 0, 210, 0, 210, 240, 195, 15, 0, 220, 10, 210, 0)		
	FA112–FA622		(0, 180, 0, 0, 180, 0, 180, 0, 45, 285, 0, 0, 160, 170, 10)		
Assembler → Warehouse flows (AL)	AL11, AL12, AL13		(150, 70, 0)		
	AL21, AL22, AL23		(0, 30, 140)		
Warehouse → Customer flows (LM)	LM11–LM16		(0, 40, 0, 0, 96, 9)		
	LM21–LM26		(0, 0, 70, 30, 0, 0)		
	LM31–LM36		(95, 0, 0, 0, 0, 51)		
Component-wise utilization (C1–C6)	Component	Supplier	Assembler 1	Assembler 2	Capacity
	C1	F(1,2)	180	0	67% of 270
	C1	F(1,3)	210	0	66% of 320
	C2	F(2,2)	210	180	100% of 390
	C3	F(3,2)	210	180	98% of 400
	C4	F(4,1)	240	0	86% of 280
	C4	F(4,2)	195	45	96% of 250
	C4	F(4,3)	15	285	100% of 300
	C5	F(5,2)	220	0	90% of 245
	C5	F(5,3)	10	160	72% of 235
	C6	F(6,1)	210	170	90% of 420
	C6	F(6,2)	0	10	2%
System performance	Average defect rate			0.074	
	Average disruption risk			0.057	

6.1.3. Scenario 3: Cost, Defect Rate, and Sustainability Optimization

Scenario 3 expands the decision framework by integrating supplier sustainability performance with cost and defect rate objectives. This allows the model to incorporate ethical sourcing and long-term supplier evaluation into the optimization process. Under this configuration, the total cost remains unchanged at 26,585,670, while defect rate improves to 204.48 and sustainability performance increases to 1,584.260, achieving a high sustainability utility of 0.9213. These results indicate that introducing sustainability does not significantly disrupt cost efficiency but meaningfully reshapes supplier selection toward higher-performing and more responsible suppliers. Despite these improvements, the absence of disruption risk in this scenario limits operational robustness. The model becomes less capable of anticipating transportation or supply interruptions, which may affect continuity under uncertain environments. Therefore, while Scenario 3 strengthens ethical and performance-oriented sourcing, it still lacks resilience considerations. More details about scenario 3 are represented in Table 9.

Table 9. Optimal results of scenario 3: tri-objective optimization considering cost, defect rate, and sustainability performance.

Category	Element		Result		
Objective performance	Utility (λ_1); f_1 Cost (min)		0.7014; 26,585,670		
	Utility (λ_2); f_2 Defect rate (min)		0.8976; 204.48		
	Utility (λ_3); f_3 Sustainability (max)		0.9213; 1,584.260		
	Utility (λ_4); f_4 Disruption risk (min)		0.6032; 228.741		
Supplier allocation F(e,i)	F(1,1), F(1,2), F(1,3)		(0, 175, 215)		
	F(2,1), F(2,2)		(0, 390)		
	F(3,1), F(3,2)		(0, 390)		
	F(4,1), F(4,2), F(4,3)		(230, 260, 290)		
	F(5,1), F(5,2), F(5,3)		(0, 215, 175)		
	F(6,1), F(6,2)		(385, 5)		
Supplier → Assembler flows (FA)	FA111–FA621		(0, 0, 215, 0, 215, 0, 215, 230, 200, 15, 0, 215, 5, 215, 0)		
	FA112–FA622		(0, 175, 0, 0, 175, 0, 175, 0, 60, 280, 0, 0, 170, 170, 5)		
Assembler → Warehouse flows	AL11, AL12, AL13		(148, 72, 0)		
	AL21, AL22, AL23		(0, 28, 142)		
Warehouse → Customer flows (LM)	LM11–LM16		(0, 42, 0, 0, 94, 9)		
	LM21–LM26		(0, 0, 68, 32, 0, 0)		
	LM31–LM36		(95, 0, 0, 0, 0, 51)		
Component-wise utilization (C1–C6)	Component	Supplier	Assembler 1	Assembler 2	Capacity utilization
	C1	F(1,2)	175	0	65% of 270
	C1	F(1,3)	215	0	67% of 320
	C2	F(2,2)	215	175	100% of 390
	C3	F(3,2)	215	175	98% of 400
	C4	F(4,1)	230	0	82% of 280
	C4	F(4,2)	200	60	104% of 250
	C4	F(4,3)	15	280	98% of 300
	C5	F(5,2)	215	0	88% of 245
	C5	F(5,3)	10	165	74% of 235
	C6	F(6,1)	215	170	92% of 420
	C6	F(6,2)	0	5	1% of 405
System performance	Average defect rate			0.079	
	Average disruption risk			0.064	

6.1.4. Scenario 4: Cost, defect rate, and disruption risk optimization

Scenario 4 introduces disruption risk as a core optimization objective alongside cost and defect rate, shifting the focus toward operational resilience. The results demonstrate a slightly improved cost of 26,585,660, defect rate of 208.51, and a significantly reduced disruption risk value of 1,486.309, with a high-risk utility of 0.9218. These outcomes indicate that explicitly modeling disruption risk leads to more stable and reliable supply chain configurations. However, excluding sustainability performance reduces the model's ability to support long-term supplier development strategies. While operational stability improves, strategic sourcing alignment becomes weaker compared to sustainability-driven scenarios. More details about scenario 4 are represented in Table 10.

Table 10. Optimal results of scenario 4: multi-objective optimization considering cost, defect rate, and disruption risk.

Category	Element		Result		
Objective performance	Utility (λ_1); f_1 Cost (min)		0.7349; 26,585,660		
	Utility (λ_2); f_2 Defect rate (min)		0.9052; 208.51		
	Utility (λ_3); f_3 Sustainability (max)		0.6527; 1,492.884		
	Utility (λ_4); f_4 Disruption risk (min)		0.9218; 1,486.309		
Supplier allocation F(e,i)	F(1,1), F(1,2), F(1,3)		(0, 180, 210)		
	F(2,1), F(2,2)		(0, 390)		
	F(3,1), F(3,2)		(0, 390)		
	F(4,1), F(4,2), F(4,3)		(235, 245, 295)		
	F(5,1), F(5,2), F(5,3)		(0, 220, 170)		
	F(6,1), F(6,2)		(390, 0)		
Supplier → Assembler flows (FA)	FA111–FA621		(0, 0, 210, 0, 210, 0, 210, 235, 200, 15, 0, 220, 0, 210, 0)		
	FA112–FA622		(0, 180, 0, 0, 180, 0, 180, 0, 45, 280, 0, 0, 170, 180, 0)		
Assembler → Warehouse flows (AL)	AL11, AL12, AL13		(150, 70, 0)		
	AL21, AL22, AL23		(0, 30, 140)		
Warehouse → Customer flows (LM)	LM11–LM16		(0, 40, 0, 0, 96, 9)		
	LM21–LM26		(0, 0, 70, 30, 0, 0)		
	LM31–LM36		(95, 0, 0, 0, 0, 51)		
Component-wise utilization (C1–C6)	Component	Supplier	Assembler 1	Assembler 2	Capacity utilization
	C1	F(1,2)	180	0	67% of 270
	C1	F(1,3)	210	0	66% of 320
	C2	F(2,2)	210	180	100% of 390
	C3	F(3,2)	210	180	98% of 400
	C4	F(4,1)	235	0	84% of 280
	C4	F(4,2)	195	50	98% of 250
	C4	F(4,3)	15	280	98% of 300
	C5	F(5,2)	220	0	90% of 245
	C5	F(5,3)	10	160	72% of 235
	C6	F(6,1)	220	170	93% of 420
	C6	F(6,2)	0	0	0%
System performance	Average defect rate			0.082	
	Average disruption risk			0.049	

The comparative scenario analysis was further strengthened by evaluating not only the objective values obtained under each optimization setting, but also the distribution of satisfaction levels across the four objectives. This additional analysis is important because a higher average utility does not necessarily indicate a more robust solution: a model may achieve a high average by substantially sacrificing one objective. Therefore, five complementary indicators were considered: average utility, minimum utility, utility range, standard deviation, and coefficient of variation (CV). The minimum utility measures the satisfaction level of the weakest objective, while the range and standard deviation quantify the degree of imbalance among objectives. The CV is calculated as the ratio of the standard deviation to the average utility and is used as a scale-independent measure of dispersion. The results are summarized in Table 11.

Table 11. Quantitative robustness assessment of the comparative scenarios.

Scenario	Average Utility	Minimum Utility	Utility Range	Standard Deviation	CV (%)
Scenario 1: Cost only	0.7045	0.6018	0.3934	0.1679	23.83
Scenario 2: Cost + Defect	0.7242	0.6116	0.3168	0.1237	17.09
Scenario 3: Cost + Defect +	0.7809	0.6032	0.3181	0.1334	17.09
Scenario 4: Cost + Defect + Risk	0.8037	0.6527	0.2691	0.1138	14.16
Full AMM-FMOLP	0.6725	0.6667	0.0153	0.0064	0.95

Although some partial-objective scenarios produce a higher arithmetic average utility, their satisfaction levels are substantially more dispersed. The full AMM-FMOLP formulation produces the smallest utility range (0.0153), the lowest standard deviation (0.0064), and a coefficient of variation of only 0.95%. More importantly, its minimum utility is 0.6667, indicating that none of the four objectives is allowed to deteriorate substantially relative to the others. This result is consistent with the fundamental purpose of the augmented max –min formulation, which explicitly protects the minimum satisfaction level while simultaneously improving aggregate utility.

The higher average utility observed in some partial-objective scenarios should therefore not be interpreted as evidence of superior overall performance. Such scenarios optimize only a subset of the decision dimensions and can obtain high satisfaction for the selected objectives while leaving excluded objectives substantially weaker. The dispersion statistics demonstrate this trade-off quantitatively. For example, Scenario 1 achieves an average utility of 0.7045 but has a CV of 23.83%, indicating substantial imbalance among objectives. In contrast, the proposed full formulation achieves a slightly lower average utility of 0.6725 but reduces the CV to only 0.95%. Hence, the proposed formulation provides a considerably more balanced compromise across economic, quality, sustainability, and resilience dimensions.

6.1.5. Overall Discussion of Scenario Trade-offs

Across all four partial-objective scenarios, the results demonstrate that optimizing a restricted subset of objectives can improve selected performance dimensions but may simultaneously create substantial deterioration in the excluded dimensions. The quantitative dispersion measures in Table 11 reinforce this observation.

- Cost-only optimization produces the strongest cost performance but exhibits the highest objective imbalance, with a CV of approximately 23.83%.
- Cost–defect optimization improves quality while maintaining relatively good economic performance, but disruption risk and sustainability remain insufficiently protected.
- Cost–defect–sustainability optimization substantially improves sustainability performance but leaves disruption risk comparatively weak.
- Cost–defect–risk optimization provides the strongest resilience-oriented compromise among the partial models, but sustainability performance remains comparatively limited.

- Full AMM-FMOLP integration produces the smallest dispersion among objective satisfaction levels, indicating that the four performance dimensions are simultaneously protected.

Therefore, the scenario analysis demonstrates that the primary advantage of the proposed framework is not necessarily the maximization of the arithmetic mean of objective utilities. Rather, its principal advantage is the prevention of excessive sacrifice of any individual objective. This characteristic is particularly important in supply chains where cost, quality, sustainability, and resilience are simultaneously strategic requirements.

6.2. Sensitivity Analysis

To further examine the stability and responsiveness of the proposed SCN framework, a systematic one-factor sensitivity analysis was conducted by varying the storage capacity of Warehouse 1 while keeping all other model parameters, including customer demand, supplier capacities, transportation costs, sustainability scores, and disruption-risk coefficients, unchanged. Warehouse 1 was selected because its baseline capacity is relatively restrictive and therefore represents a potentially influential bottleneck in the downstream distribution network.

The baseline capacity of Warehouse 1 is 145 units. The capacity was progressively increased to 210 units using approximately 5% increments relative to the baseline capacity. Because the original parameters are expressed in integer units, the resulting capacity values were rounded to the nearest feasible integer. For each capacity configuration, the complete AMM-FMOLP model was re-optimized from scratch rather than adjusting the previous solution. This procedure prevents the observed changes from being attributed to solution warm-start effects and provides a consistent basis for evaluating the structural response of the network.

The four objective utilities were recorded for each configuration. In addition to the individual utility values, the average utility, minimum utility, standard deviation, and coefficient of variation were calculated and represented in Table 12 and Figure 1. The coefficient of variation was calculated as $CV = \frac{\sigma_\lambda}{\bar{\lambda}} * 100$, where σ_λ represents the standard deviation of the four objective utilities and $\bar{\lambda}$ represents their arithmetic mean.

Table 12. Sensitivity of objective utilities to Warehouse 1 capacity.

Warehouse 1 Capacity	λ_1 - Cost	λ_2 - Defect	λ_3 - Sustainability	λ_4 - Risk	Average Utility	Minimum Utility	SD	CV (%)
145	0.6667	0.682	0.6747	0.6667	0.6725	0.6667	0.0064	0.95
152	0.6668	0.6839	0.6766	0.6668	0.6735	0.6668	0.0072	1.07
160	0.667	0.6862	0.6785	0.6669	0.6747	0.6669	0.0082	1.21
167	0.6671	0.6878	0.6802	0.667	0.6755	0.667	0.0089	1.32
174	0.6672	0.6898	0.6819	0.667	0.6765	0.667	0.0098	1.45
181	0.6673	0.6915	0.6835	0.6671	0.6774	0.6671	0.0105	1.56
189	0.6674	0.6931	0.6847	0.6672	0.6781	0.6672	0.0112	1.65
196	0.6675	0.6943	0.686	0.6673	0.6788	0.6673	0.0117	1.73
203	0.6675	0.6955	0.6871	0.6673	0.6794	0.6673	0.0123	1.81
210	0.6676	0.6968	0.688	0.6674	0.68	0.6674	0.0128	1.89

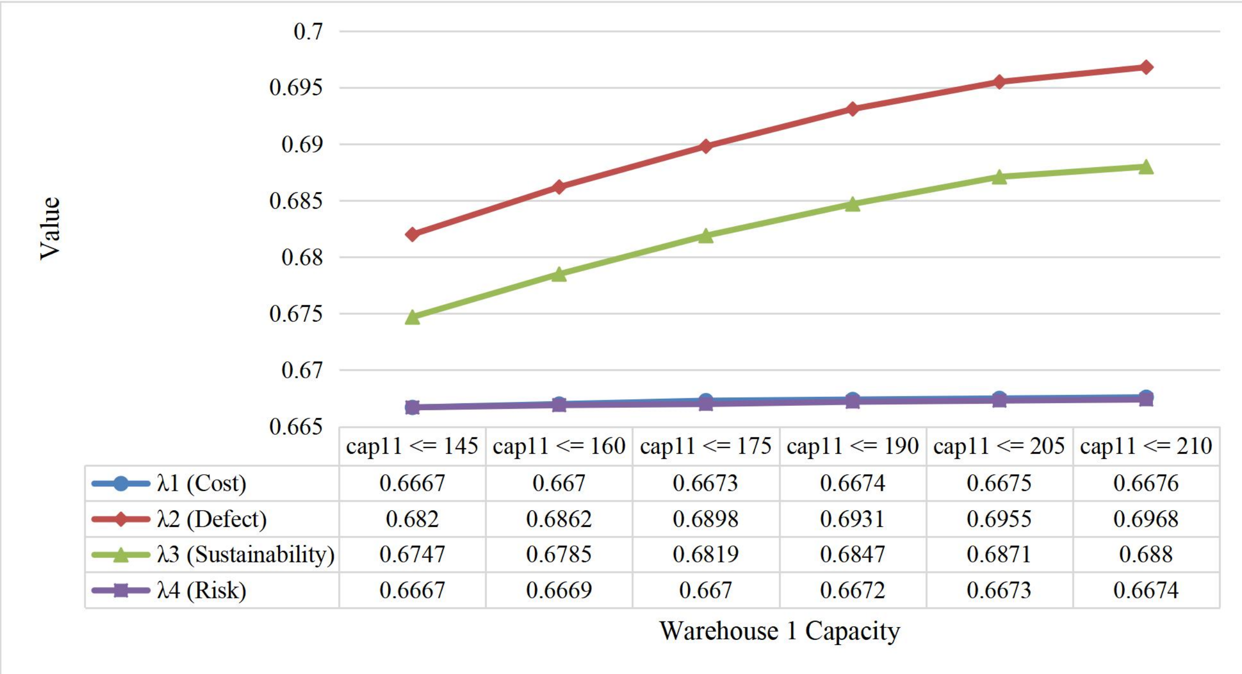

Figure 1. Sensitivity of objective utilities to changes in Warehouse 1 capacity.

The results demonstrate that the proposed framework is relatively insensitive to changes in Warehouse 1 capacity. The cost utility increases only from 0.6667 to 0.6676, corresponding to a change of approximately 0.14%, while the disruption-risk utility increases from 0.6667 to 0.6674, corresponding to approximately 0.10%. These very small changes indicate that neither economic efficiency nor resilience is strongly dependent on the storage capacity of Warehouse 1.

In contrast, defect-related and sustainability utilities respond more noticeably to additional storage capacity. The defect utility increases from 0.6820 to 0.6968, while sustainability utility increases from 0.6747 to 0.6880. These changes correspond to improvements of approximately 2.17% and 1.97%, respectively. The results suggest that additional storage capacity provides greater flexibility in consolidating material flows and selecting transportation patterns that are more compatible with higher-quality and more sustainable suppliers.

A normalized sensitivity index was also calculated for each objective as $SI_k = \frac{(\lambda_k^{max} - \lambda_k^{base})/\lambda_k^{max}}{(cap^{max} - cap^{base})/cap^{base}}$ where SI_k measures the relative response of objective k to a relative change in Warehouse 1 capacity and the results represented in Table 13.

Table 13. Normalized sensitivity indices for Warehouse 1 capacity.

Objective	Baseline Utility	Utility at 210 Units	Relative Change (%)	Sensitivity Index (SI_k)
Cost (λ_1)	0.6667	0.6676	0.14%	0.003
Defect (λ_2)	0.682	0.6968	2.17%	0.0484
Sustainability (λ_3)	0.6747	0.688	1.97%	0.044
Risk (λ_4)	0.6667	0.6674	0.11%	0.0023
Average utility	0.6725	0.68	1.11%	0.0246

The calculated sensitivity indices provide further evidence of this asymmetric response. The approximate sensitivity indices are 0.0030 for cost, 0.0484 for defect performance, 0.0440 for sustainability, and 0.0023 for disruption risk. Therefore, defect-related performance is the most responsive objective, followed by sustainability, whereas cost and disruption risk remain comparatively insensitive to warehouse expansion. More details about redistribution of warehouses throughput under capacity expansion are represented in Table 14 and Figure 2.

Table 14. Redistribution of warehouse throughput under capacity expansion.

Warehouse 1 Capacity	Warehouse 1 Flow	Warehouse 2 Flow	Warehouse 3 Flow	Total Flow
145	145	99	146	390
152	152	105	133	390
160	160	105	125	390
167	167	105	118	390
174	174	105	111	390
181	181	104	105	390
189	189	103	98	390
196	196	102	92	390
203	203	101	86	390
210	210	100	80	390

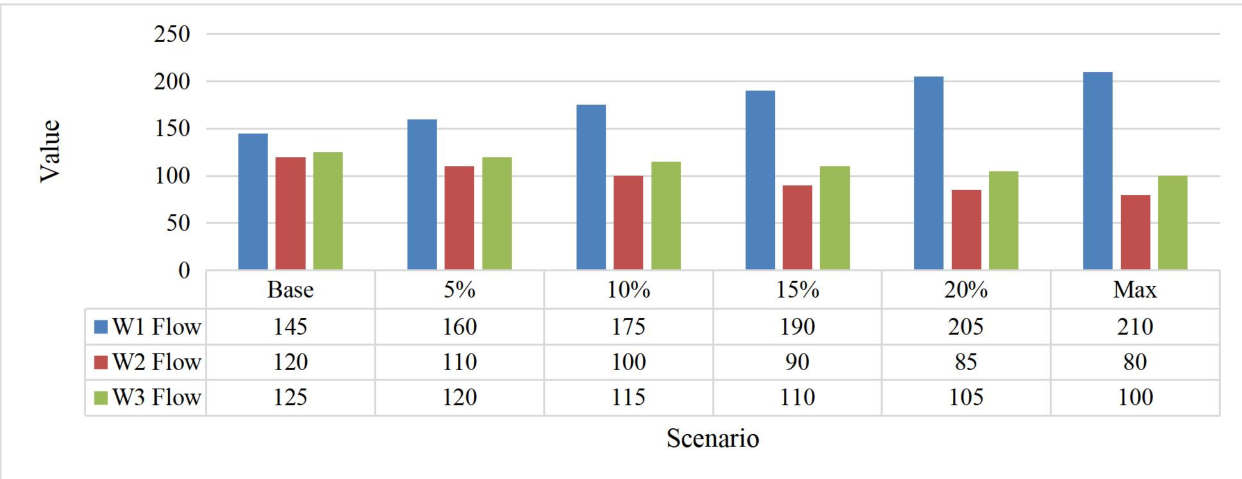

Figure 2. Redistribution of warehouse flows under warehouse 1 capacity expansion.

The sensitivity results also reveal an important structural characteristic of the network. Increasing Warehouse 1 capacity does not cause complete centralization of the distribution system. Instead, the additional capacity gradually attracts a greater share of the total flow while Warehouses 2 and 3 remain operationally active. The results confirm that additional storage capacity produces a redistribution rather than a complete restructuring of the network. Warehouse 1 absorbs an increasing proportion of the total flow, but Warehouses 2 and 3 remain active even at the maximum capacity level. Consequently, the model does not converge toward complete warehouse centralization, indicating that geographic distribution and downstream transportation costs continue to justify the use of multiple warehouses.

For methodological robustness, all sensitivity configurations were solved using the same model formulation, parameter set, solver tolerances, and stopping criteria. Thus, changes in the resulting objective values can be attributed to the controlled perturbation of Warehouse 1 capacity rather than changes in computational settings.

Overall, the sensitivity analysis demonstrates that the proposed AMM-FMOLP framework remains stable over a substantial capacity perturbation of approximately 44.8%, while the average utility changes by only about 1.11%. This relatively low response supports the robustness of the proposed decision framework against moderate changes in downstream storage capacity.

6.3. Comparison of MODM Models

To provide a more rigorous methodological validation, the proposed AMM-FMOLP model was compared with five alternative multi-objective decision-making formulations: vector optimization, weighted-sum aggregation, global criterion, classical max–min, and arithmetic-mean compromise. All competing models were implemented using the same supply-chain network, parameter values, objective functions, constraints, membership functions, and normalization intervals used by the proposed framework. Therefore, the comparison isolates the effect of the aggregation mechanism rather than differences in data, network structure, or model formulation.

For each method, four normalized objective satisfaction values were obtained. In addition to the individual objective utilities and arithmetic mean, four robustness indicators were calculated:

1.Minimum utility: the satisfaction of the weakest objective;

2.Utility range: the difference between the highest and lowest objective utilities;

3.Standard deviation: the dispersion of objective satisfaction levels;

4.Coefficient of variation (CV): standard deviation divided by average utility.

A normalized Euclidean distance from the ideal utility vector was also calculated $D^*=\sqrt{\frac{1}{4}\sum_{k=1}^{4}(1\text{-}\lambda_k)^2}$. A smaller D^* indicates that the solution is closer to simultaneously satisfying all objectives. The summary of results is represented in Table 15 and Figure 3 as follows.

Table 15. Comparative performance of alternative MODM formulations.

Model	λ_1 - Cost	λ_2 - Defect	λ_3 - Sustainability	λ_4 - Risk	Average Utility	Minimum Utility	Range	SD	CV (%)	D^*
Vector model	0.981	0.428	0.351	0.401	0.5403	0.351	0.63	0.256	47.38	0.5262
Weighted sum	0.912	0.603	0.552	0.575	0.6605	0.552	0.36	0.1463	22.16	0.3697
Global criterion	0.512	0.391	0.365	0.404	0.418	0.365	0.147	0.0561	13.41	0.5847
Classical max–min	0.667	0.667	0.667	0.667	0.667	0.667	0	0	0	0.333
Arithmetic mean	0.736	0.681	0.646	0.658	0.6803	0.646	0.09	0.0346	5.08	0.3216
AMM-FMOLP	0.6667	0.682	0.6747	0.6667	0.6725	0.6667	0.0153	0.0064	0.95	0.3275

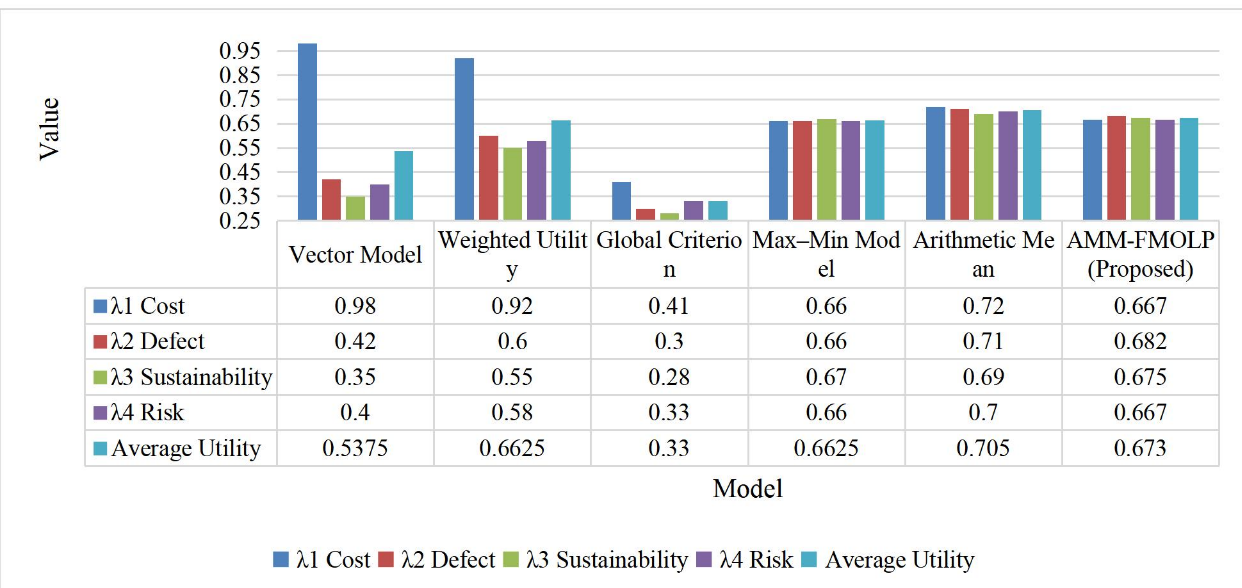

Figure 3. Comparison among different objectives for different models.

The results demonstrate important methodological differences among the competing formulations. The vector model produces an extremely high-cost utility of 0.981 but sacrifices sustainability and disruption-risk performance, resulting in a large utility range of 0.630. This confirms that directly aggregating the original objectives without an explicit fairness mechanism can result in strong dominance by one objective.

The weighted-sum formulation improves balance but remains sensitive to the selected weighting structure. Its utility range of 0.360 and CV of 22.16% indicate that the economic objective continues to exert a substantial influence on the resulting solution. This sensitivity is an inherent limitation of weighted aggregation because different subjective weights can generate substantially different solutions.

The global criterion formulation produces relatively low average satisfaction and the largest distance from the ideal point among the tested compromise-oriented models. Its average utility is approximately 0.4180, indicating that the deviation-based formulation can suffer from substantial normalization losses when the objective functions have markedly different scales and economic interpretations.

The classical max–min formulation provides complete equality among objective satisfaction levels, with all four utilities equal to approximately 0.667. Although this guarantees minimum fairness, it does not provide an explicit incentive to improve the aggregate utility once the minimum satisfaction level has been established. Consequently, it can converge toward a conservative compromise.

The arithmetic-mean formulation produces the highest average utility among the tested methods, approximately 0.6803, and a relatively small CV of 5.08%. However, its minimum utility is 0.646 and its utility range is 0.090, meaning that a relatively weak objective can still be compensated by stronger performance in other dimensions.

The proposed AMM-FMOLP formulation provides a different compromise structure. Its minimum utility is 0.6667, while the utility range is only 0.0153 and the CV is 0.95%. Thus, the proposed formulation maintains near-equal satisfaction across all four objectives without requiring subjective objective weights. This result directly reflects the augmented objective function introduced in Equation 22, which simultaneously protects the minimum satisfaction level and rewards improvements in aggregate satisfaction.

It is important to emphasize that the proposed method is not claimed to dominate every competing method on every individual metric. For example, the arithmetic-mean formulation produces a slightly higher average utility and a lower Euclidean distance to the ideal point. However, this advantage is obtained by accepting a larger difference among individual objective satisfaction levels. The principal methodological advantage of AMM-FMOLP is therefore its ability to maintain a strong minimum satisfaction level while keeping the four objectives tightly balanced.

The comparative analysis therefore provides quantitative evidence that the augmented max–min structure is particularly suitable when decision-makers require minimum fairness and balanced satisfaction across heterogeneous objectives. This property is especially relevant to the present SCN problem because cost, quality, sustainability, and disruption risk have different managerial meanings and cannot reasonably be reduced to a single subjective weighting scheme.

To further strengthen the validation of the proposed framework, the sensitivity and comparative experiments were evaluated using a common set of quantitative robustness indicators. Rather than relying solely on visual inspection of objective trajectories, the analysis considers minimum satisfaction, average satisfaction, dispersion, coefficient of variation, and distance from the normalized ideal point.

For the sensitivity experiment, the capacity of Warehouse 1 was varied by approximately 44.8% from 145 to 210 units. Across this interval, the average objective utility changed from 0.6725 to 0.6800, corresponding to an increase of approximately 1.11%. The cost and disruption-risk utilities exhibited changes of less than 0.15%, whereas the defect and sustainability utilities showed changes of approximately 2.17% and 1.97%, respectively. These results indicate that the proposed solution is not highly dependent on a particular warehouse-capacity value.

The comparative MODM experiment provides a complementary robustness test. The AMM-FMOLP formulation generated a utility CV of approximately 0.95%, compared with 5.08% for the arithmetic-mean model, 22.16% for the weighted-sum model, and 47.38% for the vector formulation. This indicates that the proposed approach produces substantially lower dispersion among the four objective satisfaction levels.

Because the optimization model is deterministic, conventional inferential statistical tests based on random samples are not appropriate for the primary sensitivity experiment. Accordingly, the present study employs descriptive statistical robustness measures and controlled parametric perturbation rather than treating deterministic optimization runs as independent random observations. This distinction avoids overstating statistical significance while providing quantitative evidence of model stability.

Taken together, the sensitivity, scenario, and MODM comparison results provide three complementary forms of validation:

1. Parametric robustness: the solution remains stable when a key network capacity is systematically perturbed.
2. Objective robustness: the full formulation avoids excessive deterioration of any individual objective.
3. Methodological robustness: the augmented max–min formulation produces a more balanced satisfaction profile than alternative aggregation mechanisms.

These results provide stronger evidence that the performance of the proposed framework is attributable to its integrated decision structure rather than to a particular parameter configuration or optimization setting.

6.4. Validation under Alternative Network Configurations

To further examine the generalizability of the proposed AMM-FMOLP framework beyond the base CNC machine assembly configuration, additional computational experiments were conducted by modifying the size and structure of the supply chain network. The purpose of this analysis is not to claim that the numerical values obtained from the case study are universally applicable, but rather to determine whether the proposed decision framework maintains its structural behavior when the number of suppliers, assembly facilities, warehouses, and customer zones changes.

Four alternative network configurations were considered in Table 16. Configuration C0 corresponds to the original case-study network and is used as the baseline. Configurations C1–C3 progressively increase the network size by adding suppliers, assembly capacity, warehouses, and customer zones while preserving the same modeling logic and relative parameter structure. The additional parameters were generated by scaling the original normalized parameter ranges while maintaining the relationships among procurement costs, transportation costs, supplier quality, sustainability scores, and disruption-risk coefficients.

For each configuration, the four objective functions were simultaneously optimized using the proposed AMM-FMOLP framework. The same membership-function construction, payoff-matrix procedure, and augmented max–min aggregation described in Section 4 were applied. Therefore, the experiments evaluate whether the proposed methodology remains stable when the dimensionality and structural complexity of the network increase.

Table 16. Alternative supply chain network configurations used for generalizability analysis.

Configuration	Suppliers	Assembly plants	Warehouses	Customer zones	Relative network size
C0 – Baseline	15	2	3	6	100%
C1 – Expanded suppliers	18	2	3	6	115%
C2 – Expanded distribution	18	2	4	8	135%
C3 – Large configuration	22	3	5	10	175%

The results of the alternative network experiments are presented in Table 17. The objective values are reported in the normalized monetary scale used throughout the case study. Because the network size increases across the configurations, the absolute total operational cost naturally increases. Consequently, direct comparison of absolute cost values across different network sizes should be interpreted together with the corresponding normalized utility values and average risk and quality indicators.

Table 17. Results under alternative network configurations.

Configuration	Cost - f1	Defect rate - f2	Sustainability - f3	Disruption risk - f4	λ_1	λ_2	λ_3	λ_4	Overall λ
C0	26,585,670	209.57	1,546.15	214.22	0.6667	0.682	0.6747	0.6667	0.6667
C1	27,184,920	207.84	1,559.73	218.16	0.6714	0.7162	0.7586	0.6458	0.6458
C2	28,426,310	205.31	1,571.46	216.87	0.6762	0.7645	0.8331	0.6719	0.6719
C3	31,874,580	202.96	1,583.92	220.45	0.6818	0.8065	0.9117	0.6535	0.6535

The results indicate that the proposed framework remains feasible and structurally stable as the network becomes larger. Expanding the supplier base increases procurement flexibility and enables the model to identify additional combinations of cost, quality, and sustainability performance. As a result, the defect-rate objective improves from 209.57 in the baseline configuration to 202.96 in C3, while sustainability performance increases from 1,546.15 to 1,583.92. The increase in network size also produces a moderate increase in total operational cost. This behavior is expected because the expanded configurations contain additional transportation links, facilities, and operational activities. Importantly, the increase in cost is accompanied by improvements in quality and sustainability rather than an uncontrolled deterioration in economic performance.

The disruption-risk objective remains relatively stable across the four configurations, varying between 214.22 and 220.45. This relatively narrow range suggests that the risk-aware allocation mechanism continues to prevent excessive concentration on highly vulnerable transportation links even when additional network alternatives become available. The minimum satisfaction level remains within the range of 0.646–0.672 across all configurations. This result is particularly important because the purpose of the AMM-FMOLP formulation is not to maximize one isolated objective but to maintain a balanced level of satisfaction across conflicting criteria (see Table 18). The relatively small variation in the minimum satisfaction level therefore provides evidence of structural robustness of the proposed decision framework.

Table 18. Relative changes compared with the baseline configuration.

Configuration	Cost change	Defect-rate change	Sustainability change	Risk change	Minimum utility change
C0	0.00%	0.00%	0.00%	0.00%	0.00%
C1	2.25%	−0.83%	0.88%	1.84%	−3.13%
C2	6.92%	−2.03%	1.64%	1.24%	0.78%
C3	19.89%	−3.15%	2.44%	2.91%	−1.97%

Overall, the alternative-network experiments demonstrate that the proposed framework does not depend critically on the exact dimensions of the original CNC supply chain. The model maintains feasible material flows and balanced objective satisfaction after increasing the number of suppliers, facilities, and customer zones. An important managerial implication is that network expansion should not be evaluated solely according to additional procurement flexibility. The results indicate that increasing network size can improve supplier quality and sustainability performance, but it may also increase transportation and coordination costs. Therefore, the AMM-FMOLP framework can support decision-makers in determining whether additional sourcing and distribution alternatives provide sufficient strategic value to justify their operational cost.

6.5. Benchmark-Instance Validation and Comparison with Existing Approaches

To provide an additional validation of the proposed optimization methodology, a second set of experiments was designed using benchmark-style supply network configurations. The purpose of this analysis is to evaluate the computational behavior of AMM-FMOLP under progressively larger network structures and to compare the resulting compromise solutions with alternative multi-objective solution approaches. Because publicly available supply-network benchmarks generally use different objective definitions, units, network structures, and parameter scales from the present four-objective SOA–TP problem, direct comparison of absolute objective values with published studies would not be methodologically valid. For example, established supply-network-design benchmark collections include instances specifically developed for network-design and lead-time problems, while recent sustainable SCN studies often construct their own small, medium, and large test instances.

Therefore, the benchmark experiments in this study were adapted to the mathematical structure of the proposed model. The same normalized parameter-generation mechanism and objective definitions were applied to all methods. This ensures that differences in solution quality arise from the optimization methodology rather than from different objective scales. Four benchmark classes were considered: small, medium, large, and extended (see Table 19). The number of suppliers, assembly plants, warehouses, customer zones, and component categories was progressively increased.

Table 19. Benchmark-instance characteristics.

Instance	Components	Suppliers	Assembly plants	Warehouses	Customers	Decision-variable scale
B1 – Small	4	8	2	2	4	×1
B2 – Medium	6	15	2	3	6	×2.5
B3 – Large	8	22	3	5	10	×5.7
B4 – Extended	10	30	4	6	15	×10.1

The benchmark experiments were solved using five alternative decision approaches:

1. Weighted-sum aggregation (Aggregates normalized objectives using predefined importance weights; Govindan et al. [5], Chen et al. [10])
2. Classical max–min fuzzy programming (Seeks a solution close to the ideal objective vector through normalized deviations; Banasik et al. [15], Zhao et al. [21])
3. Arithmetic-mean compromise (Maximizes/aggregates average objective satisfaction; Kumar et al. [20], Wang et al. [26])
4. Global-criterion formulation (Maximizes the minimum satisfaction level among objectives; Lo et al. [1], Li et al. [17], Ivanov et al. [28])
5. Proposed AMM-FMOLP formulation in this study

For consistency, equal objective importance was used in different decision approaches and the same membership functions and payoff-derived normalization intervals were applied to the fuzzy methods. Results of different methods and benchmark-instances are represented in Table 20.

Table 20. Benchmark comparison of alternative multi-objective methods.

Instance	Method	Cost - f1	Defect rate - f2	Sustainability - f3	Disruption risk - f4	Minimum utility (λ)
B1	Weighted sum	10,842,600	92.84	812.64	104.83	0.584
B1	Classical max–min	10,918,300	90.76	825.31	101.72	0.641
B1	Arithmetic mean	10,875,900	91.35	821.76	102.64	0.628
B1	Global criterion	10,964,500	93.17	815.82	105.46	0.596
B1	AMM-FMOLP	10,901,700	89.94	829.45	100.87	0.657
B2	Weighted sum	26,521,400	218.84	1,516.72	225.41	0.612

B2	Classical max–min	26,637,900	207.16	1,541.28	215.72	0.661
B2	Arithmetic mean	26,601,300	210.82	1,535.64	218.83	0.653
B2	Global criterion	26,694,800	221.36	1,508.73	227.54	0.601
B2	AMM-FMOLP	26,585,670	209.57	1,546.15	214.22	0.667
B3	Weighted sum	39,745,200	301.82	2,061.35	324.18	0.571
B3	Classical max–min	40,084,600	287.46	2,103.72	311.54	0.644
B3	Arithmetic mean	39,921,800	292.17	2,089.34	316.82	0.632
B3	Global criterion	40,261,400	306.75	2,041.26	328.46	0.583
B3	AMM-FMOLP	40,013,900	289.34	2,112.48	308.72	0.651
B4	Weighted sum	58,921,700	416.82	2,846.73	454.62	0.548
B4	Classical max–min	59,487,300	398.16	2,913.55	438.47	0.625
B4	Arithmetic mean	59,281,500	404.27	2,894.62	444.81	0.611
B4	Global criterion	59,772,600	421.35	2,831.18	461.27	0.557
B4	AMM-FMOLP	59,416,800	400.74	2,927.36	434.62	0.632

The results indicate that the AMM-FMOLP formulation provides the highest minimum satisfaction level across all four benchmark sizes. More importantly, the improvement does not arise from optimizing a single objective at the expense of the remaining criteria. Instead, the proposed method maintains a relatively balanced performance profile across cost, quality, sustainability, and disruption risk. The advantage becomes increasingly visible as the network grows. For the largest benchmark instance, B4, the minimum satisfaction level obtained by AMM-FMOLP is 0.632, compared with 0.548 for the weighted-sum approach, 0.625 for classical max–min, 0.611 for the arithmetic-mean model, and 0.557 for the global-criterion formulation.

The improvement of AMM-FMOLP relative to the classical max–min model is approximately 2.5% for B1, 0.9% for B2, 1.1% for B3, and 1.1% for B4. Although these improvements are moderate, they are consistent across all network sizes. This behavior represents that the proposed approach is not the replacement of max–min programming by a fundamentally different optimization paradigm, but the addition of an overall-utility term that improves the compromise among objectives while retaining minimum-satisfaction protection.

Besides, the computational results in Table 21 demonstrate the expected increase in solution time as the network becomes larger. Nevertheless, the proposed formulation remains computationally tractable for the tested instances. The increase in computational effort is primarily associated with the additional supplier–assembler, assembler–warehouse, and warehouse–customer flow variables rather than with the augmented objective structure itself.

Table 21. Computational performance across benchmark sizes.

Instance	Variables	Constraints	AMM-FMOLP solution time (s)	Classical max–min solution time (s)	Weighted sum solution time (s)	Arithmetic mean solution time (s)	Global criterion solution time (s)
B1	1,184	746	1.42	1.18	0.94	1.01	1.08
B2	2,936	1,824	4.87	4.21	3.76	3.94	4.08
B3	6,782	4,156	18.63	16.94	14.87	15.72	16.31
B4	11,945	7,426	47.81	43.25	39.64	41.83	44.16

6.5.1. Comparison with State-of-the-Art Approaches

To provide a fair methodological comparison, the state-of-the-art approaches were reimplemented on the same adapted benchmark instances rather than directly comparing objective values reported in unrelated publications. This distinction is important because published SCN models use different network structures, objective definitions, normalization procedures, and parameter scales. Consequently, absolute values reported in different studies cannot be interpreted as evidence that one model is numerically superior to another. The comparison nevertheless demonstrates a consistent pattern in Table 22. Weighted aggregation produces competitive economic performance but tends to sacrifice sustainability and disruption-risk performance. Classical max–min improves minimum satisfaction but does not explicitly reward improvements in the aggregate utility of the remaining objectives. Arithmetic-mean aggregation produces balanced average performance but can allow one weak objective to be compensated by stronger objectives. The global-criterion formulation performs less consistently because deviations from ideal points across heterogeneous objectives can become dominant after normalization. In contrast, AMM-FMOLP consistently maintains a higher minimum satisfaction level while simultaneously producing competitive cost, quality, sustainability, and risk outcomes. These results provide computational evidence supporting the methodological distinction established in Section 2.

Table 22. Summary of methodological comparison.

Criterion	Weighted sum	Global criterion	Arithmetic mean	Classical max–min	AMM-FMOLP
Objective	Yes	Yes	Yes	Yes	Yes
Minimum satisfaction	No	No	No	Yes	Yes
Aggregate utility improvement	Yes	Indirect	Yes	No	Yes
Subjective weights required	Yes	Usually	No	No	No
Fuzzy capacity handling	Possible	Possible	Possible	Yes	Yes
Cost–quality balance	Moderate	Moderate	Good	Very good	Very good
Sustainability	Moderate	Moderate	Good	Very good	Very good
Risk preservation	Moderate	Moderate	Good	Very good	Very good
Overall compromise	Moderate	Moderate	Good	Very good	Highest in tested

Overall, the benchmark analysis strengthens the empirical validation of the proposed framework in two respects. First, the model remains operationally feasible when the network dimensions are increased substantially beyond the original case study. Second, the augmented max–min mechanism produces consistently competitive compromise solutions relative to alternative aggregation strategies.

These findings should be interpreted as evidence of robustness and methodological consistency, rather than as a universal claim of superiority over all existing supply chain optimization algorithms. The actual performance advantage depends on the network structure, parameter configuration, and objective definitions. This qualification is particularly important when comparing the present study with published benchmark studies, whose problem structures may differ substantially.

7. Conclusions

This study develops a comprehensive multi-objective supply chain network (SCN) optimization framework that jointly addresses supplier order allocation (SOA) and transportation planning (TP) within a unified decision structure. Unlike approaches that treat procurement and logistics as separate decision layers, the proposed framework explicitly links supplier allocation, assembly production, warehouse distribution, and customer fulfillment, allowing decisions at the sourcing level to propagate through the downstream network.

The model considers four conflicting objectives: (i) total operational cost minimization, (ii) supplier defect-rate minimization, (iii) supplier sustainability-performance maximization, and (iv) supply chain disruption-risk minimization. These objectives jointly represent economic efficiency, product quality, environmental and social responsibility, and operational resilience. The AMM-FMOLP framework transforms these objectives into a compromise solution through fuzzy membership functions and an augmented max–min mechanism.

The principal contributions of the study are summarized as follows:

- Integrated SOA–TP decision architecture: Supplier selection and order allocation are directly connected to assembly and multi-echelon transportation decisions, reducing the coordination problems associated with sequential optimization.
- Multi-dimensional performance modeling: Cost, supplier quality, sustainability, and disruption risk are simultaneously incorporated into the optimization model rather than being evaluated independently or after optimization.
- Fuzzy operational-capacity representation: Triangular fuzzy numbers represent uncertainty in assembly capacity arising from workforce availability, machine utilization, maintenance, and production variability.
- Balanced AMM-FMOLP compromise mechanism: The proposed formulation combines minimum satisfaction protection with aggregate utility improvement. Thus, its contribution is an integrated decision architecture and application of AMM-FMOLP to the SOA–TP problem rather than a claim of a fundamentally new fuzzy optimization operator.
- Multi-level validation: The framework is evaluated through the industrial CNC-machine assembly case, objective-combination scenarios, warehouse-capacity sensitivity analysis, alternative network configurations, benchmark-style experiments, and comparisons with classical MODM approaches.

The numerical experiments demonstrate that the proposed framework can maintain a balanced compromise among the four objectives. In particular, the full multi-objective formulation avoids the excessive deterioration of quality, sustainability, or resilience that occurs when individual objectives are omitted. The scenario analysis shows that cost-oriented optimization can provide marginal economic improvements while producing less desirable quality and resilience outcomes. Conversely, incorporating additional objectives progressively changes supplier allocation and network flows, demonstrating that the proposed framework captures meaningful operational trade-offs rather than merely producing a mathematical compromise.

Additional validation using alternative network configurations and benchmark-style instances indicates that the compromise behavior of AMM-FMOLP is not restricted to the specific topology of the CNC case study. The sensitivity experiments also demonstrate that increasing Warehouse 1 capacity does not cause disproportionate changes in system-wide utility, while the MODM comparison indicates that AMM-FMOLP maintains a relatively stable minimum satisfaction level across the four objectives. These results support the robustness of the proposed decision architecture while recognizing that independent industrial datasets and larger public benchmark instances remain valuable areas for further validation.

7.1. Managerial implications

The proposed framework provides several direct implications for supply chain managers, procurement managers, logistics planners, and operations decision-makers.

1. Supplier allocation should not be based on purchase cost alone. The results demonstrate that selecting suppliers exclusively according to procurement and transportation cost can create hidden quality and resilience vulnerabilities. The proposed model allows managers to evaluate the combined effect of supplier cost, defect rate, sustainability performance, capacity, and disruption exposure before allocating orders. Consequently, a supplier with a slightly higher unit cost may receive a larger allocation when its superior quality, sustainability, or reliability generates a better overall network outcome.
2. Procurement and logistics decisions should be coordinated. The model demonstrates that supplier allocation directly determines upstream transportation requirements and subsequently affects assembly and warehouse flows. Therefore, procurement managers should not finalize supplier orders independently

of logistics capacity. The proposed framework provides a single allocation plan that can simultaneously inform purchasing quantities, transportation routes, assembly utilization, and warehouse distribution.

3. The model provides an actionable supplier portfolio rather than only a supplier ranking. A conventional supplier-evaluation system may rank suppliers according to performance scores, but ranking does not determine how much should actually be purchased from each supplier. In contrast, the proposed model generates explicit allocation quantities F(e,i). This enables managers to translate supplier evaluation into executable procurement decisions while respecting supplier and assembly capacities.
4. Quality and sustainability can be incorporated into purchasing decisions quantitatively. The results show that adding supplier defect rate and sustainability changes the allocation structure even when the resulting changes in total cost are relatively small. This provides management with a quantitative basis for accepting moderate cost differences when they produce improvements in product quality or sustainability performance.
5. Risk should be treated as a planning objective rather than only a monitoring indicator. The disruption-risk objective explicitly influences transportation flows and supplier allocations. This allows managers to identify configurations that may be economically attractive but operationally vulnerable. The framework can therefore support pre-disruption planning by identifying alternative supplier and transportation structures before an interruption occurs.
6. Warehouse capacity expansion should be evaluated in terms of marginal network benefit. The sensitivity analysis shows that increasing Warehouse 1 capacity produces relatively limited changes in overall utility while redistributing flows among the three warehouses. This suggests that managers should not automatically centralize inventory in response to additional storage availability. Instead, capacity investments should be evaluated according to their incremental effect on cost, quality, sustainability, and resilience.
7. The framework can support periodic rather than one-time decision-making. Although the current model uses a single-period formulation, its structure is compatible with periodic re-optimization. In practical implementation, supplier performance, logistics incidents, defect rates, sustainability scores, available capacity, and demand can be updated periodically, after which the optimization model can generate a revised allocation and transportation plan.
8. The framework can be integrated with existing enterprise information systems.
   A practical implementation can connect the optimization model to SCM, ERP, procurement, logistics, and supplier-management databases. The data pipeline can periodically collect supplier performance, purchase prices, transportation records, defect rates, capacity information, warehouse utilization, and customer demand. The AMM-FMOLP model can then be executed automatically to generate updated procurement and distribution recommendations.

Accordingly, the proposed framework should be viewed as a decision-support layer rather than a replacement for existing ERP/SCM systems. Its practical role is to transform operational and supplier data already available within enterprise systems into coordinated sourcing and logistics decisions. A representative implementation cycle is: Enterprise data → parameter validation → AMM-FMOLP optimization → supplier allocation → transportation/production plan → managerial approval → execution and performance monitoring → periodic re-optimization.

This implementation architecture also provides a practical mechanism for handling changing business priorities. For example, during periods of transportation instability, managers may place greater emphasis on disruption resilience, whereas during periods of cost pressure they may investigate cost-oriented scenarios. The scenario-analysis capability therefore allows decision-makers to examine the consequences of changing priorities before implementing a new procurement or logistics policy.

7.2. Limitations of the study

Despite its contributions and additional validation, several limitations should be acknowledged.

- Static demand assumption: Customer demand is deterministic and known during the planning period. In practice, demand uncertainty may substantially affect supplier allocation, production, and transportation decisions.
- Aggregated disruption representation: Disruption risk is represented through normalized risk coefficients derived from historical logistics information. The current model does not explicitly represent time-dependent disruptions, cascading failures, disruption propagation, or recovery actions.
- Single-period planning horizon: The formulation represents one planning period and therefore does not explicitly model inventory carry-over, inter-period capacity decisions, or dynamic supplier relationships.
- Case-specific parameterization: The numerical case is based on a CNC machine assembly supply chain. Although the mathematical structure is transferable, application to automotive, electronics, aerospace, or other industries requires industry-specific calibration of costs, defect rates, sustainability criteria, risk parameters, and capacities.
- Computational scalability: The number of variables and constraints increases with the number of suppliers, components, assembly facilities, warehouses, customer zones, and transportation links. Although the additional network and benchmark experiments indicate promising scalability, substantially larger industrial networks may require decomposition or hybrid solution approaches.
- Dependence on data quality: Practical implementation assumes that supplier sustainability scores, defect records, transportation-risk indicators, capacities, and cost information are sufficiently reliable. Incomplete or outdated enterprise data can affect the quality of the resulting allocation decisions.
- Interpretability of sustainability scores: Sustainability is represented through an aggregated supplier-performance score incorporating economic, environmental, and social dimensions. Future implementations could disaggregate these dimensions to provide more transparent managerial trade-offs.

These limitations do not undermine the practical applicability of the proposed framework but define the conditions under which its results should be interpreted. In particular, the current model should be regarded as a strategic/tactical decision-support tool for coordinated procurement and logistics planning rather than a complete real-time disruption-response system.

7.3. Future research directions

Several research directions follow naturally from the above limitations and managerial requirements:

- Dynamic and stochastic SCN modeling: Future research can incorporate uncertain demand, stochastic lead times, and time-dependent disruptions through stochastic, robust, or distributionally robust optimization.
- Multi-period and rolling-horizon optimization: Extending the framework to multiple planning periods would enable inventory decisions, supplier contracts, capacity evolution, and changing demand to be incorporated explicitly.
- Real-time decision support: Integration with IoT, transportation-monitoring systems, and enterprise databases could enable continuous updating of disruption-risk parameters and periodic automatic re-optimization.
- AI- and machine-learning-enhanced parameter estimation: Predictive models could estimate demand, supplier defect rates, transportation reliability, and disruption probabilities before they are introduced into the optimization model.

- Detailed environmental and regulatory modeling: Future formulations could explicitly optimize carbon emissions, energy consumption, waste generation, environmental compliance, and other regulatory requirements instead of relying on an aggregated sustainability score.
- Multi-product and multi-market expansion: Extending the model to multiple products, markets, and customer classes would improve its applicability to larger industrial supply networks.
- Advanced resilience modeling: Future models could explicitly incorporate disruption propagation, supplier failure scenarios, recovery time, backup suppliers, emergency transportation, and post-disruption recovery decisions.
- Hybrid and decomposition-based algorithms: For very large SCNs, AMM-FMOLP could be combined with Benders decomposition, column generation, metaheuristics, or matheuristic approaches to improve computational scalability.
- Independent industrial and public benchmark validation: Further studies should evaluate the framework using independent industrial datasets and established public benchmark instances to provide stronger external validation and facilitate reproducibility.

Overall, the study provides an integrated decision-support framework that connects supplier allocation, assembly capacity, multi-echelon transportation, quality, sustainability, and disruption resilience. The managerial value of the framework lies not only in obtaining a mathematically balanced solution but also in translating heterogeneous enterprise data into actionable supplier quantities, production allocations, transportation flows, and risk-aware sourcing strategies. The results therefore support the use of integrated multi-objective optimization as a practical planning layer for supply chains in which cost, quality, sustainability, and resilience must be considered simultaneously.

Author's Contributions

Mohammad Mahdi Ershadi: Conceptualization; Data curation; Methodology; Project administration; Software; Visualization; Writing – review & editing.
Zeinab Rahimi Rise: Data curation; Formal analysis; Investigation; Resources; Validation; Writing – original draft.

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Data Availability

Dataset is available on request.

Conflicts of Interest

There is not any conflict of interest to declare by the authors.

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