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Designing a reliable-sustainable supply chain network: adaptive m -objective ε -constraint method

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Abstract

In the current era emphasizing sustainability and circularity, supply chain network design is a critical challenge for making reliable decisions. The optimization of facility location-allocation inventory problems (FLAIPs) holds the key to achieving dependable product delivery with reduced costs and carbon emissions. Despite the importance of these challenges, a substantial research gap exists regarding economic, reliability, and sustainability criteria for FLAIPs. This paper aims to fill this gap by introducing a multi-objective mixed-integer linear programming model, focusing on configuring a reliable sustainable supply chain network. The model addresses three key objectives: minimizing costs, minimizing emissions, and maximizing reliability. A notable contribution of this research lies in elaborating on five levels of a supply chain network catering to the delivery of multiple products across various periods. Another novelty is the simultaneous incorporation of economic, environmental, and reliability objectives in the network design—a facet rarely addressed in prior research. Results highlight that varying demand levels for each facility lead to altered trade-offs between objectives, empowering practitioners to make diverse decisions in facility location allocation. The proposed mathematical model undergoes validation through numerical examples and sensitivity analysis of parameters. The paper concludes by presenting theoretical and managerial implications, contributing valuable insights to the field of sustainable supply chains.

Keywords Sustainable supply chain · Carbon emissions · Facility location · Reliable supply chain · Multi-objective optimization

1 Introduction

Globalization has significantly influenced the geographical distribution of manufacturing, warehousing, and distributing facilities in the supply chain networks. Consequently, companies worldwide seek guidance for formulating and implementing strategies that ensure reliable and sustainable operations, harmonizing various stakeholders to meet customer needs (Gupta et al., 2021; Xue and Lee, 2023). The Facility Location Problem (FLP) is extensively explored in many supply chain research; however, an integrated approach, encompassing supply chain network design, location-allocation, and inventory decisions are determining and leads to facility location-allocation inventory problems (FLAIP). Integrating this design helps supply chain managers in optimizing product flow and meeting circularity requirements.

Extended author information available on the last page of the article

Factors such as capacity, geography, sustainability, reliability, and order quantity limitations influence FLAIP decisions (Li & Ouyang, 2010; Sun et al., 2023).

Supply chain networks consistently face unexpected uncertainties disrupting product flow between different facilities (Abbasian et al., 2023). For example, the COVID-19 outbreak impacted material flow, logistics, and routing optimization, causing disruption in supply chain networks (Li et al., 2020; Singh et al., 2021). Facility disruption may necessitate customer reassignment, leading to increased transportation costs or customer loss. Hence, developing reliable supply chain network designs become crucial in mitigating the impact of unexpected circumstances. Reliable designs are vital across decisions levels, as disruptions in one level significantly affect the entire chain, impacting sales revenue, return on investment, purchasing strategies, and overall supply chain performance (Amirian et al., 2022; Li et al., 2022). A reliability index, adjustable by disruption probability, can be proposed for each facility. Demand uncertainty is another determinant affecting facilities' performance in SCND, necessitating a reliable model that considers environmental objectives alongside minimizing operational costs in an uncertain environment (Yildiz et al., 2016).

Sustainability considerations has gained prominence, with carbon emissions being a major environmental concern (Sepehri et al., 2021). Carbon emissions are unpredictable in FLAIPs, given different transportation modes, manufacturing methods, and material handling approaches with varying environmental impacts (Rezaei Vandchali et al., 2020; Tavana et al., 2023). Many companies adopt practices to mitigate emissions and meet environmental stakeholder requirements (Jahani et al., 2021).

Despite the challenges in SCND, there's a need for an integrated approach covering cost efficiency, emission mitigation, and reliability simultaneously. This study addresses this gap by formulating research questions, developing a methodology, and proposing numerical experiments. Research questions include formulating facility reliability in SCND, using sustainability criteria, integrating reliability and sustainability in SCND, and adapting SCND to real-world conditions. A mathematical model optimizes cost, emissions, and reliability concurrently, aiming to find the optimal number, location, and capacity of distribution centers. The study focuses on economic and environmental aspects to avoid model complexity. The following research questions are proposed.

- How reliability of facilities can be formulated in SCND problems?
- What sustainability criteria can be used in the formulation of SCND?
- What objectives and constraints exist when integrating reliability and sustainability criteria aspects of SCND?
- How a SCND problem formulation can be changed to make it closer to real-world conditions?

Due to capacity constraints complexity, a Lagrangian relaxation approach with an adaptive m -objective ε -constraint technique determines the Pareto front, showing the correlation between objective functions. The model transforms into a single-objective MILP problem solved by the CPLEX solver in GAMS software. The study's main contribution is proposing a model for a five-level supply chain network, designed for multiple products and periods, addressing three conflicting objectives with a novel ε -constraint method.

The manuscript is organized as follows. Section 2 reviews related literature, emphasizing the study's novelty. Section 3 states the problem, introduces terminology, assumptions, and the mathematical model. Section 4 proposes the solution procedure, while Sect. 5 presents numerical examples and sensitivity analysis. Section 6 provides theoretical and managerial insights, summarizes findings, and discusses future research directions.

2 Literature review

Selecting facility locations is a pivotal challenge in SCND, crucial for material and information flow across suppliers, manufacturers, distributors, retailers, and customers. Effective allocation, considering uncertainties, minimizes disruptions, fostering a reliable supply chain network. Addressing time, cost, and emissions during product transportation further enhances reliability (Snyder & Daskin, 2005).

To comprehend these challenges, this section reviews two literature streams, concurrently addressing reliability and sustainability aspects in SCND. By highlighting recent trends and identifying research gaps, this study contributes by formulating a problem that integrates reliability and sustainability, employing a novel solution approach.

2.1 Reliable SCND

Establishing reliability in the location-allocation of facilities leads to minimizing costs, disruption, and environmental impacts. The uncertainty has added complexities to the SCND problem based on different constraints such as the storage capacity of facilities and environmental regulations.

An early work in this elaboration was proposed by Xi-feng et al. (2008) who formulated a model with a stochastic service level function in which the total costs of establishing facilities and transportation between facilities are minimized when meeting a certain service level. A trade-off between minimizing costs and maximizing reliability is discussed by Yildiz et al. (2016) when the upstream impact of the supply chain on the reliability of individual entities is discussed as an approach to address the mentioned trade-off. Reliability was addressed as customer satisfaction maximization by Jalali et al. (2016) when multiple capacity levels are considered for facilities within a supply chain network. They proposed a bi-objective model that minimized the relevant costs and maximize the customers' demand satisfaction and solved the model using a stochastic programming approach.

Relief networks that are significant in controlling disruptions during disasters were addressed by Yahyaei and Bozorgi-Amiri (2019) who considered the risk of disruption for each facility. Separating reliable and unreliable distribution centers in this study helped the practitioners to mitigate the risk of disruption. The mathematical model developed in this study was then solved by a robust optimization technique. Later, Mohammadi et al. (2020) suggested a model in which multiple objectives aimed to minimize the logistics costs, the time of relief operations, and the variation between the upper bound and lower bound of the transportation cost. The uncertain nature of the disruptive events leads to uncertainty in the demand from disaster regions, the capacity of facilities capacities, and the time and cost of transportation. To address this challenge, they employed a robust optimization to develop a reliable facility location, victims' evacuation, and truck routing problem.

Disruption can also be a result of the stochastic nature of parameters. In this regard, Tolooie et al. (2020) developed a single-objective model to minimize the costs associated with facility setup, transportation between facilities, and disruptions in a SCND. A novel multi-cut approach in stochastic MILP was adopted in this study as a solution procedure which showed an improvement in computational results and increased the reliability. Disruption due to pandemic conditions in the case of a pharmaceutical supply chain is outlined by Abbasi et al. (2021) who aimed to control it with multiple sourcing and backup fortification. The developed model in this study minimized the costs and time of product delivery to the customers for perishable medical products. In a similar case, Delfani et al. (2022) proposed a

model to minimize the total delivery cost and time separately while maximizing the reliability of transporting medical products under uncertainty. A robust optimization approach was used by Mondal and Roy (2021) to address a close-looped SCND problem based on the demand priorities of COVID-19. In this work, total costs, transportation time, and blocklog amount of forward and reverse flow were minimized.

In the case of biofuel delivery, Habib et al. (2022) considered unpredicted events that cause network disruptions. This study not only discussed the resilience of network design but also aims to minimize the total costs and emissions using a scenario-based robust probabilistic flexible programming. The trade-off between total cost and viability performance of the network under continuous changes was discussed by Wang and Yao (2023) who adopted a hybrid Lagrangian relaxation algorithm and Genetic Algorithm (GA). Alikhani et al. (2023) suggested different strategies for addressing the reliability of SCND based on the source of disruption (nature-based, pandemic-oriented, human-made, etc.). Moreover, they showed that the interaction between these strategies is affects the facility location-allocation.

Reliability was studied along with sustainability in SCND by Akbari-Kasgar et al. (2022) who elaborated a problem under uncertain conditions and aimed to maximize the total profit as the economic objective, minimize the water consumption as emissions as the environmental objective, and maximize the social utility in the establishment of potential facilities as the social objective. Then, ϵ -constraint technique and Weighted Sum Method (WSM) were applied to tackle the complexity of the model. Moadab et al. (2023) proposed another study in the same context to minimize costs, negative societal impact caused by shortages, and environmental impact using a scenario-based approach with stochastic programming.

2.2 Sustainable SCND

The sustainability aspect in SCND is attended by different sectors of a supply chain network encompassing economic, environmental, and social criteria. For instance, greenhouse gas emissions affects the facility location-allocation since they can be mitigated by minimizing the transportation frequency of products between facilities.

An early study proposed by Nagurney et al. (2007) developed the concept of sustainability in SCND in which manufacturers produce similar products. Carbon emissions which are considered as the major environmental considerations reformulated the developed model based on an elastic demand transportation network equilibrium problem. Later, economic, environmental, and service-level aspects were integrated by Xifeng et al. (2013) using three separate objectives. This research aimed to minimize the total cost of network design (cost of establishing facilities and transportation between facilities), minimize total emissions due to transportation, and maximize the service level of each facility. Manufacturing and transportation cause carbon emissions while different emission reduction regulations can be selected during the location-allocation process in SCND. To address this issue, Turken et al. (2017) aimed analyzed different carbon policies and concluded that carbon tax policy is not efficient in minimizing emissions and the mitigation policy should be based on the number of transported products per distance covered.

In another study, Das and Roy (2019) compared different modes of transportation in an Integer Programming (IP) model. Then, they proposed a solution approach based on the combination of locate-allocate heuristic and neutrosophic compromise programming under carbon cap-and-trade policy. Location allocation is also studied by Sundarakani et al. (2020) using a robust optimization approach under demand uncertainties. Four levels of an SCND are studied in this study to minimize the number of disruptions in delivery. Carbon

cap-and-trade policy in FLAIPs was also addressed by Liu et al. (2021) when multiple products are produced, demand is dependent on the selling price, and production capacity is limited. The mixed-integer quadratic programming model developed in this work was solved by adopting a piecewise-linear envelope method. Later, Golpira and Javanmardan, (2022) compared different carbon emission reduction policies such as carbon tax, carbon cap, and carbon cap-and-trade when the only objective is to minimize the amount of carbon emissions in SCND.

Stochastic parameters were analyzed by Lotfi et al. (2021) to combine sustainability and reliability in SCND using a robust optimization approach. In another study, Midya et al. (2021) aimed to minimize transportation costs, time required for transportation, and total carbon emissions simultaneously under an intuitionistic fuzzy environment. The developed deterministic model was solved using a hybrid weighted Tchebychev metrics programming and min–max goal programming.

Designing a network for perishable items was studied Ali et al. (2021) for the case of a dairy supply chain. This study focused on managing the items' delivery with the least number of losses due to deterioration. The same problem was then addressed by Pervin et al. (2023) when the demand for items is dependent on their lifespan. The total costs consist of costs for ordering, inspection, production, holding, deteriorating, transportation, and carbon tax was aimed to be minimized in this study.

Three economic, environmental, and social aspects of sustainability were addressed by Ghosh et al. (2022) in an Mixed Integer Non-Linear Programming (MINLP) model for the case study of solid waste management. Total costs and emissions are aimed to be minimized and the total number of generated job opportunities are aimed to be maximized in this study. Joint economic and social aspects were also discussed by Tirkolaee et al. (2023) considering the adverse impact of COVID-19 on a blood supply chain network design. This study formulated the problem in an uncertain environment when donation centers, disposal rate of items, and market demand are stochastic and needs to be determined.

Sustainability and reliability aspects of a SCND problem were discussed by Rajabi-Kafshgar et al. (2023) for a close-looped supply chain when total costs (fixed and variable costs) are aimed to be minimized. Besides, this study minimized the number of disruptions in the whole network when the emissions are maintained as low as possible. This study then solves the model using meta-heuristic algorithms and the results are compared to determine the efficiency of each algorithm. A summary of the reviewed studies is shown in Table 1 to highlight the research gaps and the contribution of this research to the literature.

3 Research gaps

The reviewed studies focused sustainability and reliability in SCND, with sustainability categorized into economic, environmental, and social objectives, and reliability addressing disruptions and parameter uncertainties. Despite the increasing number of studies on FLAIP, the simultaneous investigation of economic, environmental, and reliability aspects in SCND remains limited. The complexity of SCND is heightened by multiple levels of actors, diverse product types, and varied transportation modes, reflecting real-world supply chain scenarios.

This study aims to bridge this gap by considering the aforementioned complexities, developing a problem that aligns with real-world conditions. The objective is to create an environmentally-friendly SCND while emphasizing the reliability of each facility in the face of disruptions. The proposed model incorporates three objectives: minimizing total costs,

Table 1 Summary of the reviewed studies

| References | Products | | Periods | | Transportation Mode | | Objective | | Carbon Emission | Reliability | Condition | | Number of levels | Model | Methodology |
|---------------------------|----------|----------|---------|----------|---------------------|----------|-----------|----------|-----------------|-------------|-----------|-----------|------------------|-------|--|
| | Single | Multiple | Single | Multiple | Single | Multiple | Single | Multiple | | | Certain | Uncertain | | | |
| Jalali et al. (2016) | ✓ | | ✓ | | ✓ | | ✓ | | | ✓ | | ✓ | 4 | MILP | Biogeography-based optimization algorithm |
| Yildiz et al. (2016) | ✓ | | ✓ | | ✓ | | ✓ | | | ✓ | ✓ | | 4 | MILP | GA |
| Turken et al. (2017) | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | | 2 | MINLP | Convex piecewise linearization technique |
| Das and Roy (2019) | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | | ✓ | | 3 | IP | Locate-allocate heuristic, neurosophic programming |
| Sundarakani et al. (2020) | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | | | ✓ | 4 | MILP | Robust optimization |
| Mohammadi et al. (2020) | ✓ | | ✓ | | | ✓ | | ✓ | | ✓ | | ✓ | 4 | MILP | Robust neurosophic fuzzy-based approach |
| Tolooie et al. (2020) | ✓ | | | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | 3 | MILP | Multi-cut approach |
| Liu et al. (2021) | | ✓ | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | | 2 | MILP | Branch and refine algorithm |
| Abbasi et al. (2021) | | ✓ | | ✓ | ✓ | | | ✓ | | ✓ | | ✓ | 4 | MINLP | Credibility-based possibilistic programming, WSM |
| Loffi et al. (2021) | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | ✓ | | ✓ | 2 | MILP | Solver and robust optimization |
| Mondal and Roy (2021) | | ✓ | | ✓ | ✓ | | | ✓ | | ✓ | | ✓ | 3 | MILP | Augmented weighted Tchebycheff method (AWTM) |
| Habib et al. (2022) | ✓ | | | ✓ | | ✓ | ✓ | | ✓ | ✓ | | ✓ | 4 | MILP | Scenario-based robust possibilistic flexible programming |

Table 1 (continued)

| References | Products | | Periods | | Transportation Mode | | Objective | | Carbon Emission | Reliability | Condition | | Model | Methodology |
|--------------------------------|----------|----------|---------|----------|---------------------|----------|-----------|----------|-----------------|-------------|-----------|-----------|-------|---|
| | Single | Multiple | Single | Multiple | Single | Multiple | Single | Multiple | | | Certain | Uncertain | | |
| Delfani et al. (2022) | ✓ | | | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | MILP | Red deer algorithm |
| Ghosh et al. (2022) | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | | ✓ | | MINLP | Fuzzy programming, Pythagorean hesitant fuzzy programming |
| Vali-Siar and Roghanian (2022) | ✓ | | | ✓ | | ✓ | | ✓ | ✓ | | | ✓ | MILP | Constructive heuristic algorithm |
| Akbari-Kasgar et al. (2022) | ✓ | | | | ✓ | | | ✓ | ✓ | ✓ | | ✓ | MILP | ϵ -constraint method, WSM |
| Wang and Yao (2023) | ✓ | | ✓ | | ✓ | | | ✓ | | ✓ | | ✓ | MILP | Lagrangian relaxation, GA |
| Trkoliaee et al. (2023) | ✓ | | ✓ | | | ✓ | | ✓ | | ✓ | | ✓ | MILP | Interactive probabilistic programming |
| Moadab et al. (2023) | ✓ | | | | | ✓ | | ✓ | ✓ | ✓ | | ✓ | MILP | Multi-choice goal programming |
| This study | | ✓ | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | ✓ | MILP | Adaptive m -objective ϵ -constraint |

minimizing emissions, and maximizing facility reliability. The approach integrates supplier selection, location-allocation, and maximum flow considerations. Supplier selection is based on sustainability levels, while facility locations aim to mitigate disruption probabilities and transportation costs. The model seeks to maximize the flow of raw materials and finished products within the supply chain, accommodating various transportation modes.

To solve the mathematical model, an adaptive m -objective ϵ -constraint approach is employed to identify the optimal Pareto front, revealing the interaction among economic, environmental, and reliability objectives. This methodology quantifies trade-offs, crucial for decision-making. The proposed approach is tested with different demand levels, providing a comprehensive understanding of the trade-offs in the SCND problem. This study strives to contribute a practical and holistic solution for supply chain managers facing the intricate challenges of sustainability and reliability simultaneously.

4 Problem and model development

4.1 Problem description

The existing literature on FLAIP lacks a comprehensive examination of multiple objectives within the SCND context. To address this research gap, a multi-objective problem is formulated, targeting FLAIP. The proposed mathematical model is designed to simultaneously minimize the total costs associated with establishing facilities and transportation, minimize emissions from manufacturing/processing and transportation, and maximize facility reliability during disruptive events like the COVID-19 pandemic.

The distinctive features of the model include the consideration of multiple types of raw materials and finished products, which are transported across five levels of the supply chain network. This extended scope of analysis for five network levels represents a notable departure from previous research. Additionally, the model introduces the flexibility for raw materials and finished products to be transported using different modes across various timestamps, reflecting real-world supply chain complexities.

An innovative aspect of the mathematical model is the emphasis on maximizing the reliability of each facility, a critical factor during disruptive situations. This feature addresses a significant gap in the literature, as previous studies have not sufficiently explored the simultaneous optimization of economic, environmental, and reliability objectives in a multi-level supply chain. Figure 1 provides a visual representation of the proposed supply chain network, illustrating the intricate connections and flows within the five-level structure.

The SCND problem involves various relevant costs, encompassing manufacturing, processing, transportation, setup, and warehousing costs. These operations, integral to the supply chain network, also contribute to carbon emissions. Each facility in the network is associated with a failure probability, dependent on its specific properties.

The formulated model addresses a multi-item forward dynamic supply chain network, responding to customer demands for a specific product (k) in a given period (t). All problem parameters are treated as certain, yet disruptions may occur at manufacturing, warehousing, and distribution centers due to unforeseen circumstances. Transportation between facilities, conducted in a forward direction, is facilitated through multiple modes such as trucks, trains, and planes.

To manage carbon emissions, the model allows for the control of emissions during transportation by selecting between road and non-road transportation modes. The latter includes

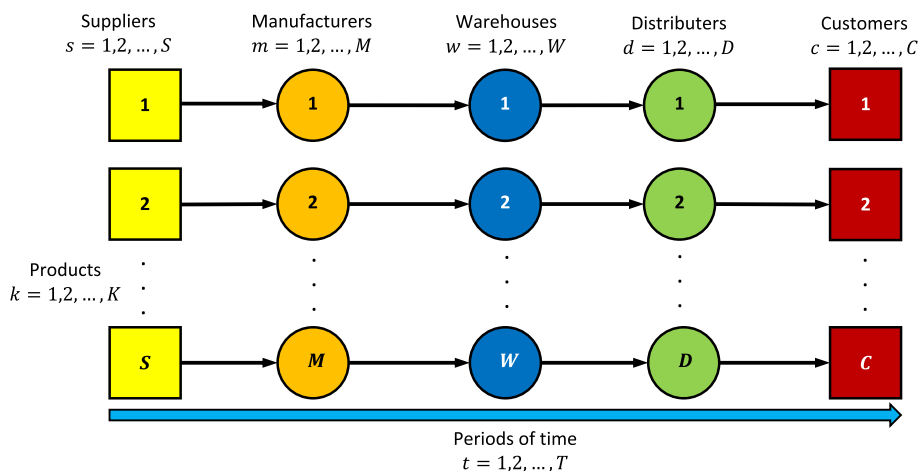


Fig. 1 Proposed supply chain network

planes and locomotives. The unit emissions are contingent on factors like engine setup, fuel type, the quantity of transported products, and the distance between facilities. Various operations in different facilities, including manufacturing, transportation, and warehousing, contribute to overall carbon emissions. Figure 2 provides a simplified representation of carbon emissions for each facility, highlighting the environmental impact associated with different operations in the supply chain network.

The development of reliability is a crucial aspect of this problem, particularly concerning disruptions faced by three intermediate facilities. In practical scenarios, these disruptions can lead to delays in receiving products from an upstream facility. Various factors, including natural disasters, piracies, changes in supply chain stakeholders, order input errors, and adverse weather conditions, contribute to disruption times T_f for facility f . These disruption times follow an exponential probabilistic distribution function with an average of τ_{ft} .

The reliability of facility f is calculated as the probability of uninterrupted operation for at least Ψ units of time. This reliability metric is essential for assessing the robustness and dependability of the supply chain network in the face of disruptions. The probabilistic

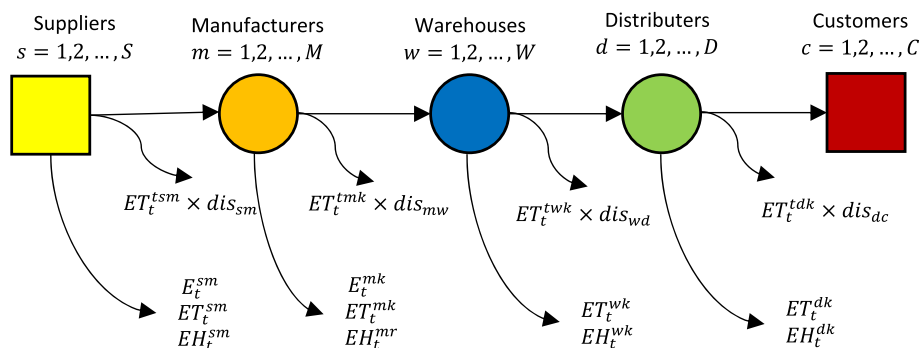


Fig. 2 Carbon emissions in the suggested supply chain network

nature of disruption times introduces a level of uncertainty, and the formulation considers the probability of facilities working without failure for a specified duration, contributing to the overall reliability assessment in the SCND problem.

$$R_f = P(T_f > \Psi) = e^{-\tau_{ft}} \quad \forall f, t. \quad (1)$$

At the start of the time horizon, facilities operate without disruptions, and once disrupted, they are irrecoverable. Decision factors for facility location include setup, capacity, and reliability costs, crucial for customer satisfaction. Balancing these factors is essential for optimal facility placement, considering setup, capacity, and reliability costs while ensuring efficient and reliable service to meet customer demands.

4.2 Assumptions

The formulated problem in the previous section is expressed as a mathematical optimization model under the following assumptions:

- Three intermediate facilities, as depicted in Fig. 2, may experience disruptions and breakdowns for specific durations. Disruptions can be attributed to natural disasters, piracies, changes in stakeholders, order input errors, and adverse weather conditions, causing delays in receiving products from an upstream facility (Tirkolaee et al., 2020).
- Disruption time T_f for each facility follows an exponential probabilistic distribution function with an average of τ_{ft} . This probabilistic model is commonly used in reliability analysis using Eq. (1) (An et al., 2015).
- This study focuses on a five-level supply chain network involving suppliers, manufacturers, warehouses, distributors, and customers. The research aims to determine the optimal location of facilities for three middle centers, while the number of suppliers and customers remains fixed (Vali-Siar & Roghanian, 2022).
- Capacity constraints exist for suppliers, manufacturers, and distributors. Manufacturers, warehouses, and distributors have fixed lead times for product delivery. Finished products are instantaneously shipped from manufacturers to warehouses (Tirkolaee et al., 2023).
- The problem is solved considering different modes of transportation in each level of the supply chain network, with each mode having capacity constraints (Delfani et al., 2022).
- Carbon emissions due to manufacturing and warehousing depend on the number of produced and stored products, respectively. Transportation-related emissions are influenced by the transport mode, distance between facilities, and the number of transported products (Liu et al., 2021).
- Each downstream facility's demand can be fulfilled by one or multiple upstream facilities in the supply chain network.
- Supplier selection is based on sustainability levels, with decisions considering factors such as cost efficiency and emissions. However, suppliers have limited capacity for product delivery.
- Shortages are permissible at warehouses and distribution centers.

Considering these assumptions, a multi-objective optimization mathematical model is developed. The model seeks to minimize relevant costs (manufacturing, warehousing, and transportation), reduce carbon emissions, and maximize the reliability of three middle facilities.

5 Notations

The mathematical model utilizes notations and terminologies summarized in Table 2 for clarity and consistency in elaboration. The table provides a reference for the key symbols and terms employed in the formulation of the model, ensuring a clear and standardized presentation of the mathematical expressions and constraints.

5.1 Mathematical model

The following multi-objective optimization mathematical model can be developed based on the mentioned notations and assumptions.

$$\begin{aligned}
 \text{minimize } Z_1 = & \sum_m \sum_t FSC_m y_{mt} + \sum_w \sum_t FSC_w y_{wt} + \sum_d \sum_t FSC_d y_{dt} \\
 & + \sum_t \sum_\alpha \sum_w \sum_m \sum_k VSC_{mtk} x_{mwtk}^\alpha + \sum_t \sum_\beta \sum_d \sum_w \sum_k VSC_{wtk} x_{wdtk}^\beta \\
 & + \sum_t \sum_\gamma \sum_c \sum_d \sum_k VSC_{dtk} x_{dctk}^\gamma + \sum_t \sum_\alpha \sum_w \sum_m \sum_k MC_{kt}^m x_{mwtk}^\alpha \\
 & + \sum_t \sum_\alpha \sum_w \sum_m \sum_k TC_{mwk}^{tm} x_{mwtk}^\alpha dis_{mw} + \sum_t \sum_\beta \sum_d \sum_w \sum_k TC_{wdk}^{tw} x_{wdtk}^\beta dis_{wd} \\
 & + \sum_t \sum_\gamma \sum_c \sum_d \sum_k TC_{dck}^\gamma x_{dctk}^\gamma dis_{dc} + \sum_t \sum_m \sum_r \sum_d \sum_i PC_{mt}^{rs} x_{mtrs}^i \\
 & + \sum_m \sum_s \sum_t \sum_r OR_{st} y'_{mtrs} + \sum_t \sum_w \sum_k HC_{wkt} IN_{wkt} \\
 & + \sum_t \sum_d \sum_k HC_{dkt} IN_{dkt} + \sum_t \sum_w \sum_k BC_{wkt} SH_{wkt} \\
 & + \sum_t \sum_d \sum_k HC_{dkt} SH_{dkt} + \sum_t \sum_\gamma \sum_c \sum_d \sum_k TC_{dck}^\gamma x_{dctk}^\gamma dis_{dc} \\
 & + \sum_t \sum_m \sum_r \sum_d \sum_i PC_{mt}^{rs} x_{mtrs}^i + \sum_m \sum_s \sum_t \sum_r OR_{st} y'_{mtrs} \\
 & + \sum_t \sum_w \sum_k HC_{wkt} IN_{wkt} + \sum_t \sum_d \sum_k HC_{dkt} IN_{dkt} \\
 & + \sum_t \sum_w \sum_k BC_{wkt} SH_{wkt} + \sum_t \sum_d \sum_k HC_{dkt} SH_{dkt} \quad (2)
 \end{aligned}$$

$$\begin{aligned}
 \text{minimize } Z_2 = & \sum_t \sum_\alpha \sum_w \sum_m \sum_k E_{mk} x_{mwtk}^\alpha + \sum_t \sum_\alpha \sum_w \sum_m \sum_k E_{wk} x_{wdtk}^\beta \\
 & + \sum_t \sum_\alpha \sum_w \sum_m \sum_k E_{dk} x_{dctk}^\gamma + \sum_t \sum_i \sum_s \sum_m \sum_r ET_i dis_{sm} x_{mtrs}^i \\
 & + \sum_t \sum_\alpha \sum_w \sum_m \sum_k ET_\alpha dis_{mw} x_{mwtk}^\alpha + \sum_t \sum_\beta \sum_d \sum_w \sum_k ET_\beta dis_{wd} x_{wdtk}^\beta \\
 & + \sum_t \sum_\gamma \sum_c \sum_d \sum_k ET_\gamma dis_{dc} x_{dctk}^\gamma \quad (3)
 \end{aligned}$$

$$\begin{aligned}
 \text{maximize } Z_3 = & \sum_t \sum_i \sum_r \sum_m \sum_s e^{-\tau_{st} \Psi} x_{mtrs}^i + \sum_t \sum_\alpha \sum_w \sum_m \sum_k e^{-\tau_{mt} \Psi} x_{mwtk}^\alpha \\
 & + \sum_t \sum_\beta \sum_d \sum_w \sum_k e^{-\tau_{wt} \Psi} x_{wdtk}^\beta + \sum_t \sum_\gamma \sum_c \sum_d \sum_k e^{-\tau_{dt} \Psi} x_{dctk}^\gamma \quad (4)
 \end{aligned}$$

Table 2 Notations used in the model

| | |
|--------------------|---|
| Indices | |
| s | Index of suppliers; $s = 1, 2, \dots, S$, |
| m | Index of manufacturers; $m = 1, 2, \dots, M$, |
| w | Index of warehouses; $w = 1, 2, \dots, W$, |
| d | Index of distributors; $d = 1, 2, \dots, D$, |
| c | Index of customers; $c = 1, 2, \dots, C$, |
| k | Index of products; $k = 1, 2, \dots, K$, |
| r | Index of raw materials; $r = 1, 2, \dots, R$, |
| t | Index of time periods; $t = 1, 2, \dots, T$, |
| i | Index of transportation modes in supply facilities; $i = 1, 2, \dots, I$, |
| α | Index of transportation modes in manufacturing facilities; $\alpha = 1, 2, \dots, A$, |
| β | Index of transportation modes in warehousing facilities; $\beta = 1, 2, \dots, B$, |
| γ | Index of transportation modes in distribution facilities; $\gamma = 1, 2, \dots, \Gamma$, |
| v | Index used to represent all the transportation modes |
| Parameters | |
| FSC_f | Fixed setup cost of facility f ; $f \in \{m, w, d\}$, |
| $VSC_{f tk}$ | Variable setup cost of facility f for product k at period t ; $f \in \{m, w, d\}$, |
| PC_{mt}^{rs} | Unit purchasing cost of raw material r from supplier s for manufacturer m at period t , |
| OR_{st} | Fix ordering cost to supplier s at period t , |
| MC_{kt}^m | Unit manufacturing cost of product k by manufacturer m at period t , |
| TC_{smr}^i | Unit transportation cost of raw material r from supplier s to manufacturer m using transportation mode i , |
| $TC_{m wk}^\alpha$ | Unit transportation cost of product k from manufacturer m to warehouse w using transportation mode α , |
| TC_{wdk}^β | Unit transportation cost of product k from warehouse w to distributor d using transportation mode β , |
| TC_{dck}^γ | Unit transportation cost of product k from distributor d to customer c using transportation mode γ , |
| $HC_{f kt}$ | Unit holding cost of product k in facility f at period t ; $f \in \{w, d\}$, |
| $BC_{f kt}$ | Unit shortage cost of product k in facility f at period t ; $f \in \{w, d\}$, |
| $dis_{ff'}$ | Distance between facilities f and f' ; $f \in \{s, m, w, d\}$ and $f' \in \{m, w, d, c\}$, |
| $Cap_{f kt}$ | Capacity of facility f to manufacture/process product k at period t ; $f \in \{m, w, d\}$, |
| Cap'_{srt} | Capacity of supplier s to supply raw material r at period t , |
| Dem_{ckt} | Demand of customer c for product k at period t , |
| μ_{rk} | Consumption coefficient of raw material r in one unit of product k , |
| E_{fk} | Unit carbon emission due to manufacturing/processing of product k by facility f ; $f \in \{m, w, d\}$, |
| ET_v | Unit carbon emissions due to transporting of raw materials/products by transportation mode v , |
| τ_{ft} | Average of the exponential probabilistic distribution function of reliability for facility f at period t ; $f \in \{s, m, w, d\}$, |

Table 2 (continued)

| | |
|---------------------|---|
| Ψ | A minimum time interval where no failure occurs, |
| B | An optional large number |
| Decision variables | |
| y_{mt} | A binary variable indicating whether manufacturing center m is set up at period t , |
| y_{wt} | A binary variable indicating whether warehouse w is set up at period t , |
| y_{dt} | A binary variable indicating distribution center d is set up at period t , |
| y'_{mtrs} | A binary variable indicating manufacturing center m purchase raw material r from supplier s at period t , |
| x^{α}_{mwtk} | Amount of product k transported from manufacturer m to warehouse w at period t using transportation mode α , |
| x^{β}_{wdtk} | Amount of product k transported from warehouse w to distributor d at period t using transportation mode β , |
| x^{γ}_{dctk} | Amount of product k transported from distributor d to customer c at period t using transportation mode γ , |
| x^i_{mtrs} | Amount of raw material r transported from supplier s to manufacturer m at period t , |
| IN_{fkt} | Amount of product k available at facility f at period t ; $f \in \{w, d\}$, |
| SH_{fkt} | Shortage of product k at facility f at period t ; $f \in \{w, d\}$, |

subject to

$$\sum_r \sum_s \sum_i \mu_{rk} x^i_{smtrk} = \sum_{\alpha} \sum_w x^{\alpha}_{mwtk} \quad \forall k, m, t, \quad (5)$$

$$\sum_{\alpha} \sum_m x^{\alpha}_{mwtk} = \sum_{\beta} \sum_d x^{\beta}_{wdtk} \quad \forall w, t, k, \quad (6)$$

$$\sum_{\beta} \sum_w x^{\beta}_{wdtk} = \sum_{\gamma} \sum_c x^{\gamma}_{dctk} \quad \forall d, t, k, \quad (7)$$

$$Dem_{ckt} = \sum_d \left(\sum_{\gamma} x^{\gamma}_{dctk} + SH_{dkt} \right) \quad \forall c, t, k, \quad (8)$$

$$\sum_i \sum_m x^i_{mtrs} \leq Cap'_{srt} \quad \forall r, t, s, \quad (9)$$

$$\sum_{\alpha} \sum_w x^{\alpha}_{mwtk} \leq Cap_{mkt} y_{mt} \quad \forall m, t, k, \quad (10)$$

$$\sum_{\beta} \sum_d x^{\beta}_{wdtk} \leq Cap_{wkt} y_{wt} \quad \forall w, t, k, \quad (11)$$

$$\sum_{\gamma} \sum_c x^{\gamma}_{dctk} \leq Cap_{dkt} y_{dt} \quad \forall d, t, k, \quad (12)$$

$$\sum_i x^i_{mtrs} \leq By'_{mtrs} \quad \forall m, r, t, s, \quad (13)$$

$$IN_{wkt} = IN_{wkt-1} + \sum_{\alpha} \sum_w x^{\alpha}_{mwtk} + SH_{wkt} - \sum_{\beta} \sum_d x^{\beta}_{wdtk} \quad \forall w, t, k, \quad (14)$$

$$IN_{dkt} = IN_{dkt-1} + \sum_{\beta} \sum_d x^{\beta}_{wdtk} + SH_{dkt} - \sum_c Dem_{ckt} \quad \forall d, t, k, \quad (15)$$

$$y_{mt}, y_{wt}, y_{dt} \in \{0, 1\} \quad \forall m, w, d, t, \quad (16)$$

$$x_{mwtk}^{\alpha}, x_{wdtk}^{\beta}, x_{dctk}^{\gamma}, x_{mt}^{rs}, IN_{fkt}, SH_{fkt} \geq 0 \quad \forall m, w, d, tm, tw, \\ td, t, k, s, r. \quad (17)$$

Equation (2) focuses on minimizing the total fixed and variable costs associated with manufacturing, warehousing, distribution, transportation, and purchasing, including costs related to facility shortages. Equation (3) targets the reduction of carbon emissions stemming from manufacturing, warehousing, and inter-facility transportation. Equation (4) aims to maximize the reliability of various facilities within the supply chain network.

To ensure balance, Eqs. (5), (6), and (7) equate the transportation of raw materials and products between facilities to the downstream facility's demand at each level. Equation (8) ensures that the final manufactured products transported from distribution centers to customers meet demand, accounting for potential shortages. Constraints (9), (10), (11), and (12) enforce that the handling of raw materials and finished products adheres to facility capacities.

Constraint (13) dictates that manufacturers only produce when they receive raw materials from suppliers. Equations (14) and (15) express inventory constraints for warehouses and distributors, respectively. Constraints (16) and (17) stipulate that all facility establishment decisions must be binary, and raw materials, products, and transportation variables must be non-negative.

6 Solution procedure

This section proposes a solution procedure for the developed MILP model to identify Pareto's optimal solutions, providing insights into the interaction between different objective functions and aiding decision-makers in selecting optimal facility locations and product shipment quantities (Hajiaghahi-Keshteli & Fathollahi Fard, 2019). An alternative approach for multi-objective optimization is the ε -constraint method, where one objective is transformed into a constraint. Subsequently, the optimal solution is obtained iteratively for different objective functions (Govindan et al., 2023).

This study employs an adaptive m -objective ε -constraint approach to solve the problem for various cases involving a reduction in the number of objective functions. The resulting Pareto fronts for these cases are compared to determine optimal facility locations, product shipment quantities, and shortages (Laumanns et al., 2006). The adaptive m -objective ε -constraint approach offers advantages over other algorithms like Goal Programming (GP) and Generalized Additive Model (GAM). Notably, it provides control over the number of efficient Pareto solutions by adjusting grid points, enabling the acquisition of exact Pareto solutions rather than approximations, especially beneficial in complex problem scenarios (Mesquita-Cunha et al., 2023).

6.1 Pareto optimality

In the context of maximizing all objective functions, let $f : X \rightarrow F$, where X is the decision space and $F \subseteq \mathbb{R}^m$ is the objective space. The components of X and F are defined as decision vectors and objective vectors, respectively. A decision vector $x^* \in X$ is considered Pareto optimal when no other vector dominates it, meaning $x^* > x$ for all decision vectors. In mathematical terms, for any $x^* \in X$, there exists no x such that $f_i(x) \geq f_i(x^*)$ for all

$i = 1, 2, 3$, and $f_i(x) \geq f_i(x^*)$ for at least one index i . The set of all Pareto optimal decision vectors X^* is defined as Pareto sets, and $F^* = f(X^*)$ is the set of all Pareto-optimal objective vectors, defined as the Pareto front.

The significance of the Pareto front in multi-objective optimization problems lies in revealing correlations between different objectives.

6.2 Adaptive m-objective ε -constraint approach

The ε -constraint technique, introduced by Haimes (1971), is a common methodology for generating the Pareto front in multi-objective problems. This approach involves selecting one objective function as the sole objective while treating the remaining objectives as constraints. The Pareto front's diverse elements can be visualized using different bounds. The ε -constraint technique operates by solving the single-objective problem with generated constraints, defined as $opt(f, \varepsilon, \varepsilon')$. For the case of maximizing all objectives in an m-objective scenario, the ε -constraint problem is formulated as follows.

$$\text{maximize } f(x) = (f_1(x), \dots, f_m(x)) \quad (18)$$

subject to

$$\varepsilon_i < f_i(x) \leq \varepsilon'_i \quad \forall i \in \{2, \dots, m\}, \quad (19)$$

$$x \in X. \quad (20)$$

Initially, various sub-regions of the optimal space are explored to address the single-objective problem, leading to the identification of Pareto optimal solutions. Subsequently, lower and upper constraints for each objective function are established, and optimal values for epsilons are determined. In this process, the solution algorithm presented by Laumanns et al. (2006) is employed to discover the Pareto front and determine the optimal facility locations selected to serve downstream facilities. The pseudo-code of this approach is shown by Fig. 3.

7 Numerical experiments

7.1 Numerical solutions

To validate the formulated mathematical model, a series of numerical experiments are conducted, utilizing random samples across small, medium, and large scales. For simplicity, stochastic parameters are assumed to follow a uniform distribution function. Following the generation of these numerical values, the model is solved using the CPLEX solver in the GAMS software version 44.3.0.

The solution approach employed is the adaptive m -objective ε -constraint method within the GAMS environment, facilitating the determination of Pareto solutions. Comparative analyses are performed on these solutions across various scenarios, considering different demand levels from downstream facilities that influence the location of middle facilities and the quantity of shipped products between them. Table 3 presents three distinct problems, representing small, medium, and large-scale instances, each differing in the number of facilities, raw materials, finished products, and transport modes within the supply chain network.

Algorithm: Adaptive tri-objective ε -constraint method

```

1   $P := \emptyset$  (already found Pareto solutions);  $Q := \emptyset$  (already searched regions);  $e_j := (-\infty, \infty) \forall j \in \{2, \dots, m\}$ 
2   $i := (|P| + 1)^2$  {starting to count sub-regions}
3   $i := i - 1$ 
4  If  $i < 0$  then stop {no new solution found}
5   $(\varepsilon, \varepsilon') = \text{getConstraints}(i, \mathbf{e}, P)$  when  $\mathbf{e}$  is a sorted vector
6  If  $[\varepsilon, \varepsilon'] \subset Q$  then go to step 3 {if the sub-regions are already searched}
7   $\mathbf{x} := \text{opt}(f, \varepsilon, \varepsilon')$  {solve single-objective problem}
8  If  $\mathbf{x} = \text{null}$  then  $Q := Q \cup [\varepsilon, \varepsilon']$ ; go to step 3 {if sub-region is empty}
9  If  $\exists y \in P: y > x$  then  $Q := Q \cup [\varepsilon, \varepsilon']$ ; go to step 3 {if solution dominated}
10  $P := P \cup \{\mathbf{x}\}$ 
11  $Q := Q \cup [\varepsilon, f(\mathbf{x})]$ 
12  $\mathbf{e} := \text{updateConstraints}(f(\mathbf{x}), \mathbf{e})$ 
13 Go to step 2 {found new Pareto optimal solution}

```

Output: Set of Pareto-optimal decision vectors P

Function $\text{getConstraints}(i, \mathbf{e}, P)$

```

1  For  $j = 2, 3$  do
2   $d := i \bmod (|P| + 1)$ 
3   $i := (i - d) / (|P| + 1)$ 
4   $\varepsilon_j = e_{j,d}$  {lower constraint of objective  $j$ }
5   $\varepsilon'_j = e_{j,d+1}$  {upper constraint of objective  $j$ }
6  End for
7  Return  $(\varepsilon, \varepsilon')$ 

```

Function $\text{updateConstraints}(\mathbf{y}, \mathbf{e})$

```

1  For  $j = 2, 3$  do
2   $i := 1$ 
3  While  $e_{j,i} < y_j$  do
4   $i := i + 1$  {search for insertion position}
5  End while
6   $e_j = (e_{j,1}, \dots, e_{j,i-1}, y_j, e_{j,i}, \dots, e_{j,|P|+2})$  {insert new constraint value}
7  End for
8  Return  $\mathbf{e} := (\mathbf{e}_2, \mathbf{e}_3)$ 

```

Fig. 3 Pseudo-code of the adaptive m -objective ε -constraint approach

Table 3 Number of each actor in the developed network (problem scale)

| Problem | S | M | W | D | C | K | R | T | I | A | B | Γ |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|----------|
| 1 | 2 | 3 | 5 | 8 | 10 | 2 | 4 | 6 | 2 | 2 | 2 | 2 |
| 2 | 4 | 6 | 10 | 13 | 20 | 3 | 6 | 12 | 3 | 3 | 4 | 3 |
| 3 | 7 | 8 | 13 | 15 | 25 | 4 | 8 | 12 | 4 | 4 | 5 | 5 |

To introduce stochasticity into the problem, all parameters are assumed to follow a uniform distribution function for simplicity. The lower and upper bounds for each parameter are estimated based on experiential knowledge, and these values are compiled in Table 4.

Leveraging the parameter values outlined in Table 4, a numerical experiment is executed in the GAMS software to derive optimal values for each objective. In each instance, a single objective is transformed into a constraint, allowing for the determination of values for all decision variables. Subsequently, the optimal value for each objective function can be ascertained (Table 5).

The Pareto front can be constructed from the acquired results for each objective function, elucidating the interplay between the two objectives. This quantification gains significance, particularly in the presence of conflicting objectives. Table 6 showcases the values of Pareto

Table 4 Parameters distribution in the problem instances

| Parameter | Value | Parameter | Value |
|-------------------|----------------------|--------------|--------------------|
| FSC_f | uniform(4000,10,000) | dis_{ffl} | uniform(4,5) |
| VSC_{ftk} | uniform(50,350) | Cap_{fkt} | uniform(500,1200) |
| PC_{mt}^{rs} | uniform(10,50) | Cap'_{srt} | uniform(1500,3500) |
| OR_{st} | uniform(1000,2000) | Dem_{ckt} | uniform(15,60) |
| MC_{kt}^m | uniform(1,6) | μ_{rk} | uniform(1,5) |
| TC_{smr}^i | uniform(8,18) | E_{fk} | uniform(0.1,0.2) |
| TC_{mwk}^α | uniform(10,24) | ET_v | uniform(0.1,0.2) |
| TC_{wdk}^β | uniform(5,15) | τ_{ft} | uniform(1,2) |
| TC_{dck}^γ | uniform(3,10) | Ψ | $T/2$ |
| HC_{fkt} | uniform(2,9) | B | 10^8 |
| BC_{fkt} | uniform(20,30) | - | - |

Table 5 Optimal values of the objective functions in different problem instances (pay-off table)

| Problem | Objective | Objective function 1 | Objective function 2 | Objective function 3 |
|---------|-----------|----------------------|----------------------|----------------------|
| 1 | min Z_1 | 775,680.967 | 3608.226 | 146.893 |
| | min Z_2 | 1,609,119.084 | 3102.097 | 133.980 |
| | max Z_3 | 1,550,228.730 | 3635.309 | 213.009 |
| 2 | min Z_1 | 3,418,316.519 | 20,706.138 | 465.176 |
| | min Z_2 | 7,383,897.964 | 16,647.045 | 424.927 |
| | max Z_3 | 7,646,911.340 | 20,398.735 | 637.826 |
| 3 | min Z_1 | 5,162,697.151 | 35,637.390 | 860.797 |
| | min Z_2 | 1.163523E + 7 | 28,467.704 | 799.513 |
| | max Z_3 | 1.097156E + 7 | 35,669.440 | 1335.375 |

points for each objective function in the three examined problems based on the eight Pareto breakpoints.

Subsequently, with the identification of Pareto points, the Pareto fronts for each problem can be delineated for distinct objective functions. Figures 4, 5 and 6 illustrate the Pareto fronts for the three problems, respectively.

In summary, while different Pareto fronts emerge in the three distinct problems illustrated in Figs. 4, 5 and 6, the overall trend of the Pareto fronts remains consistent as the problem scales increase. The Pareto front in Problems 2 and 3 exhibits nearly identical patterns, indicating that the interaction between objectives remains relatively stable with changes in the problem scale concerning the number of facilities, products, and transportation modes. Consequently, decision-makers can determine the optimal point on the Pareto front based on available resources.

Analysis of the relationship between the first and second objectives reveals that increasing costs results in decreased carbon emissions, a trend consistently observed across different

Table 6 Optimal values of the Pareto points concerning breakpoints

| Problem | Breakpoint | Objective function 1 | Objective function 2 | Objective function 3 |
|---------|------------|----------------------|----------------------|----------------------|
| 1 | 1 | 915,204.922 | 3160.749 | 152.859 |
| | 2 | 909,627.947 | 3158.749 | 154.737 |
| | 3 | 895,945.48 | 3240.645 | 165.485 |
| | 4 | 847,146.98 | 3382.158 | 182.411 |
| | 5 | 822,491.837 | 3502.006 | 183.252 |
| | 6 | 818,492.13 | 3531.195 | 182.162 |
| | 7 | 813,345.45 | 3554.457 | 178.385 |
| | 8 | 808,508.081 | 3592.991 | 173.494 |
| 2 | 1 | 4,090,977.646 | 17,654.432 | 554.601 |
| | 2 | 3,973,128.440 | 17,891.546 | 581.121 |
| | 3 | 3,891,237.873 | 18,135.452 | 578.541 |
| | 4 | 3,675,541.506 | 18,499.534 | 577.989 |
| | 5 | 3,560,689.338 | 19,183.978 | 558.155 |
| | 6 | 3,537,852.250 | 19,472.325 | 543.541 |
| | 7 | 3,523,145.926 | 20,112.658 | 515.946 |
| | 8 | 3,519,328.070 | 20,623.598 | 485.131 |
| 3 | 1 | 6,697,568.115 | 29,367.921 | 894.386 |
| | 2 | 6,496,874.952 | 29,932.154 | 951.145 |
| | 3 | 6,283,145.490 | 30,945.258 | 989.541 |
| | 4 | 6,011,398.844 | 31,618.251 | 1066.64 |
| | 5 | 5,885,998.016 | 32,068.572 | 1089.854 |
| | 6 | 5,804,327.417 | 33,198.894 | 1118.841 |
| | 7 | 5,712,235.252 | 34,097.259 | 1098.654 |
| | 8 | 5,626,732.781 | 35,668.835 | 1068.392 |

problem scales. Additionally, elevating facility reliability leads to higher carbon emissions and lower costs in the supply chain network. When prioritizing between increasing reliability, achieving demand satisfaction, lowering costs, and minimizing carbon emissions, decision-makers must carefully consider the trade-offs to optimize the supply chain network for lower costs, enhanced customer satisfaction, and increased product deliveries while minimizing disruption risks.

In this analysis, the Simple Additive Weighting (SAW) method is employed to identify the best Pareto optimal solution in each problem instance. Three weights—0.45, 0.3, and 0.25—are assigned to Z_1 , Z_2 , and Z_3 , respectively. Subsequently, the objective function values are normalized based on their types, and the final scores are presented in Table 7. The Pareto optimal solutions are then highlighted in Figs. 4, 5 and 6, emphasizing the maximum scores. For a more in-depth understanding of the application of SAW (Wang & Rangaiah, 2017).

The runtime of the solution code in GAMS experiences a notable increase when upscaling the problem. Table 8 and Fig. 7 illustrate this exponential rise in the solution time, highlighting the inefficiency of the proposed solution procedure for large-scale problems.

To assess the influence of different periods on the SCND, Fig. 8 depicts the number

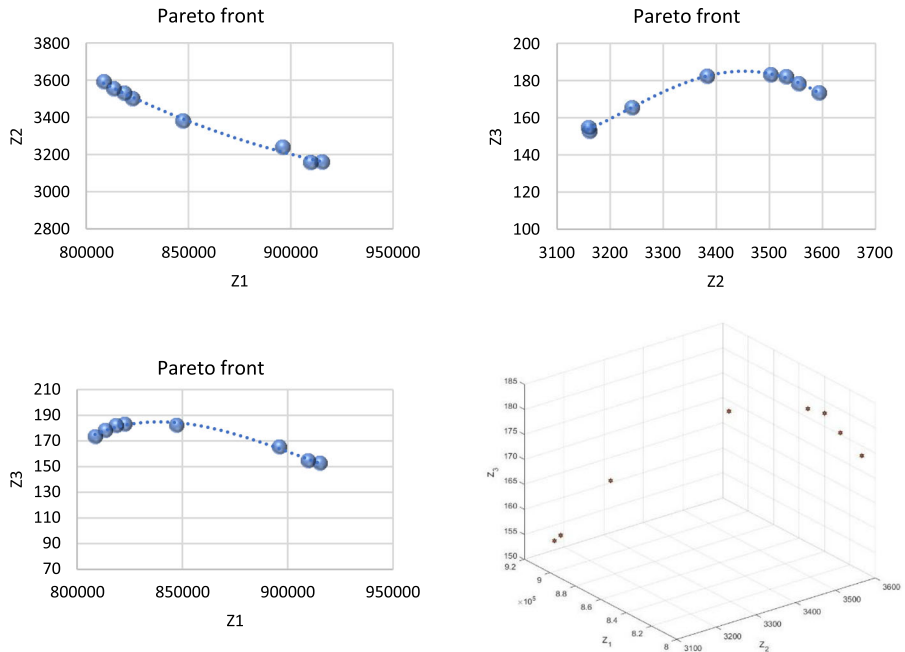


Fig. 4 Pareto front generated for Problem 1

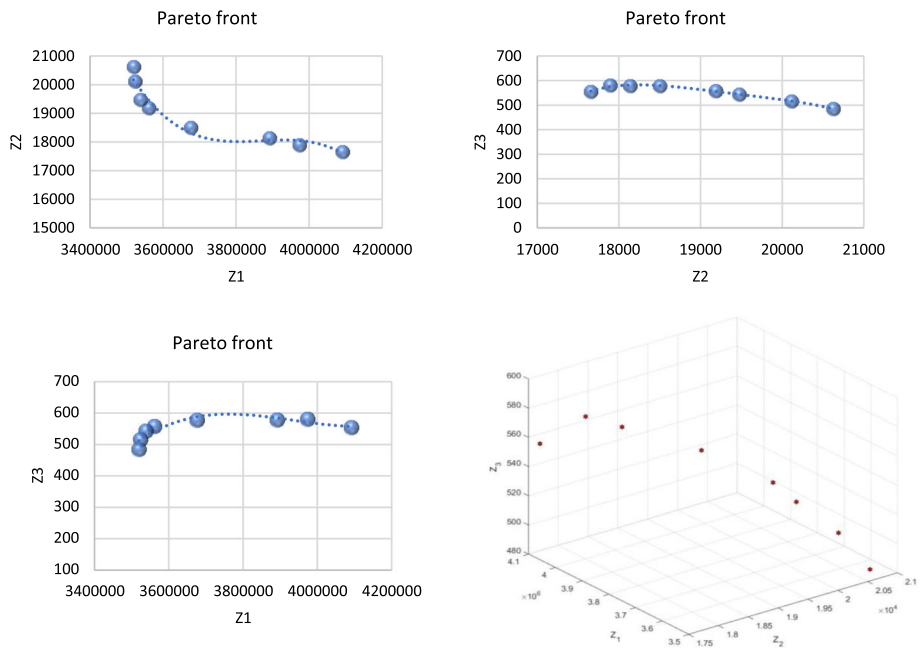


Fig. 5 Pareto front generated for Problem 2

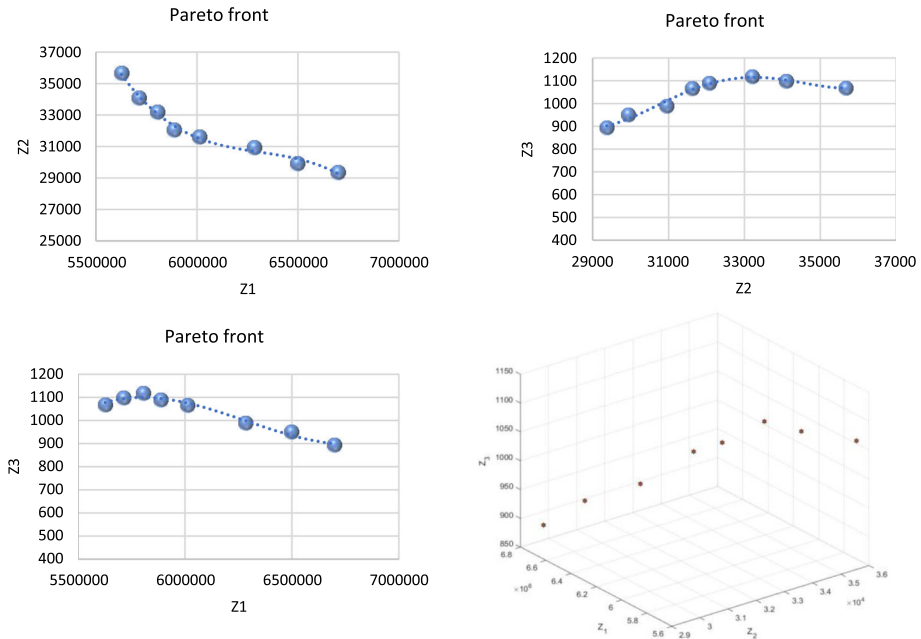


Fig. 6 Pareto front generated for Problem 3

of established facilities within the middle three levels of the network for varying periods. Concurrently, the figure illustrates the flow of finished products between these established facilities, providing insights into the selection and establishment dynamics at each level over time.

Following the categorization of the solution into six distinct time periods that influenced facility selection, further analysis is conducted in Table 9. This analysis focuses on quantifying the number of each product type transported from manufacturers to warehouses using various modes of transportation. The table provides a detailed breakdown, offering insights into the distribution and transportation patterns across different product types and modes of transport.

7.2 Sensitivity analysis

The effectiveness of the proposed adaptive m -objective ε -constraint approach is evaluated through a sensitivity analysis on the optimal values of objective functions. This analysis explores the impact of fluctuations in the total demand of customers for a specific product during a given time period (Dem_{ckt}) on facility location and product shipment decisions across the supply chain network. The sensitivity analysis is conducted simultaneously for each problem scale, providing insights into decision-making trends.

For this analysis, the demand of customers is adjusted by decreasing and increasing it by 10 and 20 percent. The initial focus is on the smallest-scale problem at the eighth breakpoint. It is observed that an increase in demand results in an overall increase in all objectives, although the proportional changes differ across the different cases. The changing trends in all objectives during demand fluctuations are summarized in Table 10.

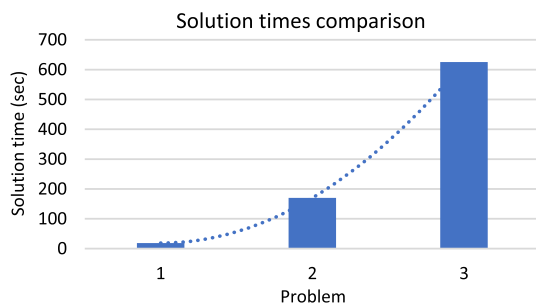
Figure 9 illustrates the interactive trends between all three objective functions by analyzing

Table 7 Pareto optimal solutions obtained by the SAW method

| Problem | Breakpoint | Normalized value of Z_1 Weight = 0.45 | Normalized value of Z_2 Weight = 0.3 | Normalized value of Z_3 Weight = 0.25 | Score |
|---------|------------|---|--|---|----------|
| 1 | 1 | 0.883418 | 0.999367 | 0.834146 | 0.905885 |
| | 2 | 0.888834 | 1 | 0.844395 | 0.911074 |
| | 3 | 0.902408 | 0.974728 | 0.903046 | 0.924264 |
| | 4 | 0.954389 | 0.933945 | 0.995411 | 0.958511 |
| | 5 | 0.982998 | 0.901983 | 1 | 0.962944 |
| | 6 | 0.987802 | 0.894527 | 0.994052 | 0.961382 |
| | 7 | 0.994053 | 0.888673 | 0.973441 | 0.957286 |
| | 8 | 1 | 0.879142 | 0.946751 | 0.95043 |
| 2 | 1 | 0.860266 | 1 | 0.954364 | 0.925711 |
| | 2 | 0.885783 | 0.986747 | 1 | 0.944626 |
| | 3 | 0.904424 | 0.973476 | 0.99556 | 0.947924 |
| | 4 | 0.957499 | 0.954318 | 0.99461 | 0.965823 |
| | 5 | 0.988384 | 0.92027 | 0.96048 | 0.960974 |
| | 6 | 0.994764 | 0.906642 | 0.935332 | 0.953469 |
| | 7 | 0.998916 | 0.877777 | 0.887846 | 0.934807 |
| | 8 | 1 | 0.856031 | 0.834819 | 0.915514 |
| 3 | 1 | 0.840116 | 1 | 0.799386 | 0.877899 |
| | 2 | 0.866068 | 0.98115 | 0.850116 | 0.896604 |
| | 3 | 0.895528 | 0.949028 | 0.884434 | 0.908805 |
| | 4 | 0.936011 | 0.928828 | 0.953344 | 0.938189 |
| | 5 | 0.955952 | 0.915785 | 0.974092 | 0.948437 |
| | 6 | 0.969403 | 0.884605 | 1 | 0.951613 |
| | 7 | 0.985032 | 0.861299 | 0.981957 | 0.947143 |
| | 8 | 1 | 0.823349 | 0.95491 | 0.935732 |

Table 8 Solution time for different problems

| Problem | 1 | 2 | 3 |
|-------------------------|-------|--------|--------|
| Solution time (seconds) | 18.67 | 170.14 | 625.17 |

Fig. 7 Solution times comparison

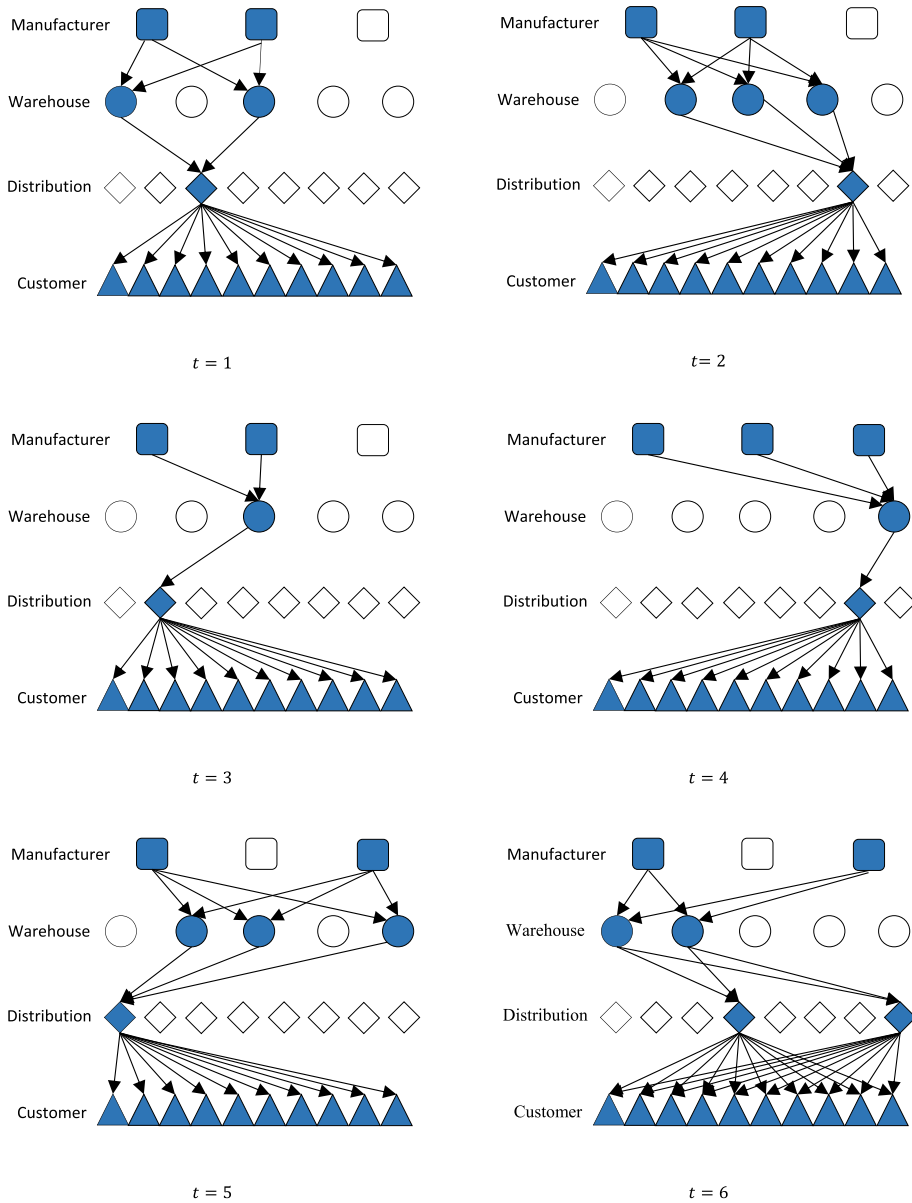


Fig. 8 Schematic view of the solution obtained for Problem 1

changes in their values between two objectives separately.

The results indicate that an increase in demand leads to an increment in total costs, total emissions, and total reliability. However, the increase in the objectives varies with a specific percentage of increase in the total demand, and the total cost experiences a lower fraction of increase. The reason for this increase is that the higher the demand, the more the number of products transported between facilities, and the variable setup cost in the first objective

Table 9 Amount of transported products from manufacturers to warehouses in Problem 1

| Period | Product | Transportation mode * | Manufacturer | Warehouse | | | | |
|--------|---------|-----------------------|--------------|-----------|----|----|----|----|
| | | | | 1 | 2 | 3 | 4 | 5 |
| 1 | 1 | 1 | 1 | 3 | 46 | 50 | 38 | |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| | | 2 | 1 | | | | | 14 |
| | | | 2 | 8 | | | | |
| | | | 3 | | | | | |
| | 2 | 1 | 1 | 35 | | | 36 | |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| | 2 | 2 | 1 | | 34 | 22 | | 10 |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| 2 | 1 | 1 | 1 | | 32 | | | 30 |
| | | | 2 | 47 | | 43 | | |
| | | | 3 | | | | | |
| | | 2 | 1 | | | | 21 | |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| | 2 | 1 | 1 | | | | | |
| | | | 2 | | 33 | 13 | | 27 |
| | | | 3 | | | | | |
| | 2 | 2 | 1 | | | | | |
| | | | 2 | 14 | | | 16 | |
| | | | 3 | | | | | |
| 3 | 1 | 1 | 1 | 3 | | | | |
| | | | 2 | 33 | 37 | | 23 | 16 |
| | | | 3 | | | | | |
| | | 2 | 1 | | | | | |
| | | | 2 | | | 50 | | 13 |
| | | | 3 | | | | | |
| | 2 | 1 | 1 | 35 | 23 | 42 | 23 | |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| | 2 | 2 | 1 | 39 | | | | 35 |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| 4 | 1 | 1 | 1 | | 32 | | | |

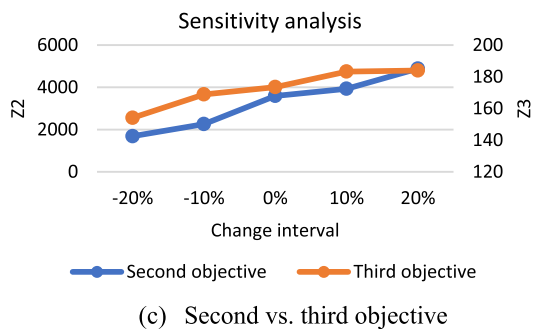
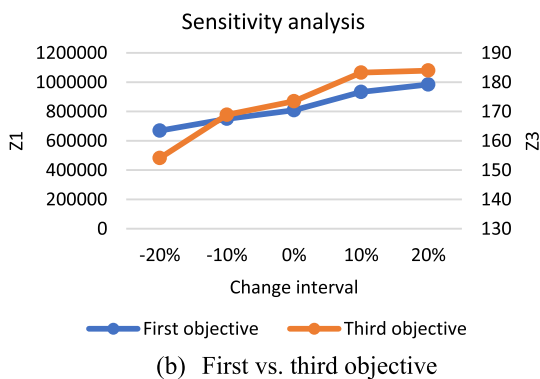
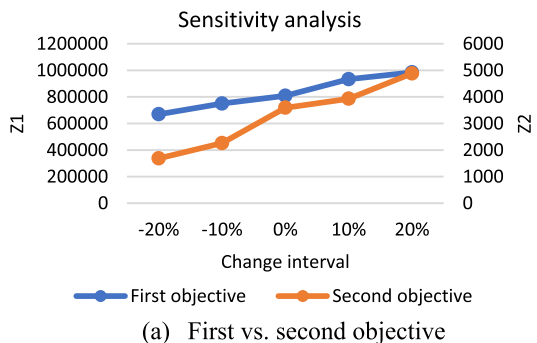
Table 9 (continued)

| Period | Product | Transportation mode * | Manufacturer | Warehouse | | | | |
|--------|---------|-----------------------|--------------|-----------|----|----|----|----|
| | | | | 1 | 2 | 3 | 4 | 5 |
| 5 | 2 | 2 | 2 | 21 | | 16 | | 18 |
| | | | 3 | | | | | |
| | | | 1 | | | | | |
| | | | 2 | | | | | 38 |
| | | | 3 | | | | | |
| | | | 1 | | | | | |
| | 1 | 1 | 2 | | | | | |
| | | | 3 | | 48 | | 47 | 19 |
| | | | 1 | | | | | |
| | | | 2 | | | | | |
| | | | 3 | 33 | | | 43 | |
| | | | 1 | | | | 22 | |
| | 2 | 2 | 2 | | | | | |
| | | | 3 | | | | | |
| | | | 1 | 14 | 48 | 38 | | 18 |
| | | | 2 | | | | | |
| | | | 3 | | | | | |
| | | | 1 | | | | | |
| 6 | 1 | 1 | 2 | | | | | |
| | | | 3 | | | | | |
| | | | 1 | | | | | |
| | | | 2 | | | | | |
| | | | 3 | 41 | | 38 | 17 | 13 |
| | | | 1 | | | | | |
| | 2 | 2 | 2 | | | | | |
| | | | 3 | | 24 | | | |
| | | | 1 | | | 45 | | |
| | | | 2 | | | | | |
| | | | 3 | 20 | 14 | | | |
| | | | 1 | | | | | 24 |
| | 1 | 1 | 2 | | | | | |
| | | | 3 | | | | 36 | |
| | | | 1 | | | | | |
| | | | 2 | | | | | |
| | | | 3 | | | | 48 | |
| | | | 1 | | | | | |
| | 2 | 2 | 2 | | | | | |
| | | | 3 | 24 | 16 | 16 | | 36 |

*Transport mode 1: Road transportation; Transport mode 2: Non-road transportation

Table 10 Sensitivity analysis of the objective functions against demand parameter

| Objective function | Changes in demand functions | | | | |
|--------------------|-----------------------------|-------------|------------|-------------|-------------|
| | − 20% | − 10% | 0% | + 10% | + 20% |
| 1 | 669,146.257 | 749,687.412 | 808,508.01 | 933,132.920 | 984,236.482 |
| 2 | 1686.435 | 2261.020 | 3592.991 | 3931.164 | 4883.924 |
| 3 | 154.095 | 168.871 | 173.494 | 183.252 | 183.945 |

Fig. 9 Sensitivity analysis of the objective functions against demand fluctuations

function is increased accordingly. Besides, total purchasing, transportation, and warehousing costs increase when more products are transshipped. A lower fraction of the decrease is illustrated when analyzing the objective of minimizing carbon emissions. Expanding the flow in the supply chain network increases the emissions due to different operations. For instance, an increase of 20% in demand results in approximately a 54% increase in total emissions. In this regard, practitioners should prioritize a trade-off between fulfilling the demand of downstream facilities and minimizing carbon emissions.

A notable surge in the total expected products distributed occurs when the demand decreases by 10%, primarily due to the exponential nature of the reliability function. A reduction in the number of shipped products across the entire supply chain leads to diminished investments in reliability-related objectives for facilities. This is because serving fewer downstream facilities or delivering fewer products doesn't necessitate an extensively reliable system. In the case of a 20% reduction in demand, the reliability-related objective experiences a 12% decrease, emphasizing the importance of maintaining reliable service. Conversely, an increase in demand correlates with a more reliable supply chain. A 10% demand increase doesn't alter the reliability-related objective, while a 20% increase results in only a marginal uptick in the reliability function. Essentially, the reliability function remains close to its optimal value, suggesting that facilities need not significantly enhance their reliability-related objective when facing larger order sizes.

Examining the influence of demand across the three discussed problems aims to assist practitioners in striking a balance between diverse objective functions amidst fluctuating demand. Given the dynamic nature of demand, its effects on total covered distance, production planning, and logistics decisions become pivotal. Consequently, understanding demand behavior and its impact on conflicting objectives enables managers and supply chain experts to strategically position facilities and navigate optimal trade-offs, mitigating disruptions effectively.

8 Discussion

This study addresses a significant challenge in the literature by incorporating green and reliability considerations into facility location decisions. The research highlights that adhering to green and reliability regulations not only fulfills environmental responsibilities but also enhances the efficiency of network design. The model developed in this work spans three dimensions, capturing the interplay of economic, environmental, and reliability factors. Additionally, the study explores the impact of dynamic demand on these objectives through a Pareto optimality approach. It is noteworthy that adjusting the facility location may lead to a trade-off, where reducing relative costs could result in increased carbon emissions. Importantly, this trade-off remains consistent regardless of the number of echelons in the supply chain network.

This study makes a significant contribution to the existing literature by developing a five-level Supply Chain Network Design (SCND) and making decisions for various facilities and their connections. This multi-level approach adds realism to the problem, considering the involvement of multiple actors in a supply chain network concurrently. Additionally, the study introduces the novel aspect of addressing three objectives—cost-efficiency, carbon emissions, and reliability simultaneously within a SCND problem. While the main findings align with previous research in this area, the proposed solution algorithm stands out by providing precise solutions to the problem.

This study makes a substantial theoretical contribution by extending the insights from empirical works, such as the one conducted by Amin and Zhang (2013), which focused on facility location decisions in closed-loop supply chains under demand uncertainty. In contrast, our research represents a pioneering effort as it concurrently incorporates considerations of carbon emissions and reliability into FLPs. This unique model not only builds on existing literature but also provides a comprehensive framework for addressing the joint economic, environmental, and reliability aspects in the context of SCND. The presented model serves as a compelling call to action for researchers and practitioners, encouraging them to explore the intricate dynamics of environmental and reliability decisions within the facility location paradigm, particularly when regulatory policies mandate carbon emission reduction and ensure reliable product transportation between facilities.

From a practical standpoint, this study holds implications for decision-makers in supply chain management, emphasizing the critical role of facility location decisions in simultaneously addressing economic, environmental, and reliability objectives. Specifically, manufacturing facilities can strategically position themselves in locations that optimize accessibility, minimize relevant costs, reduce carbon emissions, and enhance overall reliability. This integrated approach becomes particularly relevant in responding to dynamic customer demands. In times of emergencies, such as natural disasters or pandemics like COVID-19, these insights can guide the establishment of emergency facilities to improve response capabilities. Furthermore, the application of digital technologies, such as the Internet of Things (IoT), emerges as a key enabler for efficient and sustainable supply chain operations, providing real-time data for decision-making.

In the decision-making process for the facility location problem and determining the number of shipped products between facilities, decision-makers must consider legal and organizational factors that enable them to strike a balance between various scenarios. This study formulates these scenarios based on the influence of customer demand on decision-making regarding the sustainability and reliability of the Supply Chain Network Design (SCND). Additionally, considerations related to circularity can be incorporated when choosing the optimal scenario, emphasizing the facilitation of product flow between different facilities.

9 Conclusion

The optimization of materials flow is essential for effective network design and the establishment of facilities within a supply chain. Practitioners strive to address the materials flow problem to streamline manufacturing, warehousing, and distribution operations, ensuring the satisfaction of customer demands. Additionally, environmental concerns, particularly carbon emissions, pose significant challenges in supply chain operations.

Another critical aspect of supply chain network design involves ensuring the reliability of delivering raw materials and finished products to downstream facilities. Consequently, sustainable development, encompassing economic, environmental, and social considerations, becomes paramount. In this context, solving a Facility Location-Allocation and Inventory Problem (FLAIP) to create a reliable and sustainable supply chain network gains significance. This paper focuses on developing three objectives – minimizing facility location costs, minimizing total emissions, and maximizing reliability. The adaptive m-objective ϵ -constraint approach is employed to solve the mathematical model and determine optimal Pareto fronts, addressing these interconnected objectives.

It is crucial to acknowledge the study's limitations. While the model accounts for setup and transportation costs as influencing factors, other considerations, such as accessibility and governmental regulations, are not explicitly addressed. Future research could delve deeper into these factors to provide a more comprehensive understanding of facility location decisions in the context of sustainability and reliability in supply chain networks. The future research implications are outlined as follows.

- **Advanced Forecasting Methods:** Future studies could enhance the applicability of the model by developing more accurate forecasting methods for demand. This might involve using distribution functions with higher precision instead of assuming a uniform distribution. Additionally, exploring multi-attribute decision-making approaches, such as fuzzy AHP and fuzzy TOPSIS, to rank suppliers based on their service level could be a valuable extension.
- **Coordinated Models and Contractual Relationships:** Researchers may consider developing coordinated models that incorporate regulated contracts between different facilities. Exploring collaborative gaming and comparing centralized versus decentralized scenarios could provide insights. Future studies could also introduce financial considerations, such as proposing trade credit periods for downstream facilities to stimulate demand and facilitate revenue accumulation. The study addresses carbon emissions but does not discuss specific methods for controlling them in the supply chain network.
- **Optimizing for Reverse Flow:** A potential contribution to future research could involve optimizing supply chain network design based on the possibility of reverse product flow. Exploring return policies for defective raw materials or final products at various levels of the supply chain could enhance customer service.
- **Integration of Production and Inventory Processes:** Integrating production and inventory processes into the model could add novelty. Considering different methods, equipment, and policies for producing and storing items in various warehouses based on product types might significantly impact the cost and energy efficiency of the entire supply chain.
- **Comparison of Multi-Objective Solution Methods:** Researchers might explore and compare various multi-objective solution methods, such as the augmented ϵ -constraint method and AWTM, against the proposed adaptive m-objective ϵ -constraint technique to validate its performance in greater detail.
- **Investment in Green Technologies:** Another potential extension involves investigating the impact of investing in green technologies on reducing costs associated with carbon emissions. For instance, comparing carbon emissions for different modes of transport, especially when transporting materials using various modes, could be an insightful avenue of research.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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