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Sustainable supply chain network design: Integrating risk management, resilient multimodal transportation, and production strategy

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ABSTRACT

This study presents a novel advancement in sustainable supply chain network design (SSCND) by incorporating risk management, resilience, and production strategies within a multi-modal transportation framework. Focusing on the distribution, production, and inventory (DPI) triad, the literature on the SSCND emphasizes the need for strategic alignment to create a resilient supply chain capable of mitigating risks in multimodal transport. To achieve this, we develop a novel multi-objective mixed-integer programming (MOMIP) model customized to the SSCND aimed at maximizing profit, minimizing transportation time, and reducing environmental impacts. The model is solved using a specialized goal programming approach, ensuring that no objective is compromised at the expense of others. A hybrid solution methodology, combining a local search algorithm with machine learning predictive models, is introduced to navigate the complexity of the MOMIP model efficiently. The model's validity is confirmed through real-world data from the Iranian chemicals industry, and the proposed algorithm's performance is tested. On average, the algorithm achieves an optimality gap of <3 %, with a gap of 2.67 % for profit maximization, 1.63 % for transportation time reduction, and 0.71 % for minimizing environmental impact, demonstrating its efficiency and reliability. Sensitivity analyses further highlight the significant impact of risks including environmental, policy, and operational on transportation and financial outcomes, showing up to a 12 % decrease in profits due to environmental risks alone. These findings underscore the robustness of the model and its applicability in complex, real-world industrial scenarios, making valuable contributions to the literature on sustainable supply chain management, risk mitigation, and multimodal transportation optimization.

1. Introduction

Establishing sustainable and resilient supply chains is imperative in the dynamic landscape of global commerce. A critical enabler of this resilience is the effective management and digital integration of DPI information flows, which are central to ensuring operational efficiency and adaptability [1]. This DPI triad forms the operational heartbeat of any supply chain, and its real-time coordination through digital platforms and AI-enhanced systems is fundamental to achieving agile and optimal performance. When aligned with industrial information systems, a well-designed DPI structure enables automated decision-making, swift market responses, reduced lead times, and enhanced resource utilization [2–4]. Efficient DPI integration not only streamlines operations but also enhances industrial information flow across tiers, supporting sustainability by reducing waste and environmental impact [5,6]. Moreover, an effective DPI system significantly contributes to cost reduction, enhancing profitability through streamlined processes and minimized inventory costs [7]. The importance of DPI activities is further highlighted when considering different manufacturing strategies like Make-to-Stock (MTS), Make-to-Order (MTO), or Vendor-Managed Inventory (VMI) [1]. These paradigms are inherently data-driven and demand adaptive coordination mechanisms. Aligning DPI activities with these strategies ensures that production processes match customer demand variability, optimizing costs and inventory levels, and enhancing supply chain responsiveness [8,9]. MTS strategies typically offer quick responses to demand, while MTO strategies cater to customization, ensuring timely delivery of unique orders [10,11]. VMI emphasizes supplier collaboration for efficient inventory management, fostering effective communication and streamlined distribution [12–15].

In addition to operational considerations, understanding risks in multimodal transportation—encompassing environmental, policy, security, operational, supply, economic, and technological risks—is critical for supply chain resilience [16]. Robust information architectures and AI-based risk assessment models play an essential role in managing these uncertainties. Resilience is reinforced by real-time risk monitoring, contingency planning, regulatory compliance, and sustainable

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routing [17,18]. Addressing operational and security risks ensures smooth transportation activities and safeguards supply chain integrity [19–22]. Technological advancements improve transportation efficiency but require awareness of potential risks [23,24]. Collaboration within the supply chain fosters a resilient ecosystem, contributing to reliable transportation services and customer satisfaction [25,26].

This study emphasizes the critical role of industrial information flow and AI-enhanced decision-making in achieving resilient and sustainable supply chain performance. By developing a novel and comprehensive framework for sustainable multi-modal supply chain design within the DPI triad, aiming to integrate risk management and resilience strategies to enhance overall supply chain performance. By optimizing multiple objectives, namely profit, transportation time, and environmental impact, the research addresses the complex coordination of production strategies such as MTS, MTO, and VMI with broader sustainability and resilience goals. Particular attention is given to the unique challenges inherent in multi-modal transportation systems operating in high-variability, high-uncertainty sectors like the chemical industry. The study is guided by three key research questions: (1) How can risk management and resilience be effectively embedded into multi-modal transportation systems within the DPI triad in light of environmental, policy, security, operational, supply, economic, and technological risks? (2) What are the most effective strategies for aligning production, inventory, and distribution systems in multi-level supply chains to achieve both sustainability and resilience? and (3) What are the respective impacts of MTS, MTO, and VMI production strategies on shaping production, inventory, and transportation decisions within a multi-modal context? To address these questions, the article presents a novel MOMIP model that integrates risk management, resilience, and sustainability into multi-modal transportation systems, intending to optimize profit, transportation time, and environmental impact. A hybrid solution approach, combining local search algorithms with machine learning techniques, is developed to enhance computational efficiency and solution quality. The incorporation of machine learning techniques, particularly supervised learning for variable prioritization and optimization guidance, exemplifies the application of AI to overcome computational challenges in large-scale decision systems. The model is validated using real-world data from the Iranian chemicals industry, demonstrating its practical relevance and applicability. Furthermore, the study highlights the importance of tailored production strategies—MTS, MTO, and VMI—in shaping decision-making and proposes a unified framework for managing diverse risks across complex, logistics-intensive supply chains.

To provide a clear overview of this study's significance and practical relevance, the key contributions are outlined below:

1. A novel integrated MOMIP model for sustainable and resilient supply chain planning: We propose a comprehensive MOMIP model that jointly optimizes total profit, transportation time, and environmental impact. The model coordinates DPI decisions across multiple production strategies and logistics layers within a multimodal transportation network, while incorporating a risk modeling framework that accounts for disruptions from seven distinct risk categories (e.g., environmental, political, operational, etc.). This structure enables robust and forward-looking supply chain planning.
2. A hybrid goal programming and machine learning-based solution framework: Solving large-scale MOMIP problems poses considerable computational challenges due to the high dimensionality and combinatorial complexity. To address this, we develop a hybrid solution approach that combines a goal programming formulation MC-M-GP-UF with a metaheuristic algorithm (Simulated Annealing) and a supervised learning model (Gradient Boosting Machines (GBM)). This hybrid Adaptive Binary Relaxation (ABR) heuristic dynamically guides the relaxation and reinstatement of binary decision variables based on their predicted impact, enhancing both scalability and solution quality.
3. Real-world validation using an industrial case study from the chemical sector: The model is validated through a comprehensive real-world case study from the Iranian chemical industry, where customer segmentation, production capacity constraints, cross-docking operations, and multimodal routing are all modeled in detail. Risk scenarios—such as capacity disruptions due to political unrest or environmental hazards—are incorporated based on expert input. The results demonstrate the model's effectiveness in achieving sustainable, resilient, and profitable performance in complex supply chains, underscoring its practical relevance.

To establish the context for our study, Section 2 conducts a thorough literature review. Moving to Section 3, we introduce our optimization model. In Section 4, we introduce the hybrid methodology crafted to overcome the challenges identified in the literature review. In Section 5, we present a detailed case study, offering a tangible application of our approach in a real-world scenario. Section 6 provides a thorough discussion that includes theoretical, practical, and managerial implications. Finally, in Section 7, we conclude our paper by summarizing key findings and contributions. Additionally, we suggest future research directions, emphasizing areas where further exploration could enhance our understanding of this field and its optimization.

2. Literature review

This section reviews key supply chain strategies and their implications for multimodal transportation and sustainability. We begin with foundational production and inventory management approaches—MTO, MTS, and VMI—which underpin responsiveness, cost efficiency, and demand alignment. We then explore hybrid configurations that integrate these strategies, followed by a discussion of multimodal transportation risks and sustainable supply chain design. Synthesis at the end identifies critical gaps and justifies the need for an integrated multi-objective optimization framework. A comparative summary is provided in Table A1 (Appendix A).

2.1. Make-to-Order (MTO) strategy

The MTO strategy has transitioned from a traditional, bespoke manufacturing model to a demand-driven, agile system that minimizes inventory and enhances customization [27,28]. This model is particularly effective in high-variability environments where products are manufactured only after customer orders are received. Recent studies have explored diverse optimization methods to manage the inherent complexity of MTO systems [29–31]. He et al. [13] applied a memetic algorithm for integrated production-distribution scheduling in global MTO supply chains, improving responsiveness and cost-efficiency. Ganstere [32] demonstrated the utility of Aggregate Production Planning (APP) in managing demand fluctuations, while Xu et al. [33] examined how environmental regulations and emission pricing affect MTO profitability. Mard [27] addressed dynamic scheduling under uncertainty using a Mixed-Integer Programming (MIP) model, implemented in Python with Gurobi, showing improved workload balancing. Zhai et al. [31] proposed production lead-time hedging (PLTH) strategies to mitigate delivery delays, demonstrating via game-theoretic analysis that PLTH improves service levels in multi-sourcing contexts. Brzozowska et al. [30] employed artificial intelligence techniques to forecast machine assembly times, enhancing planning accuracy. Woschank et al. [29] emphasized real-time production planning using discrete-event simulation to optimize responsiveness, especially in volatile industries like electronics.

2.2. Make-to-Stock (MTS) strategy

The MTS strategy is traditionally associated with mass production, where economies of scale are achieved by producing in anticipation of demand [34]. Advances in forecasting and inventory control have significantly enhanced the adaptability and efficiency of MTS systems [2,4,8,35]. Lorenz et al. [36] introduced a data-driven process mining approach in MTS manufacturing, validated in the sanitary products industry, which improved production alignment with demand patterns. Karabağ and Gökgür [3] developed a stochastic model integrating procurement and pricing under environmental uncertainty, using a Markov chain-based framework to derive optimal decisions. Other studies emphasize forecasting-driven optimization: Li and Zhang [37] and Hutter et al. [38] explored machine learning approaches to enhance production planning and inventory accuracy in high-volume settings. These models illustrate MTS's strength in predictable, high-demand environments, while revealing its limitations in dynamic markets.

2.3. Vendor-managed inventory (VMI)

The VMI is a collaborative strategy where suppliers manage stock levels on behalf of customers, enhancing supply chain visibility, reducing holding costs, and increasing responsiveness [15,39–46]. Tarhini et al. [44] demonstrated the integration of VMI with consignment stock and redistribution hubs, significantly reducing costs in multi-echelon systems. Bogaert and Jaarsveld [45] optimized VMI for multi-supplier settings, achieving a 4–6 % cost reduction in high-tech manufacturing. Golpîra et al. [7] proposed a robust optimization model combining VMI and supply chain visibility under uncertain demand, balancing quality, cost, and service level. In perishable supply chains, Mohamadi et al. [14] employed deep reinforcement learning (Advantage Actor-Critic) to manage inventory allocation under uncertainty, improving service levels in blood supply systems. Lotfi et al. [47] introduced the Viable Supply Chain (VSC) model, merging VMI and consignment stock with stochastic optimization techniques, and demonstrating a 14.8 % cost reduction in the healthcare sector. Rashid et al. [48] emphasized the importance of information sharing and joint decision-making for successful VMI outcomes.

2.4. Combining MTO, MTS, and VMI

The mixed MTO and MTS strategy represents a hybrid production approach designed to balance flexibility and efficiency in meeting both predictable and customized demand [49–51]. This strategy allows companies to serve diverse customer bases by integrating the strengths of both MTO and MTS, often categorized by the proportion of each and how they are operationally combined [9,52]. However, successful implementation requires advanced production planning and control systems to manage the complexities of hybrid production [50,52–56]. Integrates smart production and planning systems in MTO/MTS environments for responsiveness [28,35,51]. Ghalehkhondabi and Suer [53] used queuing theory to optimize the Order Penetration Point (OPP) for impatient customers, enhancing responsiveness and reducing cost. Yousefinejad and Esmaeili [54] developed a Stackelberg game model to jointly optimize pricing and lead time, enabling differentiated fulfillment across MTS and MTO segments. Fiems et al. [10] employed stochastic modeling to assess hybrid system performance, revealing the effectiveness of threshold inventory policies. Chen et al. [56] applied a hybrid scheduling model with genetic algorithms to optimize prefabrication in the construction sector, aligning global market demands with mass customization.

The integration of MTO, MTS, and VMI offers a unified production-inventory framework that aligns operational flexibility with demand responsiveness. In isolation, each strategy has distinct limitations: MTO can incur long lead times, MTS risks excess inventory, and VMI depends heavily on supplier-buyer coordination [9,52]. However, when integrated, these approaches form a resilient architecture that can accommodate customization, reduce inventory costs, and enhance supply chain visibility [1,2]. In volatile markets, the hybridization of MTO and MTS supports differentiated demand fulfillment—using MTS for stable products and MTO for customized, low-frequency items. VMI enhances coordination across this system by enabling real-time replenishment and reduced information asymmetry. This integration becomes especially valuable when extended to multimodal transportation and sustainability goals, where the need for adaptability and efficiency is paramount. This strategy integrates MTO, MTS, and VMI to create a robust system that addresses various aspects of production and inventory management. By combining these strategies, companies can optimize production schedules, reduce inventory costs, improve customer service, and maximize supply chain synergies. Research by Ghasemi et al. [1,2] examines the complexities and logistical requirements of managing such a diverse system effectively. Ghasemi et al. [1,2] developed MIP models for integrated production-inventory-distribution systems. Their models incorporated customer-centric strategies, rolling horizon planning, and pricing dynamics under stochastic demand—validated in the pulp and paper industry—resulting in up to 1.43 % profit improvement.

2.5. Risks in multimodal transportation

Multimodal transportation introduces significant risks that can compromise supply chain efficiency and sustainability. Optimizes vehicle routing, safety, and cold logistics through advanced heuristics and AI considered by [57–61]. These risks are typically categorized into operational, environmental, legal, and security dimensions [62]. Develops decision tools and platforms for disaster-resilient supply chains and logistics under uncertainty [63–65]. Operational risks involve delays and cargo damage due to inefficiencies in handling goods across transport modes [19]. Environmental risks stem from exposure to adverse conditions and increasingly strict regulations [66], while legal risks emerge from complex international compliance and liability issues [67]. Security risks include theft, piracy, and cyberattacks, especially during transshipment, highlighting the need for advanced tracking and protective measures [68]. These risks directly impact sustainable logistics by causing delays, cost overruns, and inventory imbalances [22,69,70]. To mitigate these challenges, researchers have developed optimization models for transport mode selection, routing, and location planning. For instance, Hao and Yue [26] used dynamic programming to optimize container routing, while Rabbani et al. [71] and Fazayeli et al. [72] applied integer programming and genetic algorithms for location and route decisions. Other models integrate time windows, capacity, and environmental constraints using Lagrangian relaxation or goal programming methods [73,74]. Advanced strategies include disruption management through tracking technologies [17], alternative routing to maintain continuity [75], and the incorporation of stochastic and fuzzy elements to model uncertainty [21,76]. Recent innovations apply data mining and simulation-based optimization to improve risk visibility and control in complex multimodal systems [23,24,77,78]. Overall, these approaches strengthen the resilience of multimodal transportation networks, ensuring a better balance between cost-efficiency, responsiveness, and sustainability.

2.6. Sustainable supply chain design

The design of sustainable supply chains has evolved to address the growing need for balancing economic performance with environmental stewardship and operational resilience [79]. Contemporary research emphasizes closed-loop structures, multi-objective optimization, and advanced computational tools to enhance adaptability and sustainability in complex supply chain networks [80–84]. A key development in sustainable supply chain design is the implementation of closed-loop green supply chains (CLGSCs) that integrate forward and reverse logistics, product recovery, and environmentally responsible practices. Gholizadeh et al. [85] introduced a CLGSCN model incorporating redundancy strategies to extend product lifecycles and improve reliability. Their multi-objective MIP framework balances cost, service time, and environmental impacts using meta-goal programming and hybrid heuristics. Building on this foundation, Jahani and Gholizadeh [86] proposed a multi-stage closed-loop model using mixed-integer nonlinear programming (MINLP) with genetic algorithms and queuing-based inventory logic to improve system flexibility under uncertainty. Similarly, Chaleshigar Kordasiabi et al. [87] developed a sustainable engine oil supply chain model incorporating carbon policies (capacity limits and emissions taxes) within a robust optimization framework. These models underscore the role of sustainability regulations and lifecycle-oriented design in supply chain planning.

Recent models incorporate robust and stochastic optimization to address demand and supply variability. Ali et al. [88] applied a weighted sum method with Lagrangian relaxation and neighborhood-based heuristics to optimize a closed-loop supply chain under uncertain demand, showcasing the value of hybrid algorithms in improving solution feasibility and performance. Advanced heuristic approaches have also been introduced to increase computational efficiency. Seydanlou et al. [89] developed a multi-neighborhood search algorithm with a tabu list for closed-loop optimization, while Gholizadeh et al. [90] proposed a dynamic reconfigurable framework for the dairy industry using simulation-based optimization and response surface methodology to manage multi-product and multi-stage planning. The application of big data analytics and AI-enhanced modeling has expanded the scope of sustainable design. Khoei et al. [91] introduced a data-driven optimization framework for reverse logistics, demonstrating improved decision-making through predictive analytics and demand forecasting. In the global context, Edalatpour et al. [92] explored international sustainable supply chain networks by integrating Incoterms and transportation mode selection into their optimization framework. Their Lagrangian-based heuristic approach supports sustainability in global supplier-customer relationships, accounting for geographic diversity, environmental sensitivity, and market segmentation.

2.7. Research gap

Despite considerable advancements in the field of supply chain management, particularly in the integration of risk management and resilience within multi-modal transportation systems, significant gaps remain, particularly in the practical application and optimization of these concepts. The literature reviewed reveals extensive research on individual aspects of supply chain management such as risk management strategies, production planning, and inventory management under various models (MTO, MTS, VMI). However, there is a notable scarcity of studies that comprehensively integrate these components into a unified, multi-level framework that is both sustainable and resilient to disruptions.

1. Firstly, while previous studies have focused on optimizing individual elements of the supply chain, such as production or transportation independently, few have addressed the holistic integration of DPI systems in a way that accounts for multi-modal transportation complexities and the inherent risks. This integration is crucial for developing robust strategies that can respond dynamically to disruptions and maintain operational effectiveness across the entire supply chain.
2. Secondly, the literature demonstrates a focused exploration on conventional risk management and resilience strategies but lacks depth in the implementation of advanced multi objective mixed-integer programming models that simultaneously maximize financial performance and minimize environmental impacts and transportation time. Most existing models do not adequately balance profit maximization with crucial sustainability objectives such as reducing carbon emissions or optimizing resource usage, which are essential for modern, sustainable supply chains.
3. Thirdly, while some studies employ sophisticated mathematical and simulation techniques to tackle aspects of supply chain management, there is a gap in the use of hybrid approaches that combine local search algorithms with predictive machine learning models. Such hybrid methods can potentially offer more accurate forecasts and robust decision-making tools to handle the complexities of multi-objective optimization in real-world scenarios.

Our study seeks to bridge these gaps by introducing a novel multi-objective mixed-integer programming (MOMIP) model designed to enhance the DPI triad's alignment within multi-modal transportation frameworks. Furthermore, our study also encompasses the evaluation of multimodal transport risks in DPI triad optimization. The model uniquely combines profit maximization, transportation time reduction, and minimization of environmental impacts. We employ a specialized goal programming approach to address the multi-objective nature of the problem, ensuring that strategic goals are not compromised at the expense of others. Additionally, our research introduces a cutting-edge hybrid approach, merging a local search algorithm with machine learning predictive models. This methodology is designed to efficiently navigate the complex landscape of our MOMIP model, providing a scalable and adaptable solution that can be applied in various industrial contexts. The validation of this model using real-world data from the Iranian chemicals industry not only demonstrates its applicability but also its reliability in achieving the intended outcomes.

By addressing these research gaps, our study contributes significant advancements to the discourse on supply chain sustainability and resilience. It provides a comprehensive framework that not only enhances understanding of the interdependencies between DPI systems, production strategies, and risk management in multi-modal transportation but also offers practical tools and methodologies for improving supply chain performance in the face of evolving global challenges.

3. Problem statement

Modern supply chains are increasingly required to operate under dual pressures: sustainability imperatives and resilience to disruption. This is particularly evident in industries such as chemicals, where global sourcing, hazardous materials, and complex multimodal logistics increase vulnerability to various risk factors, including environmental disturbances, political instability, regulatory shifts, and technological disruptions. Simultaneously, these supply chains must maintain service quality, minimize costs, and reduce their environmental footprint in line with global sustainability goals. A central challenge in this context lies in the coordinated planning of DPI decisions, especially when multiple production strategies are deployed concurrently to meet diverse customer demands. Each strategy imposes different constraints and trade-offs on inventory levels, lead times, production flexibility, and transportation planning. However, most existing supply chain optimization models treat these strategies in isolation, failing to capture their interdependent effects on the overall system when combined in real-world operations.

Moreover, while multi-objective optimization approaches have been widely used to balance trade-offs (e.g., between cost and carbon emissions), they often neglect risk propagation across multimodal transportation networks or lack the adaptive capabilities to manage high-dimensional, combinatorial decision spaces. Therefore, there is a critical need for an integrated decision-support framework that simultaneously considers multiple production strategies within a unified supply chain planning model. Embeds risk-aware and resilience-enhancing features across multimodal transport operations. Optimizes economic, environmental, and temporal performance via scalable computational methods. This research is motivated by these challenges and is grounded in an industrial setting: a large-scale Iranian chemical supply chain that faces significant variability in customer demand, transportation risk exposure, and operational complexity. In this environment, the ability to tailor production strategy decisions, allocate resources dynamically, and mitigate disruption risks is essential for maintaining competitiveness and service reliability. By addressing these interlinked challenges through a novel MOMIP model and a hybrid machine learning–heuristic optimization framework, this study contributes a practical and scalable solution that enhances both sustainability and resilience in real-world supply chains.

The research draws inspiration from a practical case observed in an Iranian chemical supply chain, catering to diverse companies and customers. Subsidiary companies factor in various considerations such as production capacity, logistics costs, storage allocation, and order management based on their unique circumstances. Moreover, the customer base, characterized by geographical diversity, exhibits varying product demands on a weekly and monthly basis, influenced by local conditions. The supply chain structure, depicted in Fig. 1, illustrates the transportation routes of products from factories to customers. These shipments may occur through direct routes or involve multiple cross docks utilizing multimodal transportation. Additionally, intermediate storage in external warehouses may be carried out before the final delivery to customers.

The company aims to enhance profitability while simultaneously reducing overall transportation costs, time, and environmental footprint, all while meeting customer demands. This is achieved by implementing various production strategies such as MTO, VMI, or MTS, coupled with utilizing multimodal transportation. To achieve these objectives, this paper discusses tactical decisions regarding the selection of customers to be served under each production strategy, alongside operational decisions pertaining to DPI management, and route selection for multimodal transportation. The problem-solving approach involves determining the optimal customer allocation for each strategy, followed by decisions on production scheduling, production volumes at each factory, inventory levels at warehouses, and the selection of transportation modes and routes for product delivery.

To effectively meet high-level demands, the company must strategically determine which production strategy to employ for each customer before the planning horizon begins. Each strategy, whether it be MTO, VMI, or MTS, will entail a distinct interaction with customers as it influences both product and information flow between factories and customers. To illustrate these strategies, Fig. 2 depicts the envisioned flow of products and information within the proposed system. Each strategy is tailored to accommodate different customer demands for various products, showcasing the unique approach the company takes in fulfilling customer needs and managing its operations.

Under the MTS strategy, when customers provide their requests, the company fulfills them using the available inventory in the factories or foreign warehouses. However, there may be instances where certain customer demands cannot be met due to insufficient inventory, resulting in what we term unmet demand or lost sales. In such cases, the company is only able to fulfill a portion of the customer demand under the MTS model. This can potentially impact customer satisfaction and overall revenue generation for the company. Under the MTO strategy, customer orders must be placed within the specified deadline set by the customers. However, orders that cannot be fulfilled within this timeframe are treated as backup orders and are delivered at the end of the planning horizon. It is essential to note that maintaining a minimum target service level is crucial for meeting the expectations of MTO customers. This ensures timely delivery and enhances customer satisfaction, which are integral aspects of the MTO strategy. Under the VMI strategy, the company commits to delivering all customer orders punctually, without any orders being classified as lost sales or resulting in backorders. In this study, we implement an inventory control policy tailored to VMI customers, in line with the agreements established between the company and its VMI customers. This policy ensures that appropriate inventory levels are maintained at customer locations for each requested product. There are percentage differences in selling prices among customers of VMI and MTO and between customers of MTO and MTS. This is represented which adjusting the selling prices based on the inventory management policy adopted by the customers.

In accordance with the company's tactical decisions regarding the adoption of specific production strategies for individual customers, there arises a need for operational-level decisions pertaining to DIP management within the factories. Additionally, selecting appropriate transporters for delivering products to customers under the MTS, MTO, and VMI strategies is crucial for managing risks in transportation activities and ensuring the resilience of the transportation network. Therefore, it is imperative to devise a transportation plan that considers transportation time and delivery deadlines. Furthermore, incorporating time windows based on logic function aids in dynamically scheduling transportation activities, contributing to enhanced efficiency and customer satisfaction.

Logistics operations face numerous risk factors that can significantly disrupt activities. Therefore, categorizing and integrating these potential risks into the proposed model is crucial. Following extensive liter-

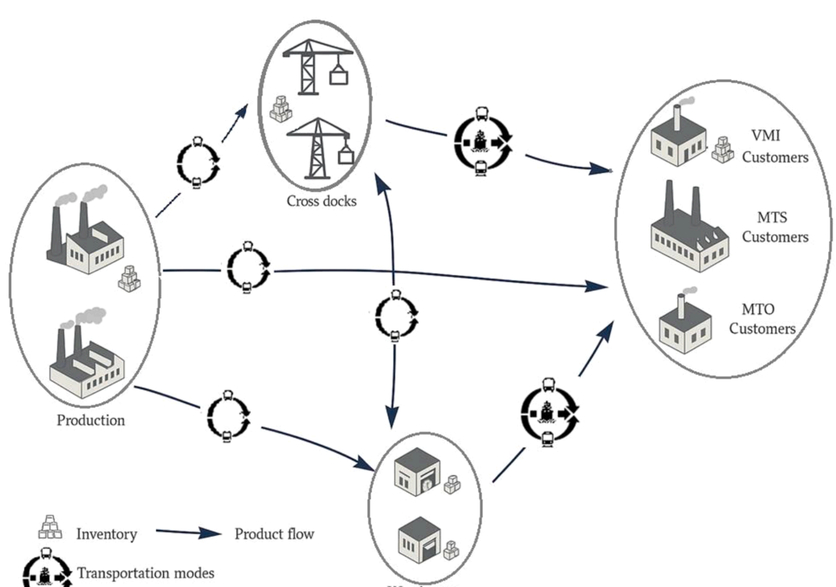


Fig. 1. Depicts a schematic representation of our study supply chain (adapted from Ghasemi et al. [1]).

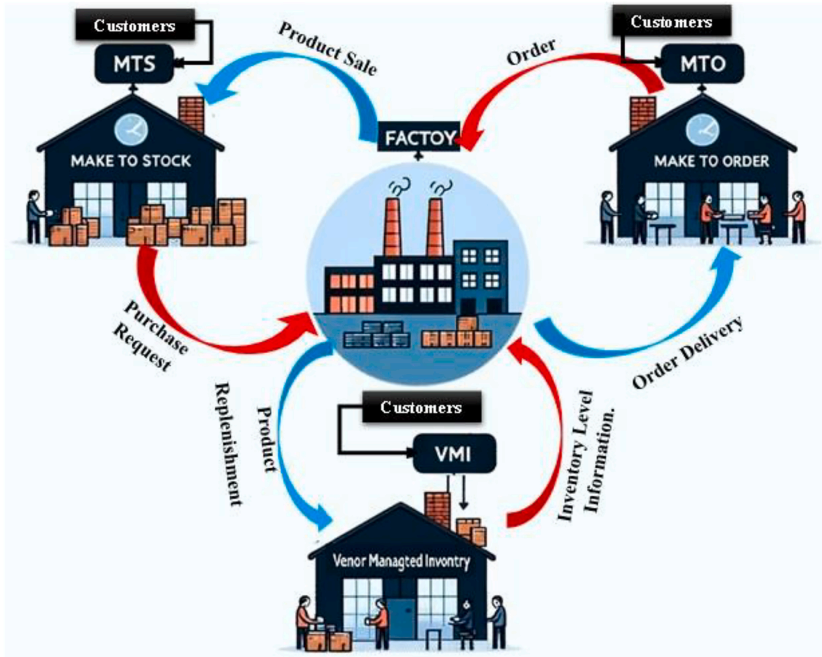


Fig. 2. illustrates the flow of products (indicated by blue lines) and information (represented by red lines) within the system under investigation.

ature review and consultation with logistics providers, transportation-related risks were categorized into seven distinct groups. Environmental risks include epidemics, natural disasters, and adverse weather conditions. Policy risks encompass import/export restrictions and political unrest. Security risks cover terrorism, crime issues, and link breakdowns. Operational risks involve interpretation problems, while capacity issues and labor shortages are categorized under supply and economic risks, respectively. Lastly, technological risks include information and communication breakdowns and inadequate transport infrastructure on links. After categorizing and specifying the risks, they are incorporated as constraints into the model MOMIP. These seven risk factors are considered active at specific points within the transportation network, represented as nodes in the model. It is assumed that all direct links from a risk-active node (RAN) to other nodes are impacted, reducing the capacity for product transport from the RAN to the other nodes. However, the transportation capacities of links from other nodes to the RAN remain unaffected. The parameter R_r, defined as the capacity coefficient factor for each risk in Section 3.1, can vary between 0 and 1. The value for each risk capacity coefficient is determined in consultation with decision-makers. Given that the proposed model considers a short time frame, these capacity coefficient factors are assumed to be constant. Moreover, the formulation of each risk as a constraint into account the insights of decision-makers.

Reduction of capacity is achieved by multiplying capacities of the normal transportation of each link (TC^{t}_{ijw}) with the coefficient factor of capacity for risk R_1across all transportation modes and periods. For Environmental risks, capacity is entirely eliminated due to the cessation of logistic operations, meaning no products can be transported from a RAN to other nodes via any transportation mode during all periods, while normal capacity limitations remain from other nodes to the RAN. For Policy risks, the capacity reduction is determined by the factor R_2; for example, if R_2 is set to 0.5, the capacity for products transported from the risk-active node in each direct link will be halved, with capacities from other nodes to the RAN unchanged. Similarly, for Security risks, capacity reduction is calculated by multiplying normal capacities with $R_3$for each transportation mode across all periods. Operational risks involves reducing capacities for specific links based on $R_4$for a particular transportation mode and time interval; for instance, if R_4 is 0.5 and the risk affects railway mode for 4 h starting from $t = 0$, the capacity for products transported via railway from the RAN will be halved during this period, without affecting capacities from other nodes to the RAN. Supply risks entails a capacity reduction by $R_5$for each transportation mode during all periods. For Economic risks, capacity reduction is calculated using $R_6$for all transportation modes within a specified time interval; for instance, if $R_6$is set to 0.5 and impacts operations for 4 h from t=0, the capacity for products transported from the RAN will be halved during this time, without altering capacities from other nodes to the RAN. Lastly, technological risks reduces capacities for certain links by $R_7$for a specific transportation mode throughout all periods; for example, if $R_7$is set to 0.5 and affects railway operations, the capacity for products transported by railway from the RAN will be halved during this period, while capacities from other nodes to the RAN remain unaffected. A detailed summary of the risk types, their operational impacts, and their coefficient values under optimistic, most likely, and pessimistic conditions is provided in Appendix B, Table B.1.

3.1. Mathematical model

In this section, we present the proposed model, detailing the objectives and constraints in relation to the defined sets, parameters, and decision variables. A complete list of model sets, parameters, and variables is provided in Appendix C.

Objective Functions

The profit maximization objective function (1) is designed to enhance the total profit generated by the supply chain. It incorporates revenue from sales and deducts costs associated with inventory holding, production, backordering, transportation, order management, unmet demand, production setup, and transshipment between two modes, and penalty costs for VMI strategy.

$$
\begin{aligned}
\textit{Maximize profit} = & \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{\substack{t,t'\in T\\ t'=t-TT_{ijw}-LT_w}} g_o^V XV_{oijw}^{tt'} + \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{\substack{t,t'\in T\\ t'=t-TT_{ijw}-LT_w}} g_o^O XO_{oijw}^{tt'} + \\
& \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{\substack{t\in T,t'\in T^{MST}\\ t'=t-TT_{ijw}-LT_w}} g_o^S XS_{oijw}^{tt'} - \sum_{j\in I\cup H\cup C}\sum_{o\in O}\sum_{t\in T} CH_j^t I_{oj}^t \\
& - \sum_{o\in O}\sum_{i\in I}\sum_{t\in T} CP_{oi}^t X_{oi}^t - \sum_{i\in I\cup H\cup C}\sum_{o\in O}\sum_{t\in T} CB_o^t BO_{oi}^t - \\
& \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in D\cup H}\sum_{w\in W}\sum_{t,t'\in T} dis_{ijw} CT_{ijw}^t X_{oijw}^{tt'} - \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{t,t'\in T} dis_{ijw} CT_{ijw}^t XV_{oijw}^{tt'} - \\
& \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{t,t'\in T} dis_{ijw} CT_{ijw}^t XO_{oijw}^{tt'} - \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{t\in T,t'\in T^{MST}} dis_{ijw} CT_{ijw}^t XS_{oijw}^{tt'} - \\
& \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{t,t'\in T} q_t XO_{oijw}^{tt'} - \sum_{o\in O}\sum_{i\in I}\sum_{t\in T} CU_{oi}^t UD_{oi}^t - \sum_{o\in O}\sum_{i\in I}\sum_{t\in T} CS_{oi}^t X_{oi}^t \\
& - \sum_{w,w'\in W}\sum_{j\in C}\sum_{t\in T} CW_{wwj'}^t \varpi_{jww'}^t - \sum_{o\in O}\sum_{i\in I}\sum_{t\in T} PC_o^V \left(I_{oi}^t - I_{oi}^t\right)^+
\end{aligned}
\tag{1}
$$

The transportation time minimization objective function (2) aims to reduce the total transportation time within the supply chain network, including travel time between nodes, and accounts for the lead time during modal shifts. This objective ensures that you not only minimize the total transit time but also optimize the efficiency of the transportation process. Larger shipments often require additional time for handling and transportation. The formulation better reflects this operational complexity. The objective function (2) encourages solutions that balance shipment sizes and delivery times effectively, avoiding inefficiencies in the supply chain, and aligning with industry logistics practices, where shipment size directly affects lead times.

$$
\begin{aligned}
\textit{Minimize Transportation time} = & \sum_{i\in I\cup D\cup H}\sum_{j\in C}\sum_{w\in W}\sum_{t'\in T} Z_{oijw}^{tt'} TT_{ijw} \\
& + \sum_{j\in D\cup H\cup C}\sum_{w,w'\in W}\sum_{t'\in T} Y_{oijww'}^{tt'} LT_w
\end{aligned}
\tag{2}
$$

The objective function to minimize GHG emissions (3) aims to reduce the environmental impact of supply chain operations by minimizing emissions from transportation and production activities. These objective functions collectively strive to balance profitability, operational efficiency, and environmental sustainability within the supply chain.

$$
\begin{aligned}
\textit{Minimize GHG emission} = & \sum_{o\in O}\sum_{i\in I\cup D\cup H}\sum_{j\in D\cup H}\sum_{w\in W}\sum_{\substack{t,t'\in T\\ t'=t-TT_{ijw}-LT_w}} dis_{ijw} EI_w X_{oijw}^{tt'} \\
& + \sum_{o\in O}\sum_{i\in I}\sum_{t\in T} EI_{oi} X_{oi}^t
\end{aligned}
\tag{3}
$$

Inventory Balance Constraints

These constraints ensure the proper flow of inventory at all locations across time.

Constraint (4) ensures the inventory balance at manufacturing units.

$$
\begin{aligned}
I_{oi}^t = I_{oi}^{t-1} + X_{oi}^t & - \sum_{j\in D\cup H}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} X_{oijw}^{tt''} \\
& - \sum_{j\in C}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} \left(XV_{oijw}^{tt''} + XO_{oijw}^{tt''}\right) \\
& - \sum_{j\in C}\sum_{w\in W}\sum_{\substack{t\in T,t''\in T^{MST}\\ t''=t+TT_{ijw}+LT_w}} XS_{oijw}^{tt''} \qquad \forall i \in I, \forall o \in O, \forall t \in T
\end{aligned}
\tag{4}
$$

$$
\begin{aligned}
\sum_{j\in D\cup H}\sum_{w\in W}\sum_{\substack{t,t'\in T\\ t'=t-TT_{ijw}-LT_w}} X_{oijw}^{tt'} = & \sum_{j\in D\cup H}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} X_{oijw}^{tt''} \\
& + \sum_{j\in C}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} \left(XV_{oijw}^{tt''} + XO_{oijw}^{tt''}\right) \\
& + \sum_{j\in C}\sum_{w\in W}\sum_{\substack{t\in T,t''\in T^{MST}\\ t''=t+TT_{ijw}+LT_w}} XS_{oijw}^{tt''} \qquad \forall i \in D, \forall o \in O, \forall t \in T
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
I_{oi}^t = I_{oi}^{t-1} + \sum_{j\in D\cup I}\sum_{w\in W}\sum_{\substack{t'\in T\\ t'=t-TT_{ijw}-LT_w}} X_{oijw}^{tt'} & - \sum_{j\in D}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} X_{oijw}^{tt''} \\
& - \sum_{j\in C}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} \left(XV_{oijw}^{tt''} + XO_{oijw}^{tt''}\right) \\
& - \sum_{j\in C}\sum_{w\in W}\sum_{\substack{t\in T,t''\in T^{MST}\\ t''=t+TT_{ijw}+LT_w}} XS_{oijw}^{tt''} \qquad \forall i \in H, \forall o \in O, \forall t \in T
\end{aligned}
\tag{6}
$$

Constraints (5) and (6) regulate the inventory balance at cross-docks and external warehouses, respectively.

$$
I_{oi}^t \geq IL_{oi} \qquad \forall i \in I \cup H, \forall o \in O, \forall t \in T \tag{7}
$$

$$
I_{oi}^t = I_{oi}^{t-1} + \sum_{j\in I\cup D\cup H}\sum_{w\in W}\sum_{\substack{t'\in T\\ t'=t-TT_{ijw}-LT_w}} XV_{oijw}^{tt'} - D_{oi}^t \gamma_i \qquad \forall i \in C, \forall o \in O, \forall t \in T \tag{8}
$$

Constraint (7) guarantees that the inventory levels at manufacturing units and external warehouses do not fall below this minimum threshold. Constraint (8) specifies the level of inventory at customers of VMI, ensuring timely delivery of products.

$$
\sum_{j\in I\cup D\cup H}\sum_{w\in W}\sum_{\substack{t'\in T\\ t'=t-TT_{ijw}-LT_w}} XO_{oijw}^{tt'} - BO_{oi}^{t-1} = D_{oi}^t \lambda_i - BO_{oi}^t \qquad \forall i \in C, \forall o \in O, \forall t \in T \tag{9}
$$

Constraint (9) addresses the levels of backordered for customers of MTO.

$$\sum_{j\in I\cup D\cup H}\sum_{w\in W}\sum_{\substack{t\in T,t''\in T^{MST}\\ t''=t+TT_{ijw}+LT_w}} XS^{tt''}_{oijw} = D^t_{oi}\psi^t_{oi} - UD^t_{oi} \qquad \forall i\in C,\forall o\in O,\forall t\in T \tag{10}$$

Constraint (10) stipulates that any unmet demand for customers of MTS is regarded as lost sales.

Production and Capacity Constraints

These constraints limit production and storage based on operational capacity.

$$X^t_{oi} \le PC^t_{oi} \qquad \forall i\in I,\forall o\in O,\forall t\in T \tag{11}$$

$$\sum_{o\in O} X^t_{oi} \le TMC^t_i \qquad \forall i\in I,\forall t\in T \tag{12}$$

Constraints (11) and (12) ensure that the production volume of products at manufacturing unit does not exceed the production capacity.

$$\sum_{o\in O}\sum_{t\in T} I^t_{oi} \le SC_i \qquad \forall i\in I\cup H\cup C \tag{13}$$

Constraint (13) ensures that the total inventory of all products at nodes of manufacturing units and external warehouses does not exceed the storage capacity.

Risk-Adjusted Transportation Constraints

These constraints ensure that transportation and loading volumes stay within capacity limits, while accounting for risk.

$$\sum_{o\in O}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} X^{tt''}_{oijw} \le TC^t_{ijw}R^t_r \qquad \forall i\in I\cup D\cup H,\forall j\in D\cup H,\ \forall w\in W,\forall t\in T,\ \forall r\in R \tag{14}$$

Constraint (14) guarantees that the volume of products transported does not exceed the transportation capacity with considering risk.

$$\sum_{o\in O}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} \left(XV^{tt''}_{oijw} + XO^{tt''}_{oijw} + XS^{tt''}_{oijw}\right) \le TC^t_{ijw}R^t_r \qquad \forall i\in I\cup D\cup H,j\in C,\ \forall w\in W,\forall t\in T,\ \forall r\in R \tag{15}$$

$$\sum_{o\in O}\sum_{j\in D\cup H}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} X^{tt''}_{oijw} + \sum_{o\in O}\sum_{j\in C}\sum_{w\in W}\sum_{\substack{t''\in T\\ t''=t+TT_{ijw}+LT_w}} \left(XV^{tt''}_{oijw} + XO^{tt''}_{oijw} + XS^{tt''}_{oijw}\right) \le LC^t_i \qquad \forall i\in I,\forall t\in T \tag{16}$$

Constraint (15) stipulates that the combined volume of products transported for VMI, MTO, and MTS policies does not exceed the transportation capacity with considering risk. Constraint (16) ensures that the total loading capacity at the manufacturing unit is not exceeded.

Customer Policy Constraints

These constraints govern the assignment of customers to fulfillment policies and the rules associated with each.

$$l^t_{oi} \le I^t_{oi} \le u^t_{oi} \qquad \forall o\in O,\forall i\in C,\forall t\in T \tag{17}$$

Constraint (17) guarantees that the inventory levels for products at customers under VMI policy remain within specified lower and upper bounds.

$$SL_i = 1 - \frac{\sum_{o\in O}\sum_{t\in T} BO^t_{oi}}{\sum_{o\in O}\sum_{t\in T} D^t_{oi}} \qquad \forall i\in C \tag{18}$$

$$SL_i \ge \vartheta\lambda_i \qquad \forall i\in C \tag{19}$$

Constraints (18) and (19) define the service level for customers under the MTO policy, calculated as the ratio of fulfilled orders to the total demand. This ensures that the service level for customers under the MTO policy meets or exceeds a predefined target.

$$\psi^t_{oj} \le \mu_j \qquad \forall j\in C,\forall o\in O,\forall t\in T \tag{20}$$

Constraint (20) determines if the demand for various products from customers of MTS is met.

$$\gamma_i + \lambda_i + \mu_i = 1 \qquad \forall i\in C \tag{21}$$

Constraint (21) ensures that each customer is assigned to exactly one of the VMI, MTO, or MTS policies.

$$BO^t_{oi} < M(1-\lambda_i) \qquad \forall i\in C,\forall o\in O,\forall t\in T \tag{22}$$

Constraint (22) guarantees that allow backorders only for customers under the MTO policy while ensuring that no backorders occur for customers under the MTS and VMI policies.

Transshipment and Mode Shift Constraints

These constraints determine when transshipment occurs and limit modal shifts to reduce operational complexity.

$$\omega^{t-TT_{ijw}}_{ijw} + \omega^t_{jkw'} \le \varpi^t_{jww'} + 1 \qquad \forall i\ne j\ne k\in H\cup D\cup I\cup C,\ \forall t\in T,\ w\ne w'\in W \tag{23}$$

$$\omega^{t-TT_{ijw}}_{ijw} + \omega^t_{jkw'} \ge 2\varpi^t_{jww'} \qquad \forall i\ne j\ne k\in H\cup D\cup I\cup C,\ \forall t\in T,\ w\ne w'\in W \tag{24}$$

Constraints (23) and (24) jointly determine whether transshipment occurs between two modes.

$$\sum_{w,w'\in W|w\ne w'}\sum_{t\in T} \varpi^t_{jww'} \le M_j \qquad \forall j\in H\cup D\cup I \tag{25}$$

Constraint (25) ensures that the number of modal shifts at transshipment points does not exceed a specified upper limit allowing flexibility in transportation mode selection based on operational requirements. This constraint prevents unnecessary modal shifts while optimizing logistics efficiency.

Linearization Constraints

These constraints linearize the shipment timing and transshipment logic for use in MILP solvers.

$$Z^{tt'}_{oijw} \ge X^{tt'}_{oijw} - M\left(1-\omega^t_{ijw}\right) \qquad \forall o\in O,\forall i\in I\cup D\cup H,\ \forall j\in C,\forall w\in W,\forall t\in T \tag{26}$$

$$Z^{tt'}_{oijw} \ge M\omega^t_{ijw} \qquad \forall o\in O,\forall i\in I\cup D\cup H,\ \forall j\in C,\forall w\in W,\forall t\in T \tag{26-a}$$

$$Z^{tt'}_{oijw} \le X^{tt'}_{oijw} \qquad \forall o\in O,\forall i\in I\cup D\cup H,\ \forall j\in C,\forall w\in W,\forall t\in T \tag{26-b}$$

$$Y^{tt'}_{oijww'} \ge X^{tt'}_{oijw} - M\left(1-\varpi^t_{jww'}\right) \qquad \forall o\in O,\forall i\in I\cup D\cup H,\ \forall j\in C,\forall w\in W,\forall t\in T \tag{26-c}$$

$$Y^{tt'}_{oijww'} \ge M\varpi^t_{jww'} \qquad \forall o\in O,\forall i\in I\cup D\cup H,\ \forall j\in C,\forall w\in W,\forall t\in T \tag{26-d}$$

$$Y^{tt'}_{oijww'} \le X^{tt'}_{oijw} \qquad \forall o\in O,\forall i\in I\cup D\cup H,\ \forall j\in C,\forall w\in W,\forall t\in T \tag{26-e}$$

Constraints (26) to (26-e) are Linearization constraints, that allow for dynamic shipment allocation while ensuring transportation efficiency is optimized.

Domain and Logical Constraints

Binary and non-negativity constraints are imposed to ensure valid and interpretable solutions.

$$\varpi^{t}_{jww'}, \omega^{t}_{ijw} \in \{0,1\} \quad \forall o \in O, \forall i,j \in H \cup D \cup I \cup C, \forall w \in W, \forall t \in T \tag{27}$$

$$\psi^{t}_{oj} \in \{0,1\} \quad \forall o \in O, \forall i \in C, \forall t \in T \tag{28}$$

$$\gamma_i, \lambda_i, \mu_i \in \{0,1\} \quad \forall i \in C \tag{29}$$

$$X^{tt'}_{oijw}, Y^{tt'}_{oijww'}, Z^{tt'}_{oijw} \geq 0 \quad \forall o \in O, \forall i \in I \cup D \cup H, \forall j \in D \cup H, \forall w \in W, \forall t \in T \tag{30}$$

$$XV^{tt'}_{oijw}, XO^{tt'}_{oijw}, XS^{tt'}_{oijw} \geq 0 \quad \forall o \in O, \forall i \in I \cup D \cup H, \forall j \in C, \forall w \in W, \forall t \in T \tag{31}$$

$$BO^{t}_{oi}, UD^{t}_{oi} \geq 0 \quad \forall o \in O, \forall i \in C, \forall t \in T \tag{32}$$

$$I^{t}_{oi} \geq 0 \quad \forall o \in O, \forall i \in I \cup H \cup C, \forall t \in T \tag{33}$$

$$SL_i \geq 0 \quad \forall i \in C \tag{34}$$

$$IL_{oi} \geq 0 \quad \forall o \in O, \forall i \in I \cup H \cup C \tag{35}$$

Finally, Constraints (27) to (35) establish the binary and non-negativity conditions for the decision variables.

4. Solution approaches

To effectively address the complexities of the multi-objective optimization problem, we propose a hybrid solution methodology that integrates MC-M-GP-UF and a heuristic approach, i.e., ABR, enhanced with Simulated Annealing (SA) and GBM.

The integration of goal programming and machine learning-driven heuristics provides a robust, adaptable, and computationally efficient framework for solving large-scale optimization problems. This approach balances theoretical rigor with practical applicability, enabling decision-makers to obtain high-quality solutions efficiently. The process begins with formulating the multi-objective optimization model using MC-M-GP-UF, incorporating goal programming principles and utility functions. A greedy heuristic then constructs an initial feasible solution, followed by ranking binary decision variables based on their impact on the objective function. To improve tractability, a subset of binary variables is relaxed into continuous ones. Next, SA metaheuristic algorithm explores the solution space, while GBM guide variable adjustments. The post-processing phase converts continuous variables back to binary through probabilistic rounding and ensures feasibility via constraint propagation. Finally, the solution's quality, convergence, and computational efficiency are assessed. This structured methodology enhances both solution accuracy and computational feasibility, making it well-suited for complex decision-making scenarios.

The rest of this section is structured as follows: Section 4.1 outlines the goal programming model, elaborating on how MC-M-GP-UF is formulated to capture the decision-maker's preferences and trade-offs among competing objectives. Section 4.2 presents the heuristic optimization approach, detailing the steps involved in ABR, the rationale behind binary variable relaxation, and the integration of machine learning-based prediction models for dynamic adjustment of decision variables.

4.1. Goal programming

Goal programming (GP) stands as a cornerstone technique in the realm of multi-objective optimization, offering a structured framework for navigating the complexities inherent in models with multiple objectives. Over time, the development of nuanced variants like weighted GP and multi-choice GP has significantly enhanced the toolkit available for decision-makers. These adaptations of the foundational GP model are tailored to meet specific situational demands, providing a customizable approach that considers both the hierarchy of objectives and the diversity of decision-making scenarios. Multi-objective decision-making often involves conflicting objectives, necessitating a structured methodology to balance trade-offs. GP is widely recognized for its ability to handle such complexities by minimizing deviations from predefined target values.

MC-M-GP-UF emerges as a sophisticated approach designed to address the multifaceted challenges encountered in scenarios where decision-makers are confronted with multiple, often conflicting, objectives [85]. This model is particularly valuable when these objectives encompass a variety of choice levels, reflecting the different degrees to which each goal can be achieved. Within the sphere of operations research, the significance of MC-M-GP-UF lies in its innovative integration of utility functions alongside traditional goal programming techniques. Utility functions are pivotal in translating the outcomes of different goals into a unified measure of satisfaction or desirability from the perspective of the decision-maker. This inclusion not only quantifies preferences but also introduces a layer of personalization to the solution process, allowing for a more nuanced exploration of the solution space. Such a feature is invaluable in real-world decision-making where subjective preferences and objective assessments intertwine.

Consider, for example, the objectives to maximize profit, minimize transportation time, and reduce environmental impacts within a logistics operation in this study. These goals, while essential to the operation's success and sustainability, naturally induce a scenario ripe with trade-offs. The maximization of profit might lead to choices that adversely affect the environment or increase transportation time due to cost considerations. Conversely, efforts to minimize environmental impacts or transportation time could potentially diminish profit margins. The utility of MC-M-GP-UF in this context becomes evident as it allows decision-makers to assign varying levels of importance to each objective through utility functions. These functions convert the achievement levels of each goal (e.g., profit amounts, transportation times, and measures of environmental impact) into utility scores. By doing so, MC-M-GP-UF supports a comprehensive and thoughtful decision-making process that respects the complexity and interdependence of the goals at hand. This approach ensures that decisions are not made in isolation or purely based on quantitative metrics but are informed by the decision-maker's subjective preferences and the intrinsic value they place on each outcome. As a result, MC-M-GP-UF stands as a potent tool in the portfolio of operations research, enabling a sophisticated, preference-informed exploration of decision-making scenarios that are as diverse and dynamic as the objectives they seek to optimize. The following presentation showcases the MC-M-GP-UF method, as outlined by Gholizadeh et al. [85].

$$Min\ (\alpha_1, \alpha_2, \alpha_3) \tag{36}$$

$$f_i(x) + n_i - p_i = K_i \quad i = 1, \ldots, v \tag{37}$$

$$O^{min}_i \leq K_i \leq O^{max}_i \quad i = 1, \ldots, v \tag{38}$$

$$U_i \leq \frac{(O^{max}_i - K_i)}{(O^{max}_i - O^{min}_i)} \quad i = 1, \ldots, v \tag{39}$$

$$U_i + \varphi_i = 1 \quad i = 1, \ldots, v \tag{40}$$

$$W_j(x) \leq y_j \tag{41}$$

$$\sum_{i=1}^{v} \beta_i \cdot \frac{p_i}{(O^{max}_i - O^{min}_i)} + \delta_1 - \alpha_1 + \sum_i \beta_i \cdot \varphi_i = S_1 \tag{42}$$

$$\beta_i \cdot \frac{p_i}{(O^{max}_i - O^{min}_i)} - D \leq 0 \quad i = 1, \ldots, v \tag{43}$$

$$D + \delta_2 - \alpha_2 + \sum_i \beta_i \cdot \varphi_i = S_2 \tag{44}$$

$$p_i - BigM_i.W_i \leq 0 \ i = 1, \ldots, \nu \tag{45}$$

$$\frac{\sum_{i=1}^{\nu} W_i}{\nu} + \delta_3 - \alpha_3 + \sum_i \beta_i.\varphi_i = S_3 \tag{46}$$

$$x, n_i, p_i, \alpha_j, \beta_j, U_i, \varphi_i \geq 0 \ W_i \in \{0,1\} \ \ i = 1, \ldots, \nu, \ j = 1, \ 2, \ 3 \tag{47}$$

Where k_i represents the goal value for the i^{th} objective function, as defined by the decision-maker. n_i *and* p_i, are denote the negative and positive deviations from the target value, respectively. $\alpha_j$and δ_j are termed as meta-deviations, indicating deviations beyond preset limits. $S_j$sets the limit for each deviation type *j* ensuring constraints are adhered to. $BigM_i$ is a significantly large number that facilitates the modeling of constraints. $W_i$is a binary variable introduced to handle conditional constraints. β_i reflects the importance weight assigned to the i^{th} objective function, guiding the prioritization of goals. *D* represents the maximum tolerable deviation, a constraint to minimize undesired deviations. O_i^{max}*and* $O_i^{min}$are define the lower and upper bounds of the target range for the objective, respectively. $U_i$captures the utility value, a measure of the desirability of outcomes. K_i is a continuous variable that along with$\varphi_i$the normalized deviation from O_i^{min} facilitates the adjustment of goals within their feasible ranges. $f_i(x)$ is the function defining the objective, while $W_j(x)$ represents the constraints within the model. $y_j$specifies the aspiration level for the j^{th} constraint vector, aiding in the alignment of model outcomes with strategic objectives.

The objective function, adaptable in either a min-max or weighted format, encapsulates these elements to construct a framework that adeptly addresses the complexities inherent in multi-objective decision-making scenarios. This paper predominantly focuses on the weighted form, advocating for a methodological approach that balances between competing objectives through the strategic weighting of their relative importance, thus providing a nuanced pathway to optimal decision resolution.

The selection of MC-M-GP-UF over alternative multi-objective decision-making (MODM) methods is driven by its ability to integrate decision-maker preferences directly into the optimization framework, eliminating the need for post-solution selection. Unlike traditional MODM techniques such as Multi-Objective Evolutionary Algorithms (MOEAs), Pareto-based Multi-Criteria Decision-Making (MCDM) methods, and conventional GP, MC-M-GP-UF offers a more structured approach by incorporating multiple aspiration levels and utility-based decision modeling. This ensures that conflicting objectives, such as cost minimization, environmental impact reduction, and service level improvement, are balanced effectively within a mathematically rigorous yet practically interpretable structure. The methodology enhances decision flexibility through meta-deviations, enabling strategic constraint relaxation, while binary decision variables allow for the dynamic activation or deactivation of specific goals based on operational priorities.

Furthermore, MC-M-GP-UF's integration of utility functions provides a superior mechanism for quantifying trade-offs, ensuring that deviations from target objectives are evaluated based on their real-world desirability rather than treated equally. This feature is particularly beneficial in complex logistics and supply chain problems, where multiple objectives with varying levels of acceptability must be managed simultaneously. By explicitly embedding decision-maker preferences into the optimization process, MC-M-GP-UF generates solutions that are both theoretically robust and practically implementable, making it an ideal choice over conventional MODM approaches. Its ability to accommodate multiple aspiration levels, balance competing priorities, and enhance model adaptability ensures that decision-makers can derive optimal solutions that align with both strategic and operational realities.

4.2. Heuristic approach

The proposed heuristic, named ABR, is aimed at efficiently solving large-scale MIP problems, where the traditional exact methods struggle due to computational complexity. The ABR method is particularly suited for problems characterized by a large number of binary decision variables, such as scheduling, facility location, and network design problems. The ABR heuristic is built on the concept of iteratively relaxing binary variables based on their marginal contribution to the objective function and constraints satisfaction, using a combination of local search and machine learning prediction models. The core idea is to identify and relax those binary variables that, when converted to continuous variables, lead to significant improvements in the solution's quality or computation time, without drastically moving away from feasibility or optimality.

The ABR heuristic was selected due to its ability to efficiently solve large-scale MIP problems, where traditional exact methods such as Branch-and-Bound (B&B), Branch-and-Cut (B&C), and Branch-and-Price (B&P) become computationally intractable. These conventional methods struggle with the exponential growth of the solution space when dealing with a high number of binary variables, leading to excessive computation times and memory usage. Unlike full linear relaxation methods, which often yield solutions that are too distant from integer feasibility, ABR selectively relaxes a subset of binary variables based on their marginal contribution to the objective function and constraint satisfaction. This approach ensures a balance between relaxation and feasibility, allowing the solution to remain close to optimality while significantly reducing computational complexity. By integrating machine learning models, ABR dynamically predicts which binary variables should be relaxed, ensuring that the relaxation process is adaptive and problem-specific rather than relying on static heuristic rules. This data-driven relaxation strategy makes ABR particularly effective for scheduling, facility location, and network design problems, where binary decision variables play a crucial role in determining feasibility and cost-effectiveness.

Furthermore, ABR's methodological foundation is rooted in hybrid optimization principles, combining mathematical programming, machine learning, and local search techniques to refine solutions iteratively. Unlike metaheuristic methods such as Genetic Algorithms (GA), SA, or Variable Neighborhood Search (VNS), which primarily focus on global search exploration, ABR efficiently leverages local search mechanisms to restore feasibility by adjusting relaxed variables where necessary. This targeted approach avoids unnecessary exploration of infeasible solutions, ensuring computational efficiency while preserving the combinatorial structure of the problem. Additionally, ABR's ability to adaptively reintroduce relaxed variables when feasibility is compromised ensures that solutions maintain high practical applicability in real-world decision-making contexts. Compared to Hybrid Benders Decomposition (HBD) or Lagrangian Relaxation, which require intricate problem decomposition and parameter tuning, maybe ABR offers a simpler yet potentially highly effective alternative that is easily adaptable to various problem structures. For this, we can specifically benefit from these approaches in future research compared to the proposed ABR. Thus, ABR was chosen for its ability to balance computational efficiency, feasibility preservation, and adaptability, making it a superior heuristic for solving complex, large-scale MIP problems in industrial and logistical applications.

To implement the ABR heuristic for binary variable relaxation in MIP problems, follow these detailed working steps:

Step 1: **Initialization**
Input: Original MC-M-GP-UF problem with binary decision variables.
Process:
Using a simple heuristic greedy algorithm to find an initial feasible solution for the MIP problem. This involves setting initial values for all binary decision variables. Identify and list all binary variables in the problem. The primary purpose of using a Greedy Algorithm in the ABR heuristic is to quickly establish a starting point for our optimization process. The algorithm selects initial values for binary

decision variables in a way that seeks to optimize the objective function immediately, albeit locally. This is typically not the global optimum but gives a solid baseline for subsequent optimization steps.

Use a greedy algorithm to set initial values for all binary decision variables X_{ij} to obtain an initial feasible solution $X_{ij}^{(0)} = \begin{cases} 1, & g_{ij} \leq threshold \\ 0, & otherwise \end{cases}$, Where g_{ij} represents the greedy criterion for variables X_{ij} such as cost or benefit.

***Step 2:* Variable Importance Ranking**

Process:

For each binary variable, calculate its sensitivity score. This involves altering the value of the variable from 0 to 1 and vice versa, while keeping other variables constant, and observing the change in the objective function value. Rank the binary variables based on their sensitivity scores. Variables that cause a larger change in the objective function are considered more important.

For each binary decision variables X_{ij}: $S_{ij} = \left| f\left(X_{ij}^{(0)} = 1, X_{-ij}\right) - f\left(X_{ij}^{(0)} = 0, X_{-ij}\right) \right|$, where S_{ij} is sensitivity scores and $f(x)$ is the objective function value with x as the decision vector. X_{-ij} represents all variables except X_{ij}.

Rank the binary variables based on their sensitivity scores in descending order. $Rank\left(X_{ij}^{(0)}\right) = Sort\left(S_{ij},\ descend\right)$.

***Step 3:* Adaptive Relaxation**

Process:

Select a subset of binary variables for relaxation. This selection is based on the importance ranking and a predefined criterion (e.g., the variables with the top 5 % highest sensitivity scores). Relax the selected variables by converting them into continuous variables that can take any value within the range [0,1].

Select variables $= \left\{ X_{ij}^{(0)} | X_{ij}^{(0)} \in\ Top\ 5\%\ Rank\left(X_{ij}^{(0)}\right)\right\}$. Convert selected binary variables $X_{ij}^{(0)}$ to continuous variables Y_{ij} within the range [0,1]. $Y_{ij} \in [0,1]\ \forall X_{ij}^{(0)} \in$ Select variables.

***Step 4:* Local Search and Machine Learning Prediction**

Process:

Apply a local search algorithm (Simulated Annealing) to find a near-optimal solution to the problem with the now partially relaxed binary variables. Inspired by the physical process of heating and then slowly cooling a material to decrease defects, SA is a probabilistic technique for approximating the global optimum of a given function. It is especially effective in navigating large, complex solution spaces by allowing occasional moves to worse solutions, thereby avoiding being trapped in local optima. SA is fundamentally used to explore the solution space efficiently, even if that space is partially or fully continuous due to the relaxation of binary variables. It can navigate large and complex landscapes to avoid local optima and find better solutions. In ABR, not all binary variables may be relaxed; some might remain binary for various iterations based on their impact on the objective function. Thus, SA can help in exploring combinations of binary and continuous decisions. In each iteration of the ABR, after SA has been applied, the results can feed back into the system, influencing which variables are relaxed or reinstated as binary in subsequent rounds. This iterative process allows the algorithm to refine its approach based on new information and improved solutions found by SA.

The SA algorithm implemented in this study initiates with a predefined solution deemed optimal based on prior heuristic analysis. Each iteration within the algorithm, ranging from 1 up to a maximum iteration count (MaxIt), involves the generation of a new solution from the neighborhood of the current optimal solution. This new solution is then assessed against the existing best solution. If it demonstrates superior performance, it is immediately accepted and becomes the new benchmark for subsequent iterations. However, in cases where the new solution does not surpass the previously established best, the algorithm employs a probabilistic decision-making rule inspired by the principles of thermal annealing. Here, temperature reduction metaphorically represents the gradual decrease in the likelihood of accepting worse solutions as the algorithm progresses, simulating the physical process of annealing where materials cool and stabilize.

The SA algorithm's unique approach allows it to probabilistically accept a new solution even if it is not immediately apparent as superior, thus avoiding local minima and promoting a comprehensive exploration of the solution space. This method ensures a thorough search for the global optimum by leveraging both improvement-driven and exploration-driven updates. The decision rule is quantitatively driven by comparing the objective functions of the new solution, $f_{(New\_Sol_i)}$, and the best current solution, $f_{(Sol_i)}$. Specifically, Sol_i represents the optimal solution at any given iteration i and Sol^*, which aligns with Sol_i, marks the overall best solution found across all iterations up to i.

Step SA:

Initialization: The initial solution for the SA process is taken from the outcome of Step 3, where some binary variables have been adaptively relaxed to continuous values within a range, typically [0,1]. This solution, which includes both the remaining binary and the newly continuous variables, serves as the starting point for the SA.

Temperature Schedule: Define a cooling schedule, starting from a high temperature and gradually cooling. The temperature controls the probability of accepting worse solutions to escape local optima. $T_{n+1} = \alpha T_n\ with\ \alpha \in (0,1)$.

Neighbor Solution Generation: At each step, generate a "neighbor" solution by making small, random changes to the current solution. This could involve slightly altering the values of the relaxed variables. Fig. 3 showcases the application of various operators, including swap, reversion, and insertion, to generate the initial solution for the neighborhood procedure. We'll use a vector that includes both binary (shown as regular numbers) and relaxed continuous variables (shown as decimal numbers between 0 and 1). In this instance, the swap operator interchanges the positions of a binary variable and a continuous variable. Swap the second element (binary, value 1) with the seventh element (continuous, value 0.7). This operation is used to explore radically different configurations by exchanging the roles of binary and continuous variables, potentially leading to significant changes in the solution structure. Conversely, the reversion operator changes the state of a binary variable to its opposite and adjusts a continuous variable towards the opposite end of its range. Flip the first element (binary, value 0 to 1) and adjust the sixth element (continuous, value 0.3 to 0.8). Useful for toggling binary decisions and adjusting continuous variables, potentially exploring opposite ends of the solution space. The insertion operator makes slight numerical adjustments to continuous variables. Increase the third element (continuous, value 0.5 to 0.55) and decrease the eighth element (continuous, value 0.7 to 0.65). Fine-tunes the values of continuous variables for minor improvements, optimizing around the current area of the solution space.

Acceptance Criterion: Decide whether to move to the neighbor solution based on the Metropolis criterion. This criterion allows moves to better solutions and, with decreasing probability as temperature decreases, to worse solutions.

1. Generate a neighbor solution New_Sol_i by slightly altering Sol_i .
2. Calculate the change in objective function: $\Delta f = |f_{(New\_Sol_i)} - f_{(Sol^*)}|$.
3. Accept New_Sol_i with probability $p = exp\ (-\Delta f / T_{n+1})\ if\ \Delta f > 0$.

Cooling and Iteration: Lower the temperature according to the schedule and repeat the neighbor generation and acceptance steps

Swap

Sol_i	0	1	0.5	1	0	0.3	1	0.7	0	1
Sol_{i+1}	0	0.7	0.5	1	0	0.3	1	1	0	1

Reversion

Sol_i	0	1	0.5	1	0	0.3	1	0.7	0	1
Sol_{i+1}	1	1	0.5	1	0	0.8	1	0.7	0	1

Insertion

Sol_i	0	1	0.5	1	0	0.3	1	0.7	0	1
Sol_{i+1}	0	1	0.55	1	0	0.3	1	0.65	0	1

Fig. 3. Neighborhood procedures of the proposed SA algorithm.

until a stopping condition is met (e.g., temperature below a threshold, no improvement over a number of iterations).

1. Update temperature: $T_{n+1} \leftarrow \alpha T_n$.
2. Stop when: $T_{n+1} < T_{min}$ or after a fixed number of iterations.

SA parameters were set as follows: initial temperature (T_0) scaled to 1.0 – 10.0, cooling rate (α) at 0.95, acceptance probability following the Metropolis criterion, and stopping criteria defined by$T_{min} = 0.01$ a maximum iteration limit of 500–1000, or lack of improvement over several consecutive iterations, ensuring computational efficiency while maintaining high solution quality.

Concurrently, use GBM as the machine learning model that have been trained on historical data of similar problems to predict the impact of further relaxing binary variables or the potential benefit of reinstating the binarity of certain variables. GBM is a powerful ensemble learning technique that builds models in a stage-wise fashion. It optimizes a differentiable loss function by sequentially adding weak learners, typically decision trees, to improve the model's predictive accuracy. It's well-suited for regression and classification problems and can handle various types of data. The selection of GBM in this hybrid optimization approach is based on its ability to capture complex, nonlinear relationships between decision variables and their impact on the optimization process. GBM is well-suited for predicting which binary decision variables should be relaxed into continuous values and which should be reinstated to improve solution feasibility and efficiency. This data-driven approach is essential for Adaptive Binary Relaxation (ABR), where dynamic decisions on variable relaxation can significantly affect computational performance. The selection process considered GBM's ability to provide feature importance rankings, which helps prioritize variables based on their sensitivity scores. By sequentially adding weak learners (decision trees) to minimize a loss function, GBM ensures high predictive accuracy while avoiding overfitting through shrinkage, subsampling, and feature selection. These characteristics make GBM a robust choice for guiding the iterative relaxation and re-binarization of decision variables in large-scale MIP problems.

The configuration of GBM involved optimizing hyperparameters such as the number of trees (n_estimators: 300–500), learning rate (0.05–0.1), max depth (4–7), and subsampling fraction (0.8) using Bayesian Optimization and 5-Fold Cross-Validation. The model was trained on historical data from previous ABR iterations, where variables' relaxation states and objective function changes were used as key features. Evaluation metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), were used to validate predictive accuracy, ensuring the model generalizes well across different instances. The trained GBM was integrated into the ABR heuristic to guide variable selection at each iteration: variables with high predicted relaxation benefits were converted to continuous, while those with high reinstatement benefits were forced back to binary. This iterative machine learning-driven decision-making process improved solution feasibility, reduced computation time, and maintained solution accuracy, making the hybrid heuristic framework a scalable and adaptive optimization tool.

Step GBM:

Training Data Preparation: Use historical data from previous iterations of the algorithm, including features such as variable importance scores, current solution quality, and problem characteristics.

Model Training: Train GBM models to predict two outcomes:

1. The potential improvement in the objective function for further relaxing specific binary variables.
2. The expected benefit of reinstating the binarity of certain variables that were previously relaxed.

GBM constructs an ensemble of weak learner models in a forward stage-wise manner by minimizing a loss function $L(z,F(x))$, where z is the true target value, and $F(x)$ is the model prediction. For each outcome z_i (where i could be Y_{relax} *or* Y_{binary}), the GBM algorithm iteratively adds a new weak learner$h_m(x)$ that best fits the current residuals, $r_{im}$where m denotes the iteration number, $r_{im} = -\left[\frac{\partial L(z_i,F_{m-1}(x))}{\partial F_{m-1}(x)}\right]_{z_i,F_{m-1}(x_i)}$. The model update equation at iteration m is $F_m(x) = F_{m-1}(x) + \upsilon . h_m(x)$, where$F_{m-1}(x)$is the ensemble model from the previous iteration, $h_m(x)$ is the newly added weak learner, and υ is the learning rate.

Prediction and Decision Making: Use the trained GBM models to make predictions on the current set of relaxed variables. Based on these predictions, identify which variables to further relax and which to convert back to binary. Once the models are trained, predictions can be made on the current set of variables to determine the action to take (whether to relax further or reinstate binarity). For a given set of features $X_{current}$,$F_{relax}(X_{current})$ or $F_{binary}(X_{current})$. These predictions guide the decision on which variables to relax further and which to revert to binary, aiming to minimize the objective function or improve computational efficiency.

Adaptive Adjustments: Incorporate the predictions into the decision-making process for the next iteration, adjusting the relaxation strategy accordingly to improve solution quality and computational efficiency. The decision to adjust variables is based on predictions. This could be represented as an optimization problem where the goal is to find the set of variablesV_{adjust} that maximizes the predicted improvement in the objective function or reduces computational complexity, $max V_{adjust} \left(F_{relax}(X_{current}) + F_{binary}(X_{current})\right)$, where V_{adjust} includes decisions on variable status adjustments based on the models' outputs.

Step 5: **Iteration**

Process:

Evaluate the solution obtained from the local search and machine learning prediction step in terms of quality and computational efficiency. If the stopping criteria (e.g., maximum iterations, satisfactory solution quality, time limit) are not met, update the importance rankings of the variables based on new sensitivity scores. Based on updated rankings, adjust the set of variables to be relaxed in the next iteration and repeat the process from Step 3.

The Simulated Annealing process provides a dynamic way to explore the solution space of the relaxed problem, while the GBM predictions guide strategic decisions on variable relaxation and binarity. Together, these methods enable a synergistic approach to solving the ABR heuristic's optimization problem, balancing exploration and exploitation to find high-quality solutions efficiently. By iteratively refining the set of relaxed variables and using informed predictions for strategic adjustments, this step is critical in evolving the solution towards optimality, ensuring that the ABR heuristic effectively addresses the challenges posed by complex MIP problems.

***Step 6:* Post-Processing**

Process:

After the final iteration, some variables will be in a continuous state. Apply the probabilistic rounding approach as a rounding strategy to these variables to convert them back to binary values (0 or 1), ensuring they comply with their original binary constraints. If the rounding results in an infeasible solution, implement the constraint propagation technique as a repair mechanism to correct this and obtain a feasible solution to the original MIP problem.

Rounding Strategy

After the final iteration of the ABR heuristic, we are left with a solution where some of the original binary variables are in a continuous state, i.e., their values are between 0 and 1. To convert these variables back to binary values (0 or 1), we apply a rounding strategy. The chosen rounding strategy is the Probabilistic Rounding approach. This approach takes into consideration the value of the continuous variables as probabilities indicating the likelihood of assigning a variable the value 1.

Probabilistic Rounding approach

Probabilistic Rounding approach X_{ij}, generate a random number, r from a uniform distribution over [0,1]. If $r \leq Y_{ij}$, set the binary variable to 1; otherwise, set it to 0. This method acknowledges the solution space's stochastic nature and helps in exploring feasible solutions that might be closer to optimality by considering the continuous relaxation's information, $X_{ij} = \begin{cases} 1, & r \leq Y_{ij} \\ 0, & \textit{otherwise} \end{cases}$.

Repair Mechanism

It's possible that after rounding, some constraints of the original MIP problem are violated, making the solution infeasible. To address this, we implemented a repair mechanism. The chosen repair mechanism is based on the constraint propagation technique, which iteratively fixes violations while minimizing the deviation from the rounded solution, $g(X) \leq b$.

Constraint Propagation

Start by identifying all constraints violated by the rounded solution. For each violated constraint $g_k(X) > b_k$, identify binary variablesX_{ij} that, if flipped, would help in satisfying the constraint. When choosing variables to flip, prioritize those with minimal impact on the objective function and other constraints. This might involve calculating the "cost" of flipping each variable, considering both the direct impact on the objective function and the indirect impact on constraint satisfaction, $Cost(X_{ij}) = \Delta f(X_{ij}) + \sum_k \Delta g_k(X_{ij})$, where $\Delta f(X_{ij})$ is the change in the objective function and $\Delta g_k(X_{ij})$, is the change in constraint k. The process is iteratively applied until all constraints are satisfied or a predefined iteration limit is reached to prevent endless loops.

5. Case study

This study's computational experiments were designed around a case study, closely mirroring a real-world scenario in the chemical industry. Our primary goal was to identify the most effective production strategies for various customers and assess how different transportation modes—especially when considering their static aspects and associated risks—affect the overall efficacy of the production-inventory system, focusing particularly on planning efficiency. We further expanded our investigation through numerous experiments under various modeling conditions, employing the ABR approach. Additionally, we conducted a thorough sensitivity analysis to understand how changes in key parameters influence outcomes, offering deeper insights into system responsiveness. For implementation, we used GAMS for developing our model and the CPLEX solver for problem-solving, utilizing their standard configurations. This computational work was performed on a 64-bit laptop equipped with an Intel® Core™ i7–11390H CPU at 1.5 GHz, 16 GB of RAM, operating under Windows 11. We utilized GAMS (version 2017) and Python (version 3.12) as our primary programming tools, ensuring that our models were both robust and efficiently solved.

This case study explores a company's complex operations, which services an extensive customer base of over 100 clients across Iran and the Persian Gulf region, producing a diverse array of products such as Olefins, Polymers, Aromatics, Fertilizers, Chemicals, Intermediates, and Gases. The company operates three main factories within Iran, complemented by 30 external warehouses that vary in storage capacity. Deliveries to customers are executed through a mix of transportation modes, including trains, trucks, and ships. Our analysis spans a seasonal planning horizon, breaking down into weekly segments over a one-year period. We structured our study around data provided by the company, including essential variables like customer demand, production and storage capacities, and logistical costs. However, due to confidentiality agreements, certain data was anonymized. Additionally, we estimated values for some variables, such as backordering costs and sales prices, by employing random generation techniques, given the absence of specific data from the company. The configuration of our case study is meticulously outlined following, which includes a comparison of sales pricing strategies for different customer types—demonstrating a 18 % price differential between MTO and MTS clients, with a similar margin applied between VMI clients and MTO clients. The selling prices for products are \$100 to \$150 per unit for VMI customers, \$85 to \$120 per unit for MTO customers, and \$70 to \$100 per unit for MTS customers. Inventory holding costs range from \$5 to \$20 per unit per period, while transportation costs between nodes range from \$0.5 to \$2 per unit per kilometer, depending on the mode. Production costs vary from \$50 to \$100 per unit, with backorder costs for MTO customers between \$10 and \$30 per unit per period. Order management costs are \$200 to \$500 per order, and production setup costs range from \$500 to \$2000 per setup. Unmet demand costs range from \$15 to \$40 per unit, and transshipment costs are \$100 to \$300 per transshipment. Storage capacities at nodes range from 1000 to 5000 units per period, while production capacities for products range from 100 to 500 units per period. Total manufacturing capacities are 2000 to 10,000 units per period, and transportation capacities are 500 to 2000 units per mode per period, with loading capacities at manufacturing units ranging from 500 to 1500 units per period. Risk capacity coefficients vary from 0.1 to 0.5. Travel times between nodes using different transportation modes range from 1 to 5 days, and transport lead times are 1 to 7 days. Inventory levels for VMI customers have lower bounds of 50 to 100 units and upper bounds of 200 to 500 units. Consumer demand for products ranges from 50 to 500 units per period. The inventory multiplier is set at 1.05, indicating a 5 % increase per period, and the service level target for MTO customers is 95 %. GHG emissions factors for transportation modes range from 0.1 to 0.5 kg CO_2 per unit per kilometer, while production emissions factors range from 0.05 to 0.2 kg CO_2 per unit. Distances between nodes range from 50 to 10,000 km, depending on the specific routes and transportation modes used. In this case study, there are 3 manufacturing companies involved, producing a total of 7 different products. The companies serve 45 customers across Iran and the Persian Gulf region. The distribution network includes 30 external warehouses and 6 cross-dock centers. The planning horizon for the study spans 48 weeks, divided into weekly segments. The model considers 7 different risk categories.

5.1. *Effectiveness of the proposed method*

To evaluate the Adaptive Binary Relaxation (ABR) method, we conducted a series of test problems, comparing its performance against the Multi-Choice Meta-Goal Programming with Utility Function (MC-M-GP-UF) approach. Our comparison focused on two critical metrics: CPU processing time and solution quality, the latter represented by the Gap Analysis Percentage (GAP) calculated as follows:

$$GAP = \frac{\mathrm{ABR}_{sol} - (\mathrm{MC} - \boldsymbol{M} - \mathrm{GP} - \mathrm{UF}_{sol})}{(\mathrm{MC} - \boldsymbol{M} - \mathrm{GP} - \mathrm{UF}_{sol})} \times 100 \tag{48}$$

Table 1 demonstrates the ABR's capability to solve problems with varying complexity within a reasonable time frame, significantly outperforming the MC-M-GP-UF, especially in problems #11 and #12. The CPU time and the solution quality (Z1: maximum profit, Z2: minimum transportation time, Z3: minimum GHG emission) show the ABR's adaptability and efficiency across different scenarios. Table 2 also provides a deeper insight into the ABR's performance by quantifying the gap percentage for each objective function. The increase in GAP values for lower problem numbers and the decrease in GAP values for higher problem numbers indicate a growing difference in solution quality between ABR and MC-M-GP-UF. This highlights the effectiveness of ABR in solving increasingly complex optimization problems. The average gaps for each objective function were 2.67 %, 1.63 %, and 0.71 % respectively. The standard deviation gaps were 1.48 %, 0.67 %, and 0.40 % respectively for each objective function. The fact that the proposed approach achieved an average gap percentage of <3 % is significant. An acceptable gap is considered to be <3 % and indicates that the proposed ABR approach consistently provides solutions that are close to the optimal solutions of the MC-M-GP-UF method. The gaps in solution quality for Z1 and Z2 are relatively higher on average compared to Z3, indicating more significant discrepancies between the ABR and MC-M-GP-UF methods for these objectives. The standard deviation for each gap percentage shows variability in the solution quality gaps across different problems, with Z1 showing the most considerable variation. Figs. 3 and 4 visually corroborate the tabulated data, offering a clear comparative perspective on the efficiency and effectiveness of ABR versus MC-M-GP-UF. Fig. 4 clearly shows that, generally, MC-M-GP-UF requires more CPU time to solve the problems compared to ABR, particularly as the problem number increases, suggesting that ABR is more efficient in terms of computation time. The paired sample *t*-test on the CPU time resulted in a t-statistic of −2.423 and a p-value of 0.038. The p-value is less than the conventional threshold of 0.05, indicating that there is a statistically significant difference in the CPU time between the ABR approach and the MC-M-GP-UF for the problems tested. Specifically, this suggests that ABR is more efficient than MC-M-GP-UF in terms of computation time, as it consistently requires less CPU time to achieve its solutions. Fig. 5 emphasizes the ABR's consistent achievement of lower GAP values, signifying superior solution quality. This analysis reveals that the ABR approach not only excels in computational efficiency but also in maintaining high-quality solutions across a diverse set of optimization problems, confirming its potential as a robust tool in complex decision-making scenarios.

Table 2 presents a comprehensive comparative analysis of four optimization methods—ABR, MC-M-GP-UF, NSGA-II [93], and SA—across three problem sizes (Small, Medium, and Large) in relation to three primary objectives: maximizing total profit, minimizing transportation time, and reducing GHG emissions. The analysis clearly highlights the superior overall performance of the ABR approach, particularly in larger problem instances where complexity and computational demand are more pronounced. In the Small problem size, ABR delivers the highest profit ($4592,088.64), the lowest transportation time (7906 h), and the lowest GHG emissions (10.24 kg CO_2), all achieved with the lowest optimality gap (1.96 %) and fastest CPU time (71 s). Conversely, SA and NSGA-II show relatively diminished performance, with higher emissions and suboptimal profits, reflecting their limitations in fine-tuning trade-offs across conflicting objectives. For the Medium problem size, ABR continues to demonstrate robust performance with a significant profit margin of $16.1 million and the lowest emissions (39.12 kg CO_2), while maintaining a lower CPU time (235 s) and a gap of just 2.19 %. In contrast, MC-M-GP-UF and SA methods yield higher transportation times and environmental impacts, alongside increased optimality gaps. NSGA-II, while more efficient than SA, still trails ABR in profit and environmental efficiency. In the Large problem instance, ABR significantly outperforms all alternatives with a profit of over $63 million and the shortest transportation time (25,875 h), coupled with the lowest GHG emissions (73.2 kg CO_2) and a remarkably low optimality gap of 1.3 %. Notably, MC-M-GP-UF failed to return results within the computational time limit (>25,000 s), confirming its scalability challenges. NSGA-II and SA, although able to deliver solutions, incur significantly higher computational costs and exhibit elevated emissions and longer delivery times. These findings underscore the efficiency, scalability, and environmental sensitivity of the ABR approach, reinforcing its suitability for large-scale, multi-objective decision-making environments. Furthermore, the inability of MC-M-GP-UF to scale efficiently, combined with the higher variability of SA and NSGA-II outcomes, validates the methodological advancements offered by ABR in balancing economic, operational, and environmental trade-offs within complex supply chain optimization problems.

Fig. 6 presents a comprehensive IGD-based performance comparison among four algorithms: the proposed ABR method and three benchmark approaches—MC-M-GP-UF, NSGA-II, and SA—across a suite of 18 multi-objective test problems. The results clearly demonstrate the superior performance of ABR in generating high-quality Pareto-optimal solutions. Specifically, ABR consistently achieves the lowest median and mean Inverted Generational Distance (IGD) values across all problem instances, indicating solutions that are not only closer to the true Pareto front but also more evenly distributed throughout the objective space. This performance is complemented by a tightly bounded interquartile range (IQR) in ABR's IGD boxplots, reflecting low variability and high algorithmic stability across varying problem complexities. In contrast,

Table 1
The results obtained by the ABR and MC-M-GP-UF.

Problem	ABR				MC-M-GP-UF				The quality of the solution with respect to the optimal gap between ABR and MC-M-GP-UF for each objective.		
	Z1	Z2	Z3	CPU time	Z1	Z2	Z3	CPU time	GAP1 % for Z1	GAP2 % for Z2	GAP3 % for Z3
1	2920,000	7700	7.22	35.3	2920,000	7700	7.22	33	0.000	0.000	0.000
2	3658,760	8693.1	8.2	51.6	3658,760	8493.1	8.2	65	0.000	2.355	0.000
3	4698,659.3	9581.9	9.41116	73.2	4580,301.6	9367.9	9.3	167.9	2.584	2.284	1.195
4	5897,286.1	10,549.3	10.6147	98.6	5737,967.41	10,332.8	10.5	383.2	2.777	2.095	1.092
5	7397,590.5	11,616.4	12.00904	134.3	7188,953.41	11,397.1	11.9	939.9	2.902	1.924	0.916
6	9308,580.9	12,791.1	13.6189	195.4	9008,660.48	12,571	13.5	2878.7	3.329	1.751	0.881
7	11,700,281.9	14,090.7	15.42448	286.3	11,284,461.5	13,865.8	15.3	6705.6	3.685	1.622	0.814
8	14,699,253.2	15,523	17.43114	477.5	14,140,846.2	15,293.9	17.3	10,694	3.949	1.498	0.758
9	18,411,544.3	17,104.6	19.74312	653.8	17,714,932	16,869.2	19.6	16,667.8	3.932	1.395	0.730
10	22,980,155	18,853.3	22.35328	825.2	22,194,586.7	18,606.7	22.2	20,775.8	3.539	1.325	0.690
11	27,809,817.2	20,705.1	24.7	947.3	–	–	–	>25,000	–	–	–
12	34,845,700.9	22,982.7	27.4	1018.5	–	–	–	>25,000	–	–	–

Table 2
Analyzing optimization approaches across problem sizes.

Problem Size	Method	Objective 1: Profit	Objective 2: Transportation Time	Objective 3: GHG Emissions	Optimality Gap (%)	CPU Time (s)
Small	ABR	4592,088.64	7906	10.24	1.96	71
	MC-M-GP-UF	4501,713.68	7982	11.85	2.66	112
	NSGA-II	4315,393.61	7998	12.83	3.37	99
	SA	4226,149.18	8033	13.63	4.81	113
Medium	ABR	16,107,607.82	14,353	39.12	2.19	235
	MC-M-GP-UF	15,798,143.41	14,834	40.4	3.34	463
	NSGA-II	15,167,279.9	15,900	42.41	3.71	363
	SA	14,867,380.37	16,194	44.24	3.71	398
Large	ABR	63,240,870.47	25,875	73.2	1.3	757
	MC-M-GP-UF	**N/A**	**N/A**	**N/A**	**N/A**	**>25,000**
	NSGA-II	59,529,154.02	28,399	79.05	4.05	1140
	SA	58,289,686.45	29,054	81.46	4.38	1220

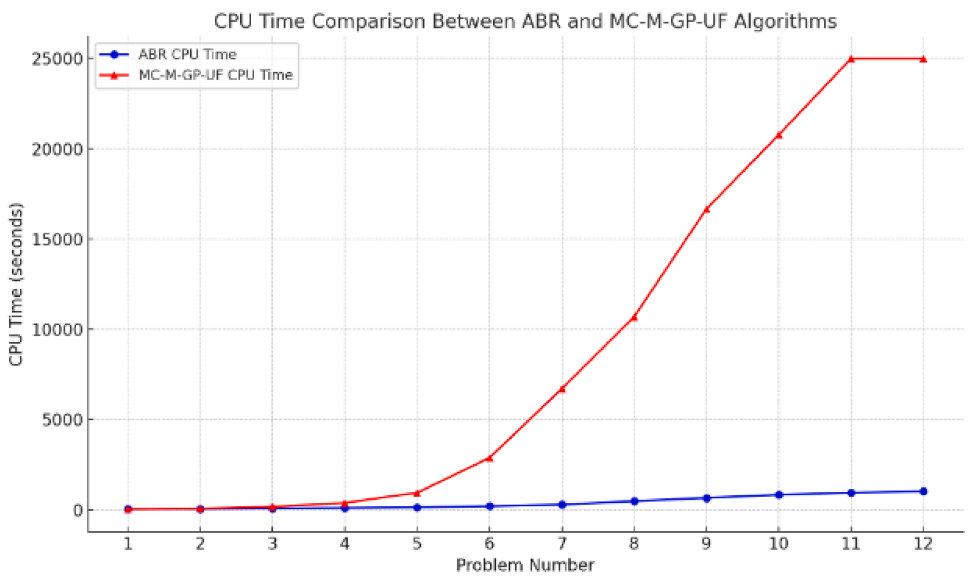


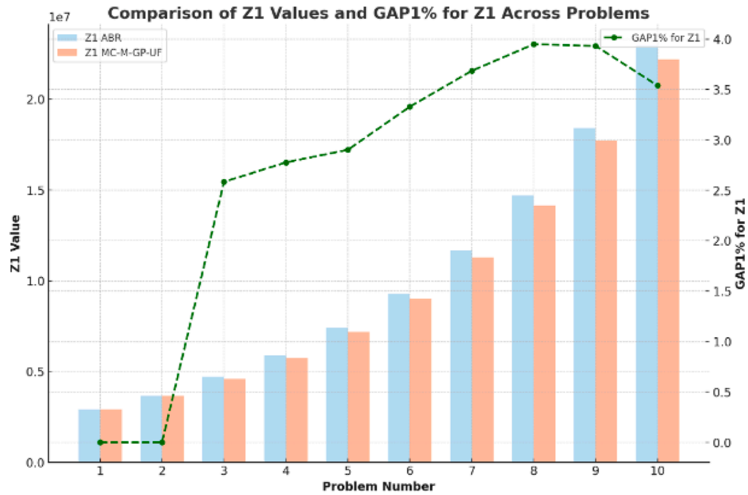
Fig. 4. The performance of the proposed ABR and MC-M-GP-UF based on the CPU time.

the MC-M-GP-UF approach shows higher IGD values and greater variance, particularly in large-scale problems. This suggests reduced reliability and increased sensitivity to problem size and structure. The presence of more pronounced outliers in MC-M-GP-UF further underscores its occasional inability to maintain proximity to the Pareto front, highlighting potential methodological limitations under complex scenarios. The NSGA-II and SA algorithms demonstrate moderate performance. However, their IGD distributions become increasingly dispersed as problem complexity rises, suggesting less stability and focus in navigating the trade-offs among conflicting objectives. While these methods may occasionally approach the Pareto front, their consistency remains inferior to that of ABR. An additional insight revealed by the IGD trends across all algorithms is a general decline in IGD values as the problem number increases. This pattern may indicate that all approaches, particularly ABR, are better suited or more effectively tuned to handle certain problem structures in the latter part of the test suite. In summary, the analysis highlights the methodological strength of ABR in solving MIP-based multi-objective supply chain problems. Its ability to consistently deliver near-optimal, well-distributed solutions under diverse and complex scenarios establishes ABR as a robust, scalable, and reliable optimization tool—one that significantly outperforms existing benchmark methods in both solution quality and algorithmic stability.

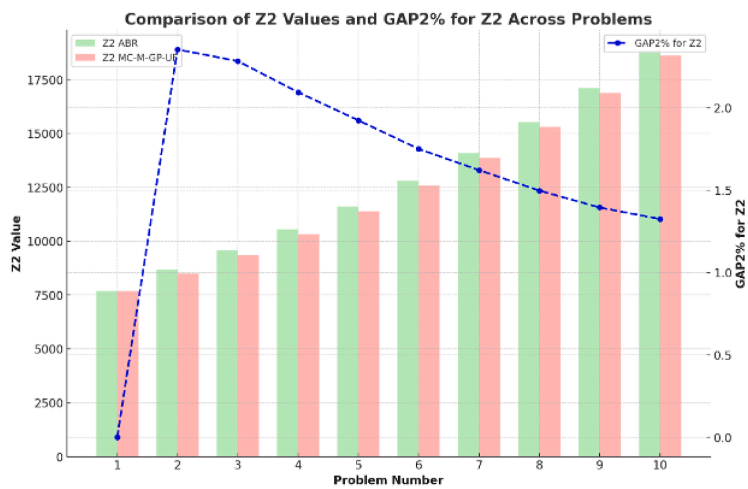
5.2. *Case study problem*

In this section, we address the primary challenge presented by our case study through the application of the ABR with MC-M-GP-UF. The solution involves tackling several sub-problems (SPs) sequentially to calculate the necessary parameters at different stages. The procedure is illustrated in Fig. 7. Initially, we determine the aspiration levels for each objective (denoted as O_i^{min} and O_i^{max}values). Subsequently, we establish the target points for S_i, leading to the resolution of the final model. The outcomes of this comprehensive process include the values of three objective functions. The first objective function's value is determined to be 4402,763.7, indicating the primary goal's outcome under the optimized conditions. The second and third objective functions are valued at 15,073.8 and 21.6, respectively, reflecting secondary and tertiary goals' achievements within the framework. Additionally, we assess the model's accuracy through meta deviations, quantified as $\alpha_1 = 0.074685$, $\alpha_2 = 0.4145261E-01$, $\alpha_3 = 0.2284519E-02$. These deviations represent the discrepancies between the achieved and the ideal outcomes, providing insight into the model's precision across various objectives. This nuanced analysis underscores the ABR's effectiveness in navigating complex optimization landscapes, showcasing its ability to deliver nuanced, closely aligned outcomes with the set aspirations.

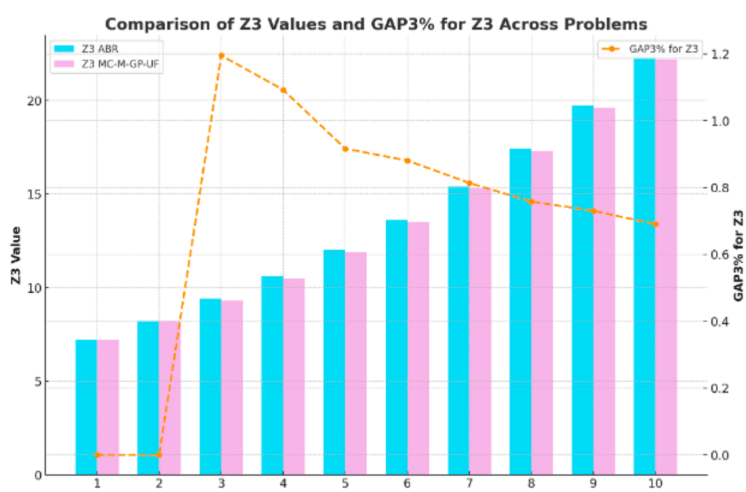
Furthermore, we meticulously analyzed a model tailored to the demand patterns observed in a specific case study, focusing on three primary areas: production, inventory, and transportation decisions, over a fixed timeframe. This analysis brought to light a differentiated customer service approach based on Vendor-Managed Inventory VMI, MTO, and MTS strategies. Our findings indicate a strategic distribution of service models among the customer base. Specifically, VMI strategies were deployed for 22 of the 45 customers, representing approximately 20 % of total demand. These customers typically placed smaller orders. In



(a) Z1



(b) Z2



(c) Z3

Fig. 5. The performance of the proposed ABR and MC-M-GP-UF based on the GAP.

contrast, the MTO approach catered to 13 customers, which, while only 29 % of the customer base, represented a significant 45 % of total demand, indicating these customers typically placed larger orders. Lastly, the MTS strategy was allocated to 10 customers, accounting for 35 % of the demand, highlighting its focus on customers with high-volume orders. By categorizing customers based on order size and demand, the company ensures timely fulfillment for VMI-related orders, effectively managing its inventory and production resources.

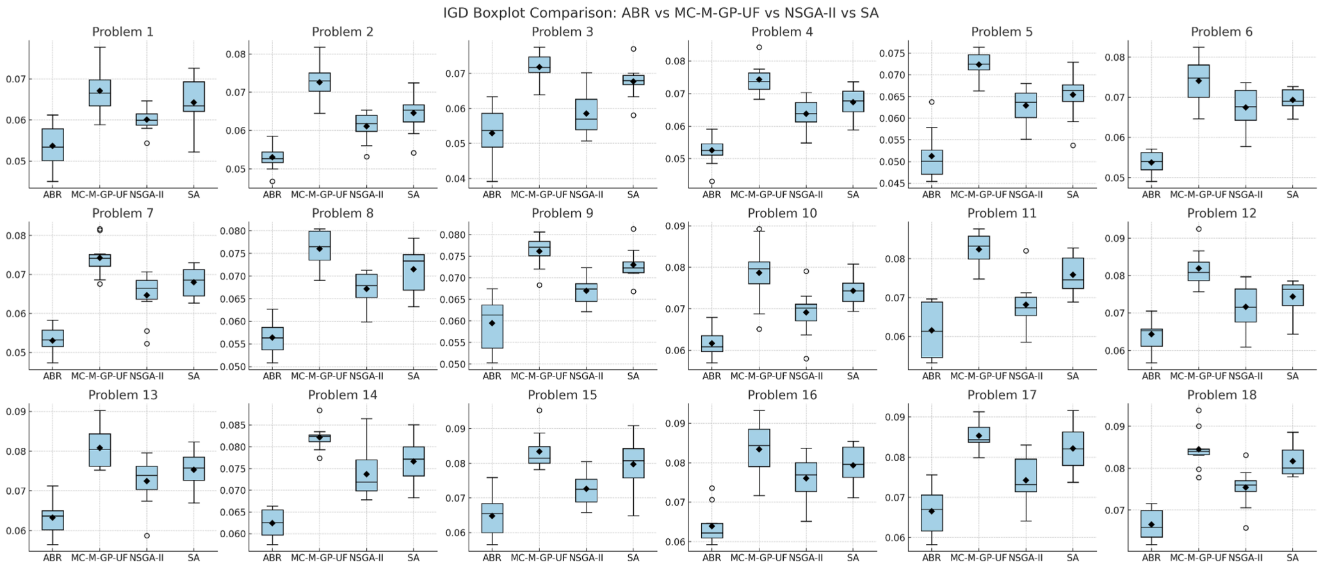


Fig. 6. Boxplot grid comparing the IGD values between the ABR, MC-M-GP-UF, SA, and NSGA-II approaches.

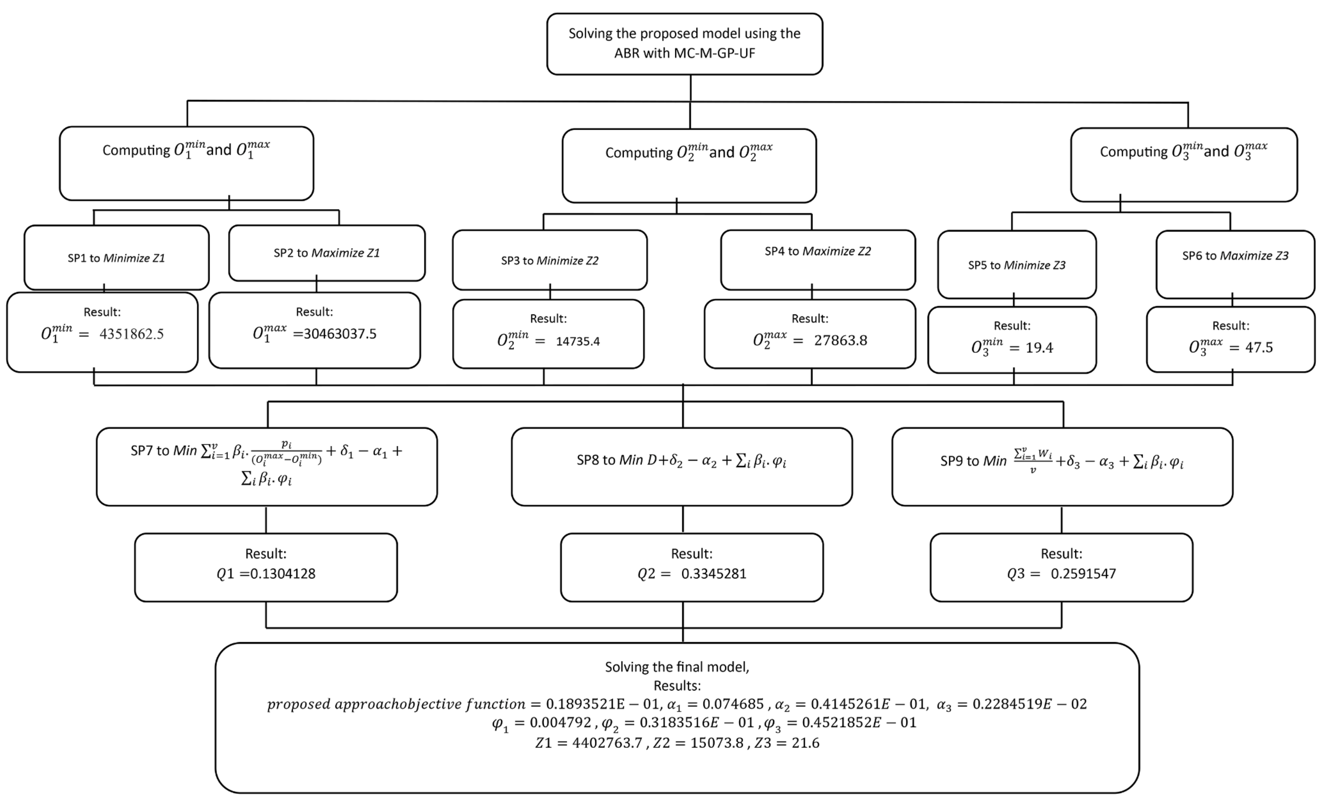
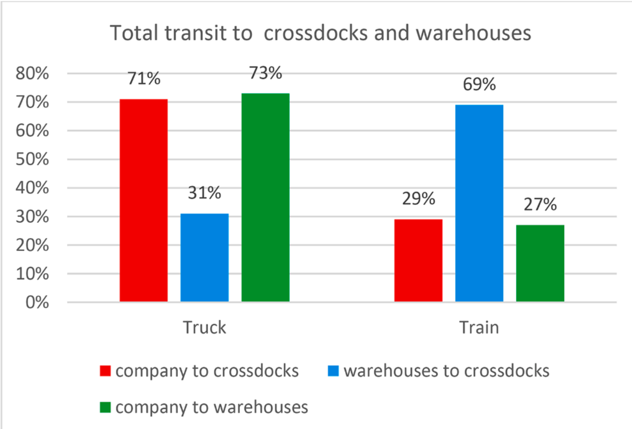
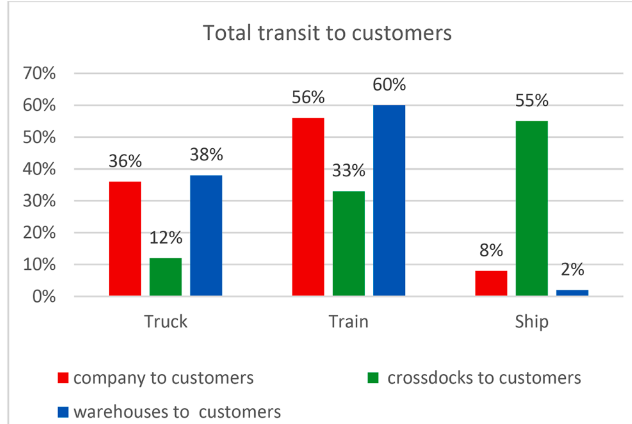


Fig. 7. The results of solving the problem by proposed approach.

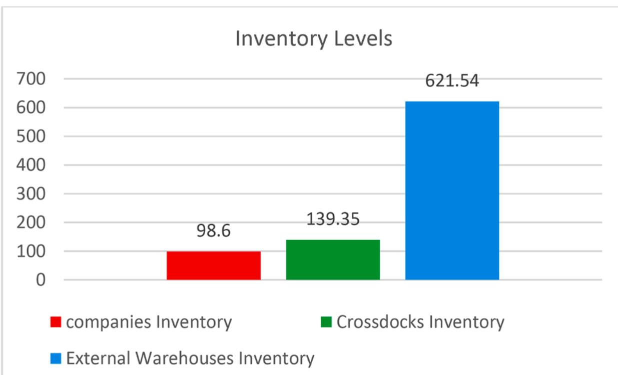
We examine the performance of the DPI system, illustrated in Fig. 8. Our analysis, grounded in the current production capacities across varied products, reveals that companies are operating at 87.9 % of their potential capacity. Consequently, this operational strategy enables us to fulfill approximately 75.2 % of customer demand. It's important to highlight our assumption that VMI customer demands are met promptly. Moreover, we aim to satisfy 78.12 % of the MTO customer demands without delay, establishing this figure as the target service level for MTO customers. Given these parameters, the company can accommodate only 46.87 % of MTS purchase requests. Consequently, the company is required to maintain average inventories of 98.6 metric tons (MT) in company warehouses, 621.54 MT in external warehouses, and 139.35 MT in cross-dock facilities. In Fig. 7 presented, we observe a heavy reliance on truck transportation for moving goods from the company to crossdocks (71 %) and warehouses (73 %), with trains serving as the secondary mode. The interplay between warehouses and crossdocks is predominantly managed through train shipments (69 %), indicating efficient utilization of rail networks for intra-logistics operations. When it comes to customer deliveries, the data shows a pronounced preference for trains (56 % from the company and 60 % from warehouses to customers), suggesting a strategic focus on rail's balance of speed and cost-efficiency. Interestingly, maritime transport emerges as the principal



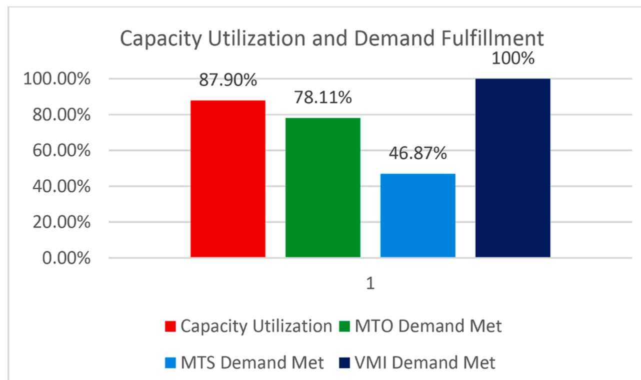
(a) Total transit to customers



(b) Total transit to crossdocks and warehouses



© Inventory Levels



(d) Capacity Utilization and Demand Fulfillment

Fig. 8. The performance of the DPI system.

method for moving goods from crossdocks to customers (55 %), which implies a significant volume of long-distance or international deliveries. In contrast, the minimal use of ships directly from the company (8 %) and from warehouses (2 %) suggests untapped potential or strategic decision-making favoring land over sea for certain logistics segments.

In our analysis, detailed in Table 3, we assess the impact of various risk categories—including environmental (R1), policy (R2), security (R3), operational (R4), supply (R5), economic (R6), and technological risks (R7)—on our case study's company's logistics and financial outcomes. We quantify the impacts in terms of potential decreases in shipment volumes, revenues, and profits, as well as possible increases in operational costs. Risks typically do not enhance the flow of products; rather, they tend to introduce inefficiencies and reductions in operational performance. Specifically, environmental risks, such as adverse weather conditions, can significantly affect transportation modes differently, leading to a 10 % reduction in truck transportation, a 12 % reduction in rail services, and an 8 % decrease in shipping activities. These conditions not only delay deliveries but also escalate transportation and demand fulfillment costs, consequently diminishing profits by 12 % due to the compounded effect of a 7.8 % surge in chain-wide costs and a 5 % decline in revenues. Political risks introduce a different set of challenges, increasing total costs by 3.8 % and reducing overall profits by 6.8 %. Conversely, security risks show no direct impact on revenue or carbon emissions but result in a 5 % decrease in transportation route profitability. Operational risks mirror the financial impact of policy risks but with a steeper 7.9 % profit decrease, attributed to inefficiencies in logistics operations, such as cross-docking and external warehousing. Additionally, supply, economic, and technological risks lead to profit reductions of 11.3 %, 9.6 %, and 9.2 %, respectively. These decreases stem from an overreliance on suppliers, inflationary pressures, demand reductions, and the high costs of adopting new technologies, which collectively disrupt the supply chain and inflate operational expenses.

According to Table 3, a sensitivity analysis of these findings reveals the intricate dynamics between different risk categories and their cumulative effects on a company's operational efficiency and financial health. Environmental and policy risks significantly affect operational costs and profitability, demonstrating a strong sensitivity to external disruptions. Operational and supply risks underline the importance of efficient logistics and reliable supplier networks, indicating a high sensitivity to internal operational strategies. Economic and technological risks highlight the company's vulnerability to market fluctuations and the pace of technological advancements, suggesting a need for agile and adaptive business models.

5.3. Sensitivity analysis

5.3.1. Demand

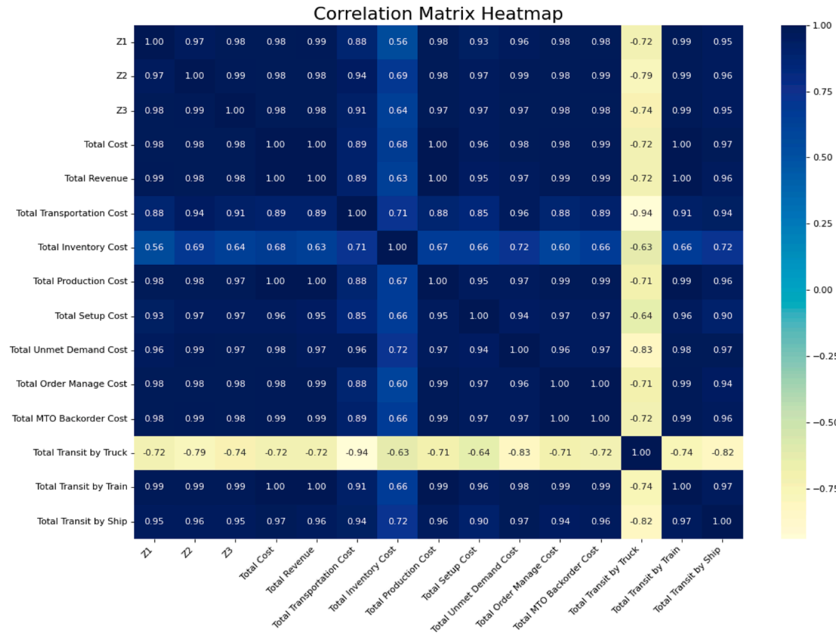
In this section, a sensitivity analysis has been conducted to demonstrate the influence of the demand parameter on key output metrics. To achieve this, the proposed model was solved under three scenario-based demand settings—Pessimistic (−50 %), Most Likely (0 %), and Optimistic (+50 %)—capturing a wide spectrum of possible real-world conditions. The analysis evaluates the response of various performance indicators including Z_1 (profit), Z_2 (transportation time), and Z_3 (CO_2 emissions), along with total cost, total revenue, and a comprehensive breakdown of cost components such as transportation, inventory, production, setup, unmet demand, order management, MTO backorders, and the volume of goods transported via truck, train, and ship. This scenario-based approach enables a deeper understanding of

Table 3
The comparison of risk analysis results.

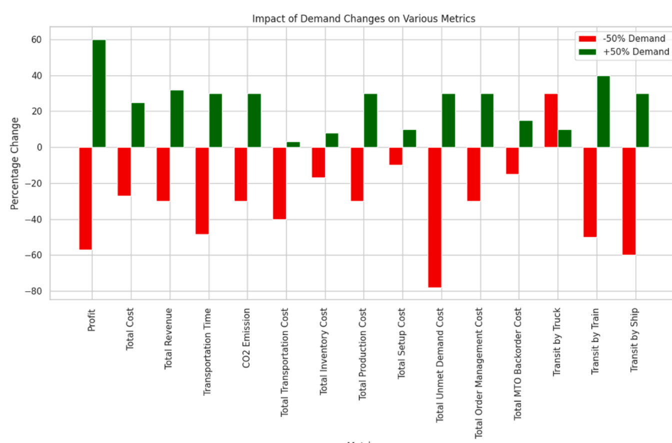
	Without risk	With Risk						
		R1	R2	R3	R4	R5	R6	R7
Z1	4402,763.7	**3874,432.06**	4103,375.77	4182,625.51	4054,945.37	**3905,251.40**	3980,098.38	3997,709.44
Z2	15,073.8	**16,581.18**	15,827.49	16,128.96	16,279.70	15,978.22	**15,073.80**	16,430.44
Z3	21.6	22.03	21.82	**21.60**	22.25	**22.46**	**21.38**	22.03
Total cost	17,611,054.8	18,984,717.10	18,280,274.90	18,491,607.54	18,650,107.00	18,896,661.80	18,245,052.80	**19,055,161.30**
Total revenue	22,013,818.5	20,913,127.60	21,353,403.90	**22,013,818.50**	21,573,542.10	21,133,265.80	**20,692,989.40**	21,793,680.30
Total Transportation cost	4050,542.60	**4455,596.86**	4253,069.73	4334,080.58	4253,069.73	4253,069.73	4172,058.88	4334,080.58
Total Inventory cost	176,110.55	184,916.07	179,632.76	181,393.86	183,154.97	**193,721.60**	179,632.76	181,393.86
Total Production cost	11,447,185.62	12,248,488.60	11,790,601.20	11,905,073.04	12,134,016.80	12,362,960.50	11,905,073.00	**12,477,432.30**
Total Setup cost	704,442.19	725,575.45	718,531.03	711,486.61	732,619.87	718,531.03	711,486.61	**739,664.30**
Total unmet demand cost	528,331.64	**607,581.38**	581,164.80	528,331.64	586,448.12	602,298.07	560,031.53	570,598.17
Total Order manage cost	352,221.10	366,309.94	362,787.73	369,832.15	373,354.36	**376,876.57**	362,787.73	366,309.94
Total MTO backorder cost	352,221.10	**405,054.26**	387,443.21	394,487.63	387,443.21	394,487.63	369,832.15	387,443.21
Total transit from company to warehouses by Truck	41,761.77	**35,497.50**	38,420.82	37,585.59	38,420.82	38,003.21	37,585.59	41,344.15
Total transit from company to crossdocks by Truck	31,140.17	28,337.55	**27,091.94**	29,583.16	30,205.96	28,026.15	29,205.49	27,714.75
Total transit from company to customers by Truck	32,265.26	30,329.34	31,619.95	29,038.73	30,910.11	**28,070.77**	31,942.60	30,006.69
Total transit from crossdocks to customers by Truck	5246.40	**4616.83**	4984.08	5193.93	4721.76	4774.22	4984.08	4826.68
Total transit from warehouses to crossdocks by Truck	2065.40	1879.51	1941.47	1858.86	2013.43	**1755.59**	2003.38	1920.82
Total transit from warehouses to customers by Truck	20,427.68	18,384.91	**17,976.35**	19,406.29	19,814.84	18,793.46	18,180.63	20,019.12
Total transit from company to warehouses by Train	15,446.13	14,364.90	13,901.51	14,828.28	14,519.36	13,747.05	14,210.43	**13,283.67**
Total transit from company to crossdocks by Train	12,719.22	11,447.29	12,083.25	11,701.68	**11,320.10**	11,574.49	12,592.02	11,828.87
Total transit from company to customers by Train	50,190.40	45,673.26	47,178.97	44,669.45	49,688.49	48,684.68	48,182.78	**44,167.55**
Total transit from crossdocks to customers by Train	14,427.61	13,706.22	13,994.78	**12,407.74**	14,283.33	12,984.84	13,417.67	13,273.40
Total transit from warehouses to crossdocks by Train	763.92	679.88	695.16	702.80	**677.85**	710.44	741.00	687.52
Total transit from warehouses to customers by Train	32,254.23	29,996.43	31,609.14	**28,061.18**	29,028.80	30,641.51	29,673.89	31,931.68
Total transit from company to customers by Ship	7170.06	**6237.95**	6739.85	6309.65	6453.05	6524.75	6596.45	6811.55
Total transit from crossdocks to customers by Ship	24,046.02	22,603.25	21,641.41	22,603.25	22,843.71	22,362.79	**21,400.95**	22,603.25
Total transit from warehouses to customers by Ship	1075.14	**935.37**	989.12	956.87	967.62	1042.88	1064.38	1032.13
Total Transit by Truck	132,906.68	**119,616.01**	126,261.34	123,603.21	124,932.27	126,261.34	130,248.54	126,261.34
Total Transit by Train	125,801.51	**106,931.28**	122,027.46	120,769.44	116,995.40	120,769.45	122,027.46	118,253.41
Total Transit by Ship	32,291.22	30,676.65	30,999.57	**29,707.92**	30,353.74	31,322.48	31,968.30	30,030.83

how fluctuations in demand levels affect both operational efficiency and sustainability outcomes within the supply chain. According to Fig. 9(a) demand change shows a very high correlation with total revenue (0.996) and total cost (0.994), indicating that as demand changes, both revenue and cost adjust in a closely related manner. The correlation is similarly strong with total production cost (0.991) and total transit by train (0.997), suggesting that these components are significantly impacted by demand changes. Z1, Z2, and Z3 show strong correlations with each other (0.969 to 0.989), total cost, and total revenue, suggesting their pivotal role in influencing overall financial metrics. Total transportation cost shows a strong positive correlation with demand changes (0.894), indicating that transportation costs increase as demand increases. However, the total transit by truck has a negative correlation with demand changes (−0.719), suggesting that as demand increases, the reliance on truck transportation may decrease relative to other modes. Conversely, total transit by train and by ship show strong positive correlations (0.997 and 0.963 respectively) with demand changes, indicating increased usage of these transportation modes as demand rises. Inventory and Setup Costs also show positive correlations with demand changes but to a lesser extent compared to production and transportation costs. This may reflect that these cost categories do not escalate as sharply with demand changes as others do.

The analysis of the impact of demand changes from −50 % (Pessimistic scenario) to +50 % (Optimistic scenario) on various operational and environmental metrics provides insightful observations, as shown in Fig. 9. This range includes the Most Likely scenario at baseline (0 %), allowing for a scenario-driven understanding of how demand volatility influences profit, costs, emissions, and transportation dynamics. Notably, Z1 (Profit) exhibits a significant sensitivity to demand fluctuations, decreasing by approximately 57 % with a 50 % drop in demand and conversely increasing by around 60 % with a 50 % rise in demand. This indicates a high elasticity of profit relative to demand changes, underscoring the importance of demand management in profitability. Similarly, total revenue responds to demand changes, decreasing by about 30 % at −50 % demand and increasing by 32 % at +50 % demand, illustrating the direct impact of demand levels on revenue generation.



(a) correlation matrix



(b) The changes in the demand

Fig. 9. The influence of fluctuating demand on various operational and environmental metrics.

Cost analyses reveal that total cost decreases by approximately 27 % with a 50 % reduction in demand and increases by about 25 % as demand rises by 50 %, indicating that while costs are indeed sensitive to demand changes, the relationship isn't as pronounced as with revenue or profit. Within this context, specific cost components like total transportation, inventory, production, setup, unmet demand, order management, and MTO backorder costs show varying degrees of responsiveness to demand shifts, reflecting the complexities of supply chain cost management under fluctuating demand scenarios. The examination of transportation times and CO2 emissions, represented by Z2 and Z3 respectively, reveals a reduction in transportation time by approximately 48.35 % and a decrease in CO2 emissions by 30 % with a 50 % drop in demand. Conversely, both metrics increase—-transportation time by 30 % and CO2 emissions by 30 %—as demand rises by 50 %, highlighting the environmental and efficiency challenges in scaling operations to meet demand. Furthermore, the flow transported by different modes of transportation—truck, train, and ship—exhibits distinct patterns in response to demand changes. Truck transportation increases by 30 % at −50 % demand and by 10 % at +50 % demand, indicating its flexibility and possibly its role in short to medium-haul logistics. In contrast, train and ship transportation, which are more efficient for large volumes and long distances, decrease significantly at −50 % demand (by 50 % and 60 %, respectively) but show robust increases (40 % for train and 30 % for ship) with a 50 % rise in demand, reflecting the scalability of these modes for bulk transport needs.

5.3.2. Production capacity

The strategic adjustment of the company's production capacity from −30 % (Pessimistic scenario) to +30 % (Optimistic scenario) has resulted in significant operational improvements and financial benefits, as shown in Fig. 10. This range of adjustments also includes the baseline (0 %) Most Likely scenario, allowing for a comprehensive evaluation of the system's performance under varying capacity conditions. Specifically, the MTS (Made to Stock) Acceptance rate experienced an increase of approximately 6.68 %, enhancing the company's ability to fulfill customer orders. The MTO service level saw a boost of approximately 2.41 %, indicating an improved commitment to meeting custom order demands. Furthermore, the improvement in company capacity utilization by about 2.39 % signifies not just an optimization of resources, but also a strategic alignment of production capabilities with market demand, ensuring that the company operates at a near-optimal level

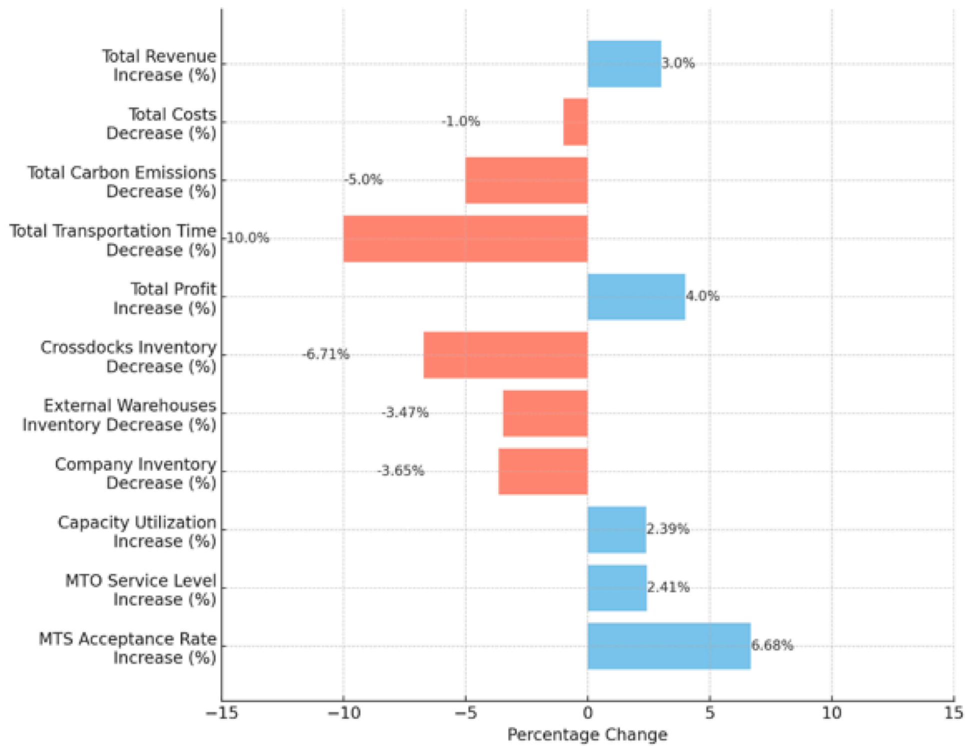


Figure 10. Impact of modulating production capacity

Fig. 10. Impact of modulating production capacity.

without overextending its resources or underutilizing its capacity. Improved capacity utilization and service levels suggest more efficient production and higher sales volumes, particularly in MTO and MTS segments. The reduction in inventory levels implies lower holding costs, further improving profit margins.

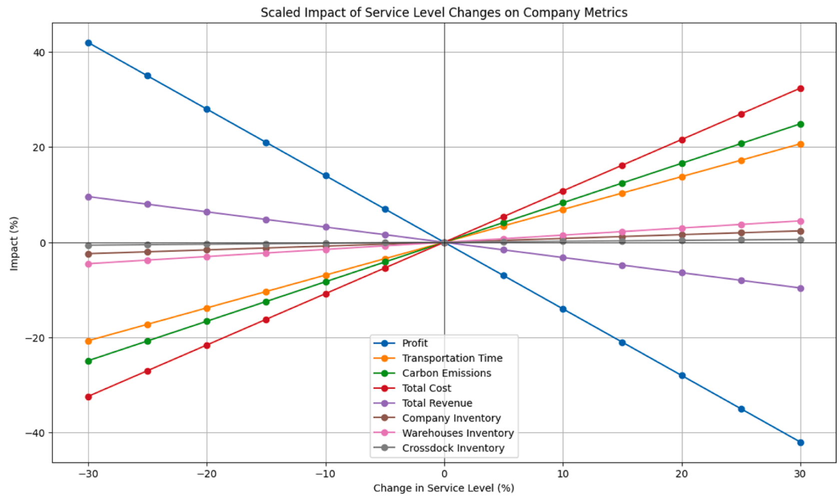
Inventory management also witnessed notable efficiencies with a decrease of approximately 3.65 % in company inventory levels, 3.47 % in external warehouses, and 6.71 % in crossdocks, signifying a leaner operational model with reduced holding costs. The planned reductions in inventory levels across the company's own warehouses, external storage, and crossdocks suggest a leaner, more efficient warehouse operation. This reduction not only lowers costs but also increases warehouse space availability, potentially improving flexibility for future production adjustments and indicating a move towards a more agile and responsive supply chain. This agility is critical for adapting to market fluctuations and reducing waste through unsold inventory.

These operational advancements have directly impacted financial metrics. Total profit saw a commendable increase of 4 %, attributed to enhanced sales volumes and operational efficiencies. Total transportation time was reduced by 10 %, indicating more efficient logistics and supply chain management. With optimized inventory levels at crossdocks and external warehouses, the company can achieve more efficient logistics and transportation processes. This optimization might reduce total transportation time due to more streamlined operations and better utilization of logistics resources. This efficiency also contributed to a Total carbon emission decrease of 5 %, showcasing the company's strides toward sustainability. Optimizing production capacity and reducing unnecessary inventory can lead to less frequent transportation needs and lower production-related emissions. The overall efficiency in logistics and production processes could contribute to a decrease in carbon footprint. Moreover, Total Costs experienced a reduction of 1 %, reflecting the cumulative impact of optimized inventory and production efficiency. Finally, Total Revenue increased by 3 %, a direct result of improved acceptance rates and service levels, driving higher sales volumes.

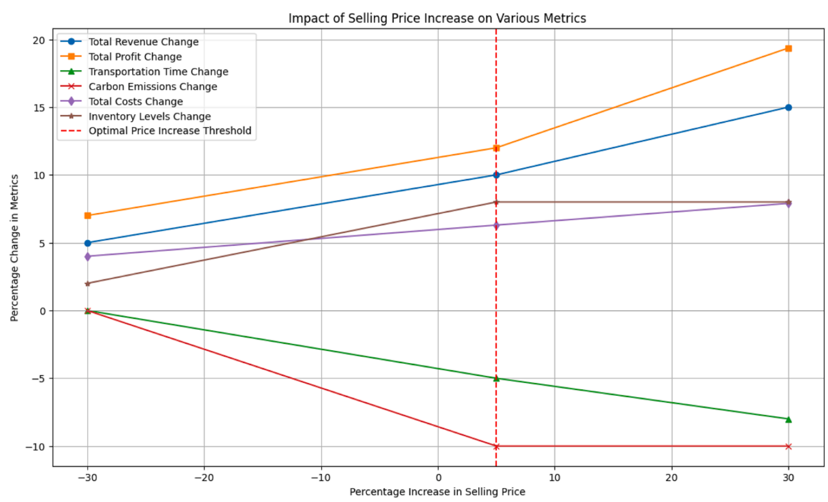
5.3.3. *Service level, sales price*

Fig. 11(a) presents an analysis of how a 10 % enhancement in the service levels of a company influences key performance metrics, including profit, transportation time, carbon emissions, overall costs, revenue, and inventory levels within various storage facilities. This analysis is conducted across a range of scenario-based service level adjustments, explicitly representing a Pessimistic scenario (−30 %), a Most Likely scenario (baseline, 0 %), and an Optimistic scenario (+30 %). It reveals that elevating service levels beyond the baseline tends to exert a negative impact on profit and revenue, while simultaneously escalating costs, emissions, and inventory. Specifically, augmenting service levels by 10 % has led to a 14 % reduction in profit, indicative of the immediate financial strain. Transportation time saw a 6.9 % increase, suggesting a more extensive distribution network or slower logistics processes. Carbon emissions escalated by 8.3 %, reflecting the environmental cost of heightened service activities. The company's overall costs rose by 10.8 %, underscoring the financial implications of improving service quality. Conversely, revenue dipped by 3.2 %, hinting at the complex relationship between service level and sales performance. Inventory levels experienced modest increases: a 0.8 % rise within company-operated warehouses, 1.5 % in external warehouses, and a 0.2 % increase in cross-docking facilities, highlighting the nuanced effects of service level changes on storage requirements.

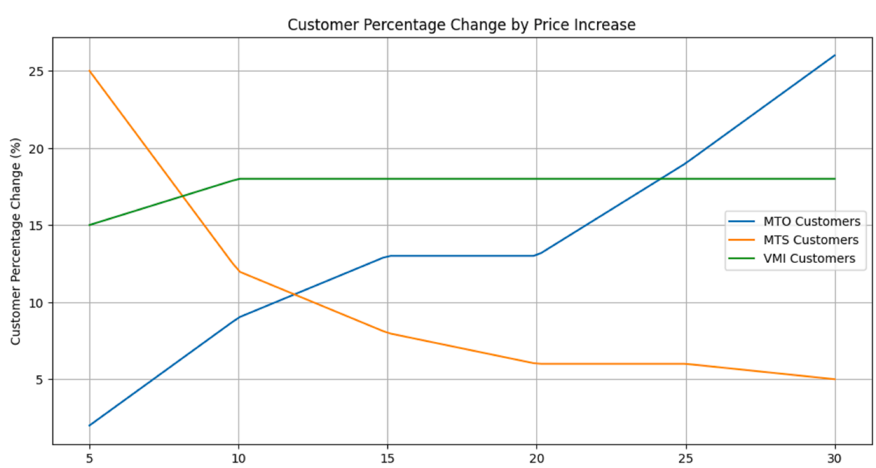
Fig. 11(c) delineates the effects of price hikes on various consumer categories: MTO, VMI, and MTS. Upon examining a 25 % price increase, it's observed that MTO customers experience a substantial 45 % surge in their expenditure, showcasing their high elasticity and positive response to value perception. Conversely, VMI clients show minimal sensitivity, with only a 3 % spending increase noted for up to a 5 % price hike, and stability beyond that up to a 25 % increase. This stability could stem from specific inventory management contracts or perceived service value. On the other hand, MTS consumers demonstrate traditional price sensitivity, reducing their demand by 20 % in response to a 25 % price increase.



(a) Service level



(b) Selling price



(c) Customer level

Fig. 11. Impact of modulating Service level, sales price.

The disproportionate revenue gain from MTO consumers potentially offsets MTS's lost revenue, suggesting a scenario where overall profits could swell by as much as 19.36 % at a certain juncture as shown in Fig. 11(b). However, this is contingent upon maintaining MTS volume; a significant drop could lessen transportation times (by up to 8 %) due to fewer deliveries, despite an uptick in MTO orders. This volume-transport time relationship also implies a direct impact on carbon emissions, with a potential decrease of up to 10 % due to reduced MTS shipments. Cost implications vary; a decrease in overall expenditure is plausible if MTO's increased demand doesn't incur additional production costs. Conversely, any inefficiencies from ramping up production could elevate costs by 7.9 %. Yet, the significant market share of MTO could bolster overall revenues, by up to 15 %, until MTS losses begin to overshadow gains. Inventory dynamics also shift, with a potential 8 % increase in company and external warehouse stock levels attributable to dwindling MTS demand, while cross-dock inventory remains unchanged.

5.3.4. Interaction effects of risk factors

To assess the complex interactions between different types of risks environmental (R1), policy (R2), operational (R3), supply (R4), economic (R5), and technological (R6). We conducted a comprehensive statistical analysis using two-way ANOVA, Pearson correlation, variance decomposition, and principal component analysis (PCA). The results provide deeper insights into how risk interactions influence supply chain performance, including cost fluctuations, revenue loss, and operational inefficiencies.

According to Table 4, the two-way ANOVA results reveal that all risk pairs significantly influence key supply chain metrics, with varying degrees of impact. The most severe cost increases occur in interactions involving supply risks (R4) and economic risks (R5), which together lead to a 14.5 % increase in total costs and a 6.3 % decline in profitability. This highlights the financial vulnerabilities that arise when supply chain disruptions coincide with economic instability, emphasizing the need for robust financial and inventory risk management strategies. Similarly, policy and supply risk interactions (R2 × R4) result in a 12.3 % rise in total costs and a 5.8 % reduction in profitability. This suggests that regulatory changes—such as new trade policies or tariffs—can significantly disrupt supplier networks and increase operational expenses. Companies operating in highly regulated industries or those dependent on international suppliers must develop adaptive sourcing strategies to mitigate regulatory uncertainties. Environmental and policy risks (R1 × R2) also exhibit significant interaction effects, leading to a 10.2 % increase in total costs. This indicates that climate-related disruptions, when compounded by regulatory constraints (such as emissions regulations or carbon taxes), impose substantial financial burdens on firms. This underscores the need for climate-adaptive logistics planning and policy compliance strategies to ensure long-term operational resilience. Additionally, the interaction between operational and supply risks (R3 × R4) shows a 13.8 % cost increase and a 5.2 % profit decline, confirming that logistics inefficiencies exacerbate supply chain disruptions. This finding highlights the importance of investing in supply chain agility, real-time monitoring, and digital logistics optimization to enhance efficiency and mitigate disruptions.

The correlation analysis further supports the ANOVA findings by quantifying the strength and direction of relationships between different risk pairs (Table 5). The highest correlation ($r = 0.81$, $p < 0.001$) is observed between supply and economic risks (R4 × R5), reinforcing the notion that economic instability intensifies supply chain vulnerabilities. This means that firms facing rising inflation, raw material shortages, or fluctuating exchange rates may experience amplified disruptions if their supplier base is not diversified. Another strong correlation ($r = 0.76$, $p < 0.001$) exists between economic and technological risks (R5 × R6), indicating that market volatility significantly influences technological investment decisions. During economic downturns, companies may delay or scale back technology adoption due to financial constraints, leading to reduced innovation capacity and competitiveness. This highlights the importance of phased technology investments and cost-sharing mechanisms to ensure continued digital transformation even in challenging economic conditions. A moderately high correlation ($r = 0.72$, $p = 0.002$) is found between operational and supply risks (R3 × R4), suggesting that logistics inefficiencies—such as bottlenecks in warehousing, distribution, or production—exacerbate supply chain disruptions. This supports the argument that companies should prioritize supply chain agility, flexible manufacturing, and alternative transportation routes to reduce operational vulnerabilities. Another notable correlation ($r = 0.68$, $p = 0.004$) exists between environmental and policy risks (R1 × R2), indicating that climate-related disruptions tend to be worsened by regulatory constraints. For example, extreme weather

Table 5
Correlation coefficients of risk interactions.

Risk Interaction	Pearson Correlation (r)	Significance (p-value)	Relationship Strength
R1 × R2 (Environmental × Policy)	0.68	0.004	Strong positive correlation
R1 × R3 (Environmental × Operational)	0.62	0.009	Moderate positive correlation
R2 × R3 (Policy × Operational)	0.65	0.007	Moderate positive correlation
R1 × R4 (Environmental × Supply)	0.71	0.002	Strong positive correlation
R1 × R5 (Environmental × Economic)	0.57	0.014	Moderate positive correlation
R1 × R6 (Environmental × Technological)	0.49	0.028	Weak positive correlation
R2 × R4 (Policy × Supply)	0.73	0.001	Strong positive correlation
R2 × R5 (Policy × Economic)	0.78	<0.001	Strong positive correlation
R2 × R6 (Policy × Technological)	0.61	0.010	Moderate positive correlation
R3 × R4 (Operational × Supply)	0.72	0.002	Strong positive correlation
R4 × R5 (Supply × Economic)	0.81	<0.001	Very strong positive correlation
R4 × R6 (Supply × Technological)	0.69	0.003	Strong positive correlation
R5 × R6 (Economic × Technological)	0.76	<0.001	strong positive correlation

Table 4
Two-way ANOVA results for risk interactions.

Risk Interaction	F-value	p-value	Total Cost (%)	Revenue (%)	Transportation Cost (%)	Unmet Demand Cost (%)	Profitability (%)
R1 × R2 (Environmental × Policy)	6.73	0.012	+10.2 %	−4.1 %	+6.5 %	+5.8 %	−4.5 %
R1 × R3 (Environmental × Operational)	5.98	0.018	+9.6 %	−3.7 %	+5.9 %	+5.2 %	−4.2 %
R1 × R4 (Environmental × Supply)	7.21	0.009	+10.7 %	−4.8 %	+6.8 %	+6.0 %	−5.0 %
R1 × R5 (Environmental × Economic)	6.45	0.014	+9.9 %	−4.3 %	+6.1 %	+5.7 %	−4.7 %
R1 × R6 (Environmental × Technological)	6.81	0.011	+10.4 %	−4.6 %	+6.4 %	+5.9 %	−4.9 %
R2 × R3 (Policy × Operational)	7.52	0.007	+11.1 %	−5.0 %	+7.1 %	+6.3 %	−5.4 %
R2 × R4 (Policy × Supply)	8.24	0.005	+12.3 %	−5.6 %	+7.9 %	+7.0 %	−5.8 %
R2 × R5 (Policy × Economic)	7.81	0.006	+11.5 %	−5.3 %	+7.3 %	+6.7 %	−5.6 %
R2 × R6 (Policy × Technological)	6.95	0.010	+10.8 %	−5.1 %	+7.0 %	+6.5 %	−5.2 %
R4 × R5 (Supply × Economic)	10.12	0.003	+14.5 %	−6.7 %	+9.3 %	+8.4 %	−6.3 %

Table 6
Variance decomposition – contribution of risks to total cost and profitability.

Risk Factor	Contribution to Total Cost (%)	Contribution to Profitability (%)
R1 (Environmental)	14.2 %	9.3 %
R2 (Policy)	16.7 %	10.1 %
R3 (Operational)	18.3 %	11.4 %
R4 (Supply)	21.5 %	13.7 %
R5 (Economic)	22.9 %	14.5 %
R6 (Technological)	20.3 %	12.9 %

Table 7
PCA-based risk clustering.

Cluster	Risks Included	Variance Contribution (%)
Cluster 1	R4 (Supply), R5 (Economic), R6 (Technological)	67.3 %
Cluster 2	R1 (Environmental), R2 (Policy), R3 (Operational)	54.6 %

events can disrupt transportation networks, while emissions regulations may limit the use of alternative fuel options, thereby compounding delivery delays and increasing costs. The strong correlation ($r = 0.69$, $p = 0.003$, R4 × R6) shows that technological advancements are closely linked to supply chain efficiency. Companies investing in automation, AI-driven demand forecasting, and smart warehousing tend to experience fewer supply chain disruptions. Firms should prioritize technology adoption in logistics and inventory management to enhance supply chain resilience. A moderate correlation ($r = 0.61$, $p = 0.010$, R2 × R6) suggests that policy decisions influence technological advancements. Governments may introduce regulations that encourage or restrict technology adoption, such as data privacy laws, AI ethics guidelines, or digital infrastructure incentives. Businesses should align their technology investments with emerging policy trends to remain competitive.

Based on Table 6, variance decomposition analysis quantifies how much each risk factor contributes to total cost fluctuations and profitability changes. The findings show that economic risks (R5) contribute the most to cost increases (22.9 %) and profitability reductions (14.5 %), reinforcing the importance of economic forecasting, financial hedging, and supply chain cost control measures. Supply risks (R4) account for 21.5 % of cost increases and 13.7 % of profit declines, confirming that unreliable supplier networks, material shortages, and transportation failures are key drivers of financial instability. This underscores the need for diversified supplier sourcing, nearshoring strategies, and inventory buffering. Technological risks (R6) contribute 20.3 % to total cost increases and 12.9 % to profitability declines, highlighting the significant upfront capital costs associated with digital transformation. This suggests that firms should adopt phased investment strategies and leverage AI-driven predictive analytics to maximize technology's cost-efficiency.

According to Table 7, Principal component analysis (PCA) identifies two major risk clusters. The first cluster confirms that financial instability, supplier disruptions, and technological risks are deeply interconnected. This suggests that firms need to integrate financial risk planning with supply chain resilience strategies while ensuring that technological investments align with long-term financial sustainability. The second cluster highlights that environmental and policy risks significantly affect operational efficiency. This implies that firms must develop adaptive logistics strategies, regulatory compliance frameworks, and contingency planning for climate-related disruptions.

6. Discussion

This section presents a comprehensive discussion of the study's findings and their broader implications. To provide clarity and structure, the discussion is organized into several subsections. First, we explore the theoretical implications of the proposed model within the context of sustainable and resilient supply chain design. Next, we examine the practical and managerial implications, highlighting the applicability of the proposed framework in real-world industrial environments. Finally, we discuss the methodological contributions and limitations of the study, offering insights into future research directions.

6.1. Theoretical implications

Our study contributes to the broader literature on supply chain management, specifically within the realm of chemical product manufacturing, through the application of the ABR with MC-M-GP-UF. Theoretically, this approach underscores the significance of integrating sophisticated optimization techniques to address multifaceted decision-making processes. The methodological intricacy of calculating necessary parameters through sequential sub-problems (SPs) exemplifies a comprehensive strategy to tackle complex operational challenges. The achievement of the objective functions, highlighted by their respective values, not only demonstrates the model's capability to cater to varying organizational goals but also its precision, as evidenced by the meta deviations. Such findings offer a nuanced perspective on the model's efficacy in closely aligning real-world outcomes with theoretical aspirations. The differentiated customer service approach, predicated on VMI, MTO, and MTS strategies, illuminates the importance of customer segmentation based on demand patterns. This strategy not only enhances operational efficiency but also fosters a dynamic supply chain capable of adapting to market fluctuations. The nuanced application of these strategies underscores the theoretical significance of flexibility and strategic alignment in supply chain management.

6.2. Practical implications

Practically, our case study illustrates the pivotal role of strategic decision-making in optimizing supply chain operations. The allocation of VMI, MTO, and MTS strategies based on customer demand patterns exemplifies a practical approach to managing production, inventory, and transportation decisions efficiently. our analysis underscores a strategic alignment of supply chain practices with customer demand patterns, revealing the nuanced application of VMI, MTO, and MTS strategies to optimize service delivery. The VMI strategy's application to smaller orders enables the company to efficiently manage inventory levels, reducing overhead costs associated with stock maintenance. Conversely, the MTO strategy, targeted at customers with larger orders, allows the company to better allocate production resources, minimizing waste and enhancing operational efficiency. The MTS strategy complements this approach by targeting high-volume customers, ensuring that demand is met promptly, thereby increasing customer satisfaction and loyalty. From a management perspective, the decision to employ a mixed strategy approach—leveraging VMI for smaller orders, MTO for larger, customized orders, and MTS for high-demand customers—reflects a robust understanding of the company's operational capabilities and market demands. This strategy not only optimizes resource allocation but also positions the company to respond flexibly to demand fluctuations, securing a competitive advantage in the marketplace. Moreover, the operational strategy enabling the company to operate at 87.9 % of its potential capacity and fulfill a substantial portion of

Table 8
Strategic supply chain approach based on demand patterns and pricing policies.

Demand Pattern	Pricing Policy	Recommended Strategy	Rationale
Low demand variability	Fixed pricing	MTS	Ensures availability at stable cost
High demand variability	Dynamic pricing	MTO	Reduces excess inventory costs
Seasonal demand	Competitive pricing	VMI	Improve customer service efficiency
Unpredictable demand	Premium pricing	Mixed (VMI + MTO)	Balances responsiveness and cost
Highly segmented demand with varied pricing tolerance	Tiered pricing (mixed)	Mixed (VMI + MTO + MTS)	Supports full spectrum service differentiation; enables cost-service optimization

customer demand emphasizes the practical benefits of aligning capacity with market demand. The sensitivity analysis on demand changes offers vital insights into managing supply chain dynamics under fluctuating demand scenarios. The high correlation between demand changes and key financial metrics (total revenue, total cost, Z1) and Z2, Z3 provides a practical framework for anticipating and responding to market trends. Furthermore, the strategic adjustment of production capacity showcases the tangible benefits of flexibility in production planning, leading to improved operational performance and financial health. Table 8 provides a strategic framework for selecting the most suitable supply chain fulfillment strategy—MTO, MTS, or VMI—based on varying demand patterns and pricing policies. It outlines how different combinations of demand variability and pricing strategies influence the optimal choice to balance service levels, operational efficiency, and cost-effectiveness. Managers can utilize this table to align their supply chain operations with market dynamics, ensuring an effective response to fluctuations in demand and pricing structures.

6.3. Managerial implications

From a managerial standpoint, the study highlights several critical areas of focus. First, the necessity for a robust understanding of customer demand patterns to effectively employ VMI, MTO, and MTS strategies. This understanding not only enables the efficient allocation of resources but also ensures that supply chain practices are strategically aligned with market demands. Second, the analysis of risk categories and their impact on logistics and financial outcomes underscores the importance of proactive risk management in safeguarding operational efficiency and profitability. Managers must consider the multifaceted nature of risks, including environmental, policy, and operational, and their cumulative effects on supply chain performance. Moreover, the findings related to service level adjustments and price hikes offer valuable managerial insights into the complex interplay between service quality, cost, and customer demand. The disproportionate impact of price increases on different customer segments (MTO, VMI, MTS) suggests that pricing strategies should be carefully calibrated to maintain a balance between revenue generation and customer satisfaction. The proposed model enables managers to simulate "what-if" scenarios, offering detailed insights into how production schedules, transportation modes, and inventory policies must adapt when specific risk categories (e.g., environmental, policy, or supply-related) are triggered. For instance, under moderate environmental risk, rail becomes a more robust option compared to trucking due to lower exposure to weather disruptions and reduced emissions. In contrast, maritime transport becomes a preferred alternative for long-haul routes under international policy disruptions. These insights are crucial factors for the company to consider during the planning process:

1. *Strategic Customer Segmentation:* companies must recognize the importance of customer demand in segmenting customers into MTO, MTS, and VMI categories. Our model showcases the effectiveness of VMI in ensuring customer satisfaction without delay, particularly for orders of smaller quantities. This strategy not only improves customer service levels but also streamlines inventory management by categorizing customers based on their order characteristics.
2. *Cost Management and Operational Efficiency:* The increased complexity and costs associated with demand variability highlight the need for robust tactical and operational planning. Managers should anticipate the financial implications of demand shifts, particularly the significant cost burdens at the operational level due to outsourcing. Effective demand forecasting and flexible supply chain strategies are essential to mitigate these costs and safeguard profitability.
3. *Strategic Outsourcing Decisions:* Our findings point to the outsized role of outsourcing costs in scenarios of increased demand, especially for MTO customers. This underscores the critical nature of outsourcing decisions and the need for a strategic approach to managing these relationships. Companies should evaluate the cost-benefit dynamics of outsourcing arrangements closely, with an eye towards minimizing unnecessary expenditures and optimizing resource allocation.
4. *Pricing Strategy as a Lever for Customer Management:* The impact of sales pricing on customer segmentation across MTO, MTS, and VMI strategies highlights pricing as a powerful tool for influencing customer behavior and demand patterns. Managers should consider dynamic pricing strategies that reflect the cost structures and service requirements of different customer segments, thereby maximizing revenue potential while ensuring customer satisfaction.
5. *Sensitivity to Backorder Costs:* The sensitivity of MTO customer numbers to backorder costs illustrates the delicate balance required in managing supply chain disruptions and inventory shortages. By understanding the implications of backorder costs, managers can better strategize on inventory levels, supplier relationships, and customer service policies to optimize the trade-off between inventory holding costs and service levels.
6. *Inventory Management and Distribution Strategy:* The maintenance of significant inventory levels across the company and external warehouses, as well as cross-dock facilities, indicates a complex distribution network and a significant investment in holding costs. Efficient inventory management strategies, possibly leveraging predictive analytics, can help reduce these costs and improve responsiveness to demand fluctuations. Management must ensure optimal inventory levels to minimize holding costs while maximizing the ability to meet customer demand promptly, especially considering the differentiated strategies for VMI, MTO, and MTS customers.
7. *Strategic Transportation and Logistics Planning:* The heavy reliance on truck and train transportation underscores the need for a diversified and flexible logistics strategy. Management should evaluate the efficiency, cost, and environmental impact of each transportation mode. Emphasizing trains for both intra-logistics operations and customer deliveries reflects a strategic preference for cost and speed efficiency, which should be continually reassessed against evolving logistics parameters and market demands. While trains are preferred for their balance of speed and cost-efficiency, the strategic use of maritime transport for long-distance deliveries suggests an opportunity to explore this mode

further, especially in minimizing logistic costs and enhancing global reach.

8. *Risk Management and Resilience Building:* The analysis of environmental, policy, security, operational, supply, economic, and technological risks provide a comprehensive overview of potential disruptions, while The impact of these on logistics and financial outcomes cannot be overstated. These risks affect shipment volumes, revenues, profits, and operational costs differently, necessitating management should develop a robust risk management framework that includes identifying and mitigating risks, contingency planning, diversification of supply chains, and investment in technology to enhance operational resilience.
9. *Adaptation to External and Internal Risks:* Given the sensitivity of operational costs and profitability to environmental and policy risks, companies must remain agile in their responses to external disruptions and profitability, highlighting the need for strategies that are adaptable to external changes. This includes adapting logistics strategies to mitigate the impact of adverse weather conditions or political changes, and potentially investing in technologies that enhance operational flexibility.
10. *Focus on Efficient Logistics and Supplier Reliability:* Operational and supply risks highlight the importance of maintaining efficient logistics operations and reliable supplier networks, pointing towards the necessity of fostering strong relationships and operational excellence. Management should prioritize the optimization of logistics processes, such as cross-docking and warehousing, and cultivate strong relationships with suppliers to ensure continuity and reliability of supply.
11. *Focus on Efficient Logistics and Supplier Reliability:* Operational and supply risks highlight the importance of maintaining efficient logistics operations and reliable supplier networks, pointing towards the necessity of fostering strong relationships and operational excellence. Management should prioritize the optimization of logistics processes, such as cross-docking and warehousing, and cultivate strong relationships with suppliers to ensure continuity and reliability of supply.

Furthermore, the use of PCA and variance decomposition has helped to identify key risk clusters (e.g., R4: Supply, R5: Economic, and R6: Technological), enabling managers to develop targeted mitigation strategies. For example, in high-impact risk pairings like supply-economic (R4 $\times$ R5), proactive actions such as supplier diversification and inflation-indexed contracts can significantly buffer performance deterioration. The scenario-based insights presented in this study (Pessimistic, Most Likely, Optimistic) offer a blueprint for day-to-day planning. Managers can use these insights to anticipate shifts in demand, assess trade-offs across service models (MTO, MTS, VMI), and make real-time decisions that align with long-term strategic goals. In sum, this work transforms a complex multi-objective model into a practical decision support tool for managers navigating uncertainty, risk, and sustainability demands in supply chain operations.

7. Conclusions and future works

This study introduces a comprehensive framework for the sustainable design of a multi-level supply chain within the chemical industry, emphasizing the integration of risk management, resilience strategies, and multimodal transportation planning. Central to the study is a MOMIP model that simultaneously maximizes profit, reduces transportation time, and minimizes environmental impacts. To enhance computational efficiency and decision support, we developed a hybrid solution approach that combines local search heuristics with machine learning-based demand prediction. Using real-world data from the Iranian chemicals sector, the model demonstrates its potential in handling complex logistics systems under uncertainty.

The application of our model to an industrial case reveals valuable insights into the effectiveness of combining AI-driven forecasting with optimization. However, practical implementation was constrained by data confidentiality, necessitating the use of anonymized and estimated inputs. Although sensitivity analyses and validation with industry benchmarks were employed to mitigate the impact of data limitations, the precision of the model's quantitative outcomes may still be affected. Furthermore, some simplifying assumptions—such as deterministic demand and the focus on direct GHG emissions—may limit the full scope of sustainability evaluation and replication across sectors.

Future research could extend this model by integrating stochastic demand structures or fuzzy parameters to better reflect real-world uncertainties. Expanding the model to other industries, such as pharmaceuticals or electronics, can be achieved through adjustments to cost functions and the inclusion of sector-specific operational constraints. Moreover, incorporating life cycle assessment (LCA) methods would enable a more comprehensive environmental evaluation by accounting for upstream and downstream emissions. The addition of social and ethical dimensions—such as labor standards, safety, and community impact—would also strengthen the sustainability perspective.

Further enhancements could involve real-time data integration through digital twin systems, which would allow for dynamic re-optimization in response to disruptions. The model could also support continuous risk monitoring, particularly in the face of emerging threats like cybersecurity risks and geopolitical instability. These extensions not only improve the model's responsiveness but also align it with the evolving priorities of modern supply chain management. Overall, this research contributes to the growing body of knowledge on sustainable and resilient logistics, providing both theoretical advancement and actionable tools for industry practitioners.

CRediT authorship contribution statement

Seyed Mahameddin Tabatabaei: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jii.2025.100897.

Appendix A. Summary of the reviewed literature

A structured summary of the reviewed literature, including key methods, contributions, limitations, and relevance to this study, is presented in Appendix A (Table A1).

Table A1
Comprehensive literature review on supply chain strategies.

Focus Area	Authors & Year	Methods/Models Used	Key Contributions	Limitations / Gaps	Relevance to Current Study / Innovation Point
Make-to-Order (MTO)	Woschank et al. (2020); He et al. (2019); Mard (2020); Zhai et al. (2021); Vinci-Carlavan et al. (2024)	PPC strategies, Discrete-event simulation, Memetic algorithm, MIP modeling	Address production scheduling, volatility, and demand uncertainty; improve responsiveness	Do not integrate transportation risks or environmental goals; isolated from inventory/ distribution planning	Our model extends MTO by integrating DPI coordination with multimodal transport risks and sustainability in one unified MOMIP framework
Make-to-Stock (MTS)	Lorenz et al. (2019); Karabağ & Gökgür (2021); Sarkar et al. (2025)	Process mining, Forecasting, Linear programming, Markov chains	Improve productivity through data-driven models; account for demand variability	Lack of integration with transportation delays, environmental impact, and hybrid models	We integrate MTS elements within a DPI framework under multimodal constraints and sustainability criteria
Vendor-Managed Inventory (VMI)	Golpîra et al. (2020); Mohamadi et al. (2022); Rashid et al. (2021)	Multi-objective optimization, Deep reinforcement learning, Robust modeling	Improve SC visibility, coordination, and inventory cost control under uncertainty	Rarely model multimodal transportation or dynamic disruption adaptation	Our model embeds VMI coordination with multimodal disruption-aware routing and carbon emission considerations
Hybrid MTO-MTS-VMI Strategies	Ghasemi et al. (2024a, 2024b); Fiems et al. (2020); Kusuma (2020); Mousavi et al. (2023)	Rolling horizon MIP, Simulated annealing, Metaheuristics	Balance production flexibility with service efficiency; optimize DPI under demand/pricing variation	No explicit modeling of multimodal transportation or environmental impacts; ML-based prediction is missing	We develop a hybrid DPI coordination model embedded in MOMIP that also integrates ML-based forecasting for dynamic decision-making
Multimodal Transport Risks	Choi et al. (2019); Hao & Yue (2020); Kaewfak & Ammarapala (2021); Rosyida et al. (2022); Mosallanezhad et al. (2023); Karamoozian et al. (2024); Abad et al. (2025)	MIP, Goal programming, Fuzzy logic, Heuristics, Risk classification	Identify multimodal risks (delay, legal, environmental); optimize routing and transport mode	Do not integrate with DPI planning or sustainability; limited multi-objective formulation	Our approach embeds risk-aware transport decisions directly into DPI optimization using a goal-programmed MOMIP
Sustainable Supply Chain Design	Gholizadeh et al. (2021–2023); Jahani & Gholizadeh (2022); Khoei et al. (2023); Foroozesh et al. (2023); Edalatpour et al. (2024); Moghadaspoor et al. (2025);	CLGSCN models, MILP/MINLP, Genetic algorithms, Big data analytics	Optimize cost, eco-impact, and resilience in closed-loop systems; use hybrid metaheuristics	Often lack real-time adaptability, local search refinement, or ML integration for complex forecasts	We introduce a novel hybrid optimization approach (local search + ML prediction) to enhance responsiveness and adaptability of the DPI system under sustainability constraints

Appendix B. Risk categories and scenario-based capacity coefficients

This appendix provides a structured overview of how each risk category is modeled in the MOMIP framework, including representative causes and the corresponding capacity reduction coefficients used under three planning scenarios: optimistic, most likely, and pessimistic.

Table B.1
Summary of risk categories and their modeling in the MOMIP framework (Three-Scenario Analysis).

Risk Category	Typical Causes	Impact Scope	Optimistic Scenario ($\boldsymbol{R_r}$)	Most Likely Scenario ($\boldsymbol{R_r}$)	Pessimistic Scenario ($\boldsymbol{R_r}$)
Environmental (R_1)	Natural disasters, extreme weather, epidemics	All outbound flows from RAN	0.3	0.0	0.0
Policy (R_2)	Trade restrictions, sanctions, regulatory change	All outbound flows from RAN	0.9	0.7	0.5
Security (R_3)	Theft, sabotage, unrest, link failure	All outbound flows from RAN	0.8	0.5	0.3
Operational (R_4)	Machine breakdown, labor issues, quality errors	Specific modes, specific intervals from RAN	0.9	0.75	0.5
Supply (R_5)	Supplier delays, raw material shortages	All outbound flows from RAN	0.85	0.65	0.4
Economic (R_6)	Inflation, labor strikes, energy costs	All outbound flows from RAN (time-bound)	0.9	0.8	0.6
Technological (R_7)	ICT failures, outdated systems, infrastructure gaps	Specific modes from RAN (all periods)	0.95	0.85	0.6

Appendix C. List of sets, parameters, and decision variables

This appendix presents a comprehensive list of all model components, including indices, sets, parameters, and decision variables used in the mathematical formulation of the MOMIP model. Definitions are provided to ensure clarity and reproducibility of the model.

Sets and Indices:
C : Denotes all customers, indexed by c
O : Denotes the categories of products, indexed by$o$
I : Denotes the manufacturing units, indexed by i
D : Denotes the cross-dock centers, indexed by d
H : Denotes the warehouse units, indexed by h
T : Denotes the Time intervals, indexed by t
T^{MTS} : Specific time intervals for customers of MTS policy
W : Denotes the transport modes, indexed by w
R : Denotes the risk categories, indexed by r
Q: Denotes the set of all nodes, indexed by j,where,$Q = h \cup d \cup i \cup c$
Parameters:
Price
g_o^V : The selling price of the product o for customers is VMI
g_o^O : The selling price of the product o for customers is MTO
g_o^S : The selling price of the product o for customers is MTS
Costs
CH_j^t : Cost of holding inventory at node j in during period t
CT_{ijw}^t : Cost of transportation between nodes i and j, utilizing mode w in during period t.
CP_{oi}^t : Cost of production of product o in manufacturing units i in during period t, which differentiated across production strategies.
CB_o^t : Cost of backorder for product o accessed by customers of MTO in during period t.
q_t: Cost of order management for customers of MTO in during period t.
CS_{oi}^t: The production setup cost for each unit of product o in manufacturing units i in during period t.
CU_{oi}^t: unmet demand cost for each unit of product o in manufacturing units i in during period t.
$CW_{ww'j}^t$: Transshipment cost between modes w and w' at node j in during period t, that including node dependence.
PC_o^V: Penalty cost for VMI customers if inventory falls below agreed levels
Capacity
SC_j: Fixed storage capacity available at node j.
PC_{oi}^t: The capacity of the manufacturing unit i for product o in during period t.
TMC_i: The total capacity of manufacturing unit i.
TC_{ijw}^t: The capacity of transportation mode w that transfers products between nodes i and j in during period t.
LC_i^t: Availability of loading capacity at the unit of manufacturing i in during period t.
R_r^t : Dynamic risk capacity coefficient for risk r during period t, allowing risk effects to vary over time rather than being constant.
Transportation time
TT_{ijw}: A time estimate of the travel time between node i to node j using the mode of transportation w .
LT_w: Length of transport lead time based on the mode of transportation w with the number of period.
Inventory level
l_{oi}^t: If the VMI policy is implemented, the lower bound of inventory level for product o is at customer i's location in during period t.
u_{oi}^t: If the VMI policy is implemented, the upper bound of inventory level for product o is at customer i's location in during period t.
IL_{oi} :The initial level of inventory for product o at node i. Where, $IL_{oi} = \varepsilon \frac{\sum_{j\in C}\sum_{t\in T}\sum_{o\in O}D_{oj}^t}{|C \| T|}$This ensures that the starting inventory is sufficient relative to forecasted demand.
Other
D_{oj}^t: The demand of consumer j for product o in during period t.
ε: The multiplier increases at a constant rate for each initial inventory value. A coefficient used to scale the initial inventory levels proportionally to the average demand across all customers over the entire planning horizon.
ϑ: Explanation of the level of service target that customers can expect when being served by MTO. The minimum acceptable service level target for customers under the MTO strategy, defined as the proportion of customer demand that must be fulfilled within the stipulated lead time.
EI_w :The average factor of the GHG emissions for using transportation mode w.
EI_{oi} :The average factor of the GHG emissions for produced product o *in* manufacturing i.
dis_{ijw} :The distances between node i and j when utilizing transportation mode w.
M_j : Maximum allowed modal shifts at transshipment point j, introduced to control shifts without forcing them. This parameter allows decision-makers to specify a realistic upper bound on modal shifts per transshipment point based on capacity and operational constraints.
M: A large number
Decision variable:
X_{oi}^t : The volume of product o produced at manufacturing unit i at the start of period t.
$X_{oijw}^{tt'}$: The volume of product o shipped from node i in end of time period to node j at the start of period t' utilizing transportation mode w.
$XV_{oijw}^{tt'}$: The volume of product o shipped from node i in end of time period to customer of VMI j at the start of period t' utilizing transportation mode w.
$XO_{oijw}^{tt'}$: The volume of product o shipped from node i in end of time period to customer of MTO j at the start of period t' utilizing transportation mode w.

(*continued on next page*)

(*continued*)

$XS^{tt'}_{oijw}$: The volume of product *o* shipped from node *i* in end of time period to customer of MTS *j* at the start of period *t'* utilizing transportation mode *w*.
I^t_{oi} :The level of inventory for product *o* in node *i* at the end of time period *t*.
BO^t_{oi} :The volume of backlogged orders for products *o* from customers of MTO *i* supported within period *t*.
SL_i :The level of service customers of MTO *i*.
UD^t_{oi}: The demand of unmet product *o* at node *i* in during period *t*.
γ_j: Is equal to 1 if customer *j* is supported under the VMI policy, otherwise 0
λ_j: Is equal to 1 if customer *j* is supported under the MTO policy, otherwise 0
μ_j: Is equal to 1 if customer *j* is supported under the MTS policy, otherwise 0
ψ^t_{oj}: Is equal to 1 If the requirement for product *o* from customer *j* of MTS is fulfilled during period *t*, otherwise 0
ω^t_{ijw}: If transportation is done from node *i* to node *j* using transportation mode *w* at leaving time *t*.
$\varpi^t_{jww'}$: If there is a modal shift from transportation mode *w* to transportation mode *w'* at node *j* during time *t*.
$Y^{tt'}_{oijww'}, Z^{tt'}_{oijw}$: The auxiliary variable to capture the combined effect of shipment volume and transportation time

Data availability

The data that has been used is confidential.

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