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Reliable scheduling and routing in robust multiple cross-docking networks design

Farid Taheri [a,*], Ali Falahati Taft [b]

[a] *Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran*
[b] *Department of Civil Engineering, Islamic Azad University Branch of Karaj, Karaj, Iran*

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ABSTRACT

This study introduces a novel framework called Reliable Pollution Scheduling and Routing with Multi-Cross-Docking. The core idea behind this framework is to optimize the processing and transportation of products through each vehicle, ensuring that each vehicle serves its specified destinations only once before returning to the cross-dock. The objective of this research is to develop a multi-objective mixed integer programming model that efficiently manages scheduling and routing complexities in a multi-cross-docking system, taking into account uncertainties in demand. The primary goals of the model are to minimize the overall costs associated with pollution, loading/unloading, and transportation, while simultaneously reducing distribution and shipping durations. Additionally, the model aims to maximize the reliability of the supply chain for perishable products, contributing to sustainable development in the supply chain domain. To address the inherent complexity of the model, especially in dealing with demand uncertainties, we employ a robust optimization method. The multi-objective challenge is tackled using an innovative hybrid approach that combines goal programming and genetic algorithms. The effectiveness of our proposed solution strategies is rigorously assessed using a variety of metrics and subjected to comprehensive statistical testing. Furthermore, we validate the competence of our methodology by conducting a real-world case study, which includes sensitivity analysis of demand parameters and robustness analysis. Our findings confirm that our solution technique produces high-quality solutions. Notably, our approach optimizes route planning for delivery and pick-up phases, resulting in a significant 36.5% reduction in transportation time and a noteworthy 17.27% decrease in the overall system costs compared to existing conditions. Additionally, we observe a substantial 23.15% reduction in vehicle arrival times at cross-docks, contributing significantly to reduced product expenses.

1. Introduction

In today's fiercely competitive market, the effective delivery of products to customers and the enhancement of customer satisfaction represents paramount objectives for businesses (Jahani and Gholizadeh, 2022). To achieve these goals, it is imperative for companies to streamline their supply chain operations. This involves fostering seamless integration between the top-tier and bottom-tier entities within the supply chain, resulting in a reduction of the order cycle duration and the optimization of operational and logistical costs (Tirkolaee et al., 2020; Khoei et al., 2023). Moreover, in light of the escalating uncertainty surrounding customer demand, there is an ever-increasing need for supply chain structures that prioritize the efficiency of distribution systems and employ logistics strategies that are agile and adaptive (Babazadeh and Sabbaghnia, 2018; Shahabi-Shahmiri et al., 2021; Gholizadeh et al., 2023). One potent approach to achieving these objectives lies in the implementation of multiple cross-docking strategies. These strategies serve as a bridge between upstream and downstream components of the supply chain, effectively shortening the order cycle, optimizing the flow of materials from suppliers to end customers, and concurrently reducing inventory overheads. Ultimately, this orchestrated synchronization of processes leads to elevated customer satisfaction levels (Tirkolaee et al., 2020; Shahabi-Shahmiri et al., 2021).

In recent years, the adoption of multiple cross-docking strategies has had a profound impact on the design and operations of various logistics and supply chain components, including warehouses, collection, and distribution centers, as well as transportation and logistics systems (Smith et al., 2022; Rijal et al., 2019). Multiple cross-docking, in

* Corresponding author.
E-mail address: Farid.taheri@gmail.com (F. Taheri).

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essence, refers to a logistics strategy where cargo is directly transferred to a warehouse by outbound vehicles without intermediate storage (Shahabi-Shahmiri et al., 2021; Abad et al., 2018). This approach brings a multitude of advantages, including enhanced transportation integration, reduced delivery times, and cost efficiencies (Shahabi-Shahmiri et al., 2021). Consequently, it has gained widespread adoption across various industries. Cross-docking itself represents a process that involves the integration of goods with minimal to no storage duration between the unloading and loading of goods (Abad et al., 2018). When temporary storage is necessary, it is limited to a brief period (Essghaier et al., 2021; Coindreau et al., 2021). The primary objective of cross-docking facilities is to consolidate a large number of small shipments from multiple senders to multiple receivers. In stark contrast to traditional warehouses, cross-docking facilities aim to minimize the storage of goods, ensuring that all shipments leave the facility within a 24-h timeframe (Zuluaga et al., 2017).

The adoption of multiple cross-docking strategies has emerged as a transformative practice, integrating upstream and downstream elements of the supply chain. This approach yields several benefits, including the reduction of order cycle times, enhanced material flow efficiency from suppliers to customers, and reduced inventory through streamlined cost optimization and operation time (Smith et al., 2022). In the context of cross-docking, products are efficiently sorted and categorized according to their destinations within the facility, with an emphasis on immediate dispatch rather than prolonged storage (Keshtzari et al., 2016; Fonseca et al., 2019). This approach has witnessed widespread acceptance across various industries due to its capacity to integrate transportation, shorten delivery times, and reduce operational costs (Essghaier et al., 2021; Coindreau et al., 2021). However, to ensure the success of the supply chain, it becomes imperative to holistically address both transportation scheduling and routing concerns within an integrated framework. Neglecting this integration may result in conflicting decisions that could lead to suboptimal outcomes (Gaudioso et al., 2021; Huerta-Muñoz et al., 2022). Furthermore, the management of perishable goods represents a critical challenge in various industries, including the food, pharmaceutical, and healthcare sectors (de Keizer et al., 2017; Gholizadeh et al., 2020a,b). These products have limited shelf lives, necessitating the design of supply chain systems that account for optimal routes and facility locations, considering the specific complexities associated with handling perishable goods (Alkaabneh et al., 2020; Gholizadeh et al., 2022). Sustainability is an increasingly significant consideration for decision-makers and consumers alike (Gholizadeh et al., 2021; Sazvar and Sepehri, 2020). While some companies utilize refrigerated vehicles to maintain the quality of perishable products during transit, it's worth noting that employing refrigerated vehicles within cross-docking systems may not always be the most cost-effective or efficient choice due to their high operational costs and lower fuel efficiency. A more pragmatic approach involves combining general transportation with refrigerated transportation within the supply chain, striking a balance between cost-effectiveness and meeting customer needs.

Stalk et al. (1992) underscored the pivotal role of cross-docking in the distribution industry, particularly highlighting its strategic significance for the retail giant Walmart. This strategic approach played a decisive role in Walmart's outperforming its competitor, K-Mart, in overall sales during the 1980s. CompUSA, another prominent player, extensively adopted cross-docking, successfully channeling a substantial 70% of its product volume through this method. Numerous transportation companies across North America have embraced cross-docking practices, with examples including Yellow Transportation, Chicago Ridge Transportation, American Freightways, and Central Freight in Portland and Dallas. Additionally, international entities like Iranian shipping companies, including Tibox, have successfully leveraged this approach to significantly reduce operational expenditures by up to 20%. These examples serve to illustrate the global relevance and effectiveness of cross-docking in various industries, further emphasizing its significance in modern supply chain management.

Cross-dock generic flows encompass standardized movement patterns of goods or products within a cross-docking facility. These patterns facilitate efficient handling, sorting, and transferring of items as they traverse the facility without the need for prolonged storage. The primary objective of cross-dock generic flows is to optimize distribution processes, reduce storage costs, and minimize handling time, thereby enhancing the overall efficiency of supply chain operations. By adhering to predetermined flow patterns, cross-docking facilities can optimize the flow of goods, enhance coordination among various transportation routes, and expedite product deliveries to their final destinations. Fig. 1 illustrates a typical operational sequence within a cross-docking center, featuring the involvement of four input vehicles and an equivalent number of output vehicles. In this configuration, input vehicles transport goods collected from various pickup locations to the central cross-dock, where unloading takes place. Within the cross-dock premises, products are carefully grouped and organized, with distinct color codes indicating different categories. After this consolidation phase, products are methodically combined into two, three, or four distinct packages. Notably, items highlighted in green are simultaneously grouped into four separate package categories. This amalgamation process is designed to optimize delivery efficiency, aided by a destination-based sorting mechanism. As a result, packaged products efficiently move through the cross-dock facility to the designated output vehicles, minimizing intermediate storage intervals during the loading process, as discussed by Abad et al. (2018).

The Pollution-Routing Problem (PRP) represents a complex optimization challenge that intertwines vehicle routing with pressing environmental concerns, notably those related to pollution and emissions. This problem typically emerges in scenarios where a fleet of vehicles is entrusted with the delivery of goods or services to diverse locations. The overarching aim is to minimize both transportation costs and adverse environmental impacts, encompassing aspects like pollution, emissions, and carbon footprint. Within this intricate problem space, multiple factors come into play. These include the imperative for efficient routing, environmental sustainability, adherence to vehicle constraints, and meeting customer requirements. Companies undertaking the PRP seek to establish distribution strategies that strike a balance between operational efficiency and sustainability. This equilibrium entails a dual focus: optimizing the scheduling and routing of transportation vehicles (entailing the minimization of travel-related metrics like distance, time, and cost while accounting for vehicle capacity, delivery time windows, and various limitations) and mitigating pollution and ecological impact arising from transportation activities. This includes a specific emphasis on curbing emissions, carbon footprint, fuel consumption, and pollutants associated with vehicular operations and costs. Simultaneously, the

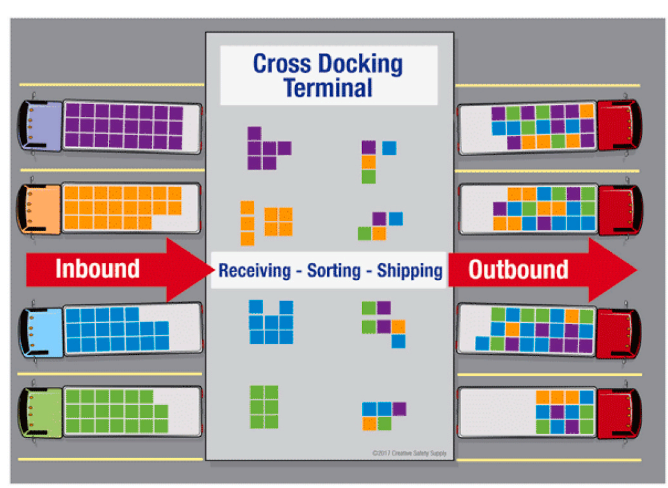


Fig. 1. Standard operational sequence observed within a cross-docking center.

PRP also aims to ensure the dependable delivery of goods, which encompasses meeting stipulated time windows, mitigating delays, and overall service enhancement. One notable approach within this domain is the integration of reliable pollution scheduling and routing coupled with multi-cross-docking. This multifaceted strategy represents a comprehensive endeavor to optimize logistics and supply chain operations. It seeks to achieve a multitude of objectives, including the efficient scheduling and routing of transportation vehicles, the reduction of pollution and environmental impact, the assurance of reliable goods delivery, and the realization of multi-cross-docking advantages. The overarching objective is to establish a sustainable and effective supply chain that not only trims operational expenses but also actively contributes to environmental sustainability by curtailing associated costs. This pursuit aligns with the broader trend within the business landscape, where endeavors to integrate sustainable methodologies into logistics and supply chain frameworks are gaining prominence.

This research seeks to address the critical challenge of efficiently managing large-scale perishable food supply chains. The primary focus of this study is the development and implementation of robust strategies, specifically tailored to incorporate dependable scheduling and routing while integrating multiple cross-docking facilities. To accomplish this objective, this paper conducts a comprehensive examination of the scheduling and routing of vehicles within the context of a perishable food supply chain equipped with multiple cross-docking facilities. The study introduces a novel multi-objective mathematical model that seamlessly integrates vehicle scheduling and PRP with the complexities of multiple cross-docking operations. This model takes into account real-world factors, including the inherent uncertainties of demand and the limited lifespan of perishable products. In addressing this intricate problem, our research introduces an innovative hybrid algorithm known as Multi-Choice Goal Programming with Utility Function and Genetics Algorithm (MCGP-UF-GA). This algorithm is applied across various scenarios to effectively solve the mixed-integer nonlinear programming (MINLP) model, providing practical solutions for optimizing the perishable food supply chain's scheduling and routing operations. The outcomes of this research hold the potential to provide valuable insights for both scholars and practitioners in the field of logistics, specifically within the domain of perishable food supply chains. These insights can significantly assist in the decision-making processes related to network design and demand management, particularly when faced with the challenges of uncertainty.

The study's contributions can be succinctly outlined as follows.

- Formulation of an innovative multi-objective mathematical model, addressing a wide-ranging problem with significant applications across various industries.
- Examination of multiple objectives: first, the minimization of overall costs linked to pollution, loading/unloading, and transportation; second, the maximization of perishable product supply reliability. Concurrently, third, to reduce distribution and shipping durations through incorporating multiple cross-docking.
- Integration of multiple cross-docking with the pollution-routing problem.
- Introduction of time windows coupled with logic functions, effectively showcasing service levels using the function $t(X) = t_0\left(1 + 0.15\left(\frac{tt}{k}\right)^4\right)$. In this context, $t(X)$ represents the logit function, t_0 symbolizes the initial travel time, k stands for vehicle capacity, and tt denotes travel time.
- Incorporation of perishable product lifespan considerations.
- Fusion of scheduling predicaments with dependable routing within the dairy industry.
- Inclusion of multi-door cross-docking protocols.
- Integration of a practical real-world case study pertaining to the supply chain of perishable goods, enhancing the problem's real-life relevance.
- Development of an advanced hybrid algorithm (MCGP-UF-GA) capable of effectively managing diverse scenarios while upholding high-quality standards.

The paper is organized into several sections to facilitate a structured presentation of the research:

***Section* 2:** Literature Review

In this section, we provide a comprehensive review of the relevant literature in the field. We examine prior research and highlight key findings and insights that inform our study. Citations and references are provided to support the claims made in this section.

***Section* 3:** Problem Definition and Mathematical Model.

Section 3 offers a detailed description of the research problem we aim to address. We introduce the proposed mathematical model that forms the foundation of our study. Additionally, we discuss how we model uncertainty within the context of our research.

***Section* 4:** Research Methodology.

In Section 4, we outline the methodologies and approaches employed in our study. We provide insights into our analysis techniques, and any experimental methods utilized to investigate the research problem.

***Section* 5:** Case Study and Numerical Results.

Section 5 presents the results of our case study, where we apply the developed model and methodologies. We provide insights into our data collection, and a thorough analysis of the numerical results and their implications, offering valuable insights into the practical applications of our research.

***Section* 6:** Conclusions and Future Research.

Finally, in Section 6, we draw conclusions based on our findings and the implications discussed in the previous sections. Additionally, we outline potential avenues for future research to further advance the field.

2. Literature review

Managing the supply chain network (SCN) in the food industry presents a formidable challenge due to the unique characteristics of the products and processes involved (Rong et al., 2011). Numerous studies have sought to address this complexity and enhance the productivity of the food supply chain through various approaches (Mohan et al., 2013; Zarei et al., 2011). However, a specific aspect of managing perishable goods within the supply chain has garnered substantial attention from both practitioners and scholars (Gholizadeh et al., 2021).

Recent research in this field has explored the potential of cross-docking as a valuable strategy for optimizing the supply chain of perishable products (Tirkolaee et al., 2020). Notably, Smith et al. (2022) introduced a novel vehicle routing problem (VRP) model designed to minimize the costs within a cross-docking network. Their approach leveraged mixed-integer linear programming (MILP) and incorporated a heuristic method based on the colony algorithm. A compelling case study conducted in the Western Cape province of South Africa illustrated the effectiveness of their approach, particularly in the context of the healthcare industry. Similarly, Essghaier et al. (2021) put forth a mixed-integer programming (MIP) model focused on optimizing the allocation of truck-to-door cross-docks, emphasizing horizontal cooperation between suppliers and cross-dock sharing. Their aim was to minimize the total costs associated with cross-dock operations, encompassing penalties and transportation costs, under conditions of fuzzy uncertainty. To tackle this challenge, they employed a fuzzy chance probability programming approach, with results showcasing the model's robustness and efficacy in both deterministic and fuzzy scenarios, underscoring the significance of cooperation in uncertainty management. In a related vein, Rijal et al. (2019) developed a MIP model geared toward addressing the intricacies of scheduling trucks and assigning them to cross-dock doors, considering mixed services to reduce total costs associated with transportation, loading, unloading, and tardiness. They harnessed the adaptive large neighborhood search algorithm to tackle this complex problem, demonstrating the potential for significant cost savings and improved supply chain efficiency.

These studies collectively provide valuable insights into the application of diverse optimization models and methods to enhance the management of perishable goods within the food industry's supply chain. They underscore the importance of strategic approaches, such as cross-docking, in achieving cost efficiencies and operational improvements.

Optimizing cross-docking networks has been the subject of extensive research, with scholars employing a wide array of methodologies and approaches. Some researchers, such as Moghadam et al. (2014) and Ahmadizar et al. (2015), have delved into the realm of non-linear methods. In parallel, others have explored heuristic, exact, and metaheuristic solutions (Wang et al., 2017; Nikolopoulou., 2017; Tirkolaee et al., 2020; Rahbari et al., 2019; Nasiri et al., 2018; Fathollahi-Fard et al., 2019; Huerta-Muñoz et al., 2022; Baniamerian et al., 2019; Morais et al., 2014; Lo and Chuang, 2023), while some studies have ventured into the application of commercial software (Maknoon and Laporte, 2017; Vincent et al., 2016). Recent research has placed particular emphasis on the selection of cross-docking facilities (Maknoon and Laporte, 2017; Nasiri et al., 2018; Tirkolaee et al., 2020). Simultaneously, other studies have delved into factors such as the optimization of arrival and departure times, node scheduling (Shahabi-Shahmiri et al., 2021; Goodarzi et al., 2020; Vincent et al., 2016), temporary storage solutions (Qiu et al., 2021; Alinaghian et al., 2016), and handling uncertainty conditions (Vincent et al., 2023; Nasrollahi et al., 2023).

Several studies have taken a holistic approach, addressing both scheduling and routing while considering time windows (Shahabi-Shahmiri et al., 2021; Tirkolaee et al., 2020; Goodarzi et al., 2020; Rahbari et al., 2019; Nasiri et al., 2018; Nikolopoulou., 2017). Furthermore, optimization models for cross-docking networks have been developed with diverse characteristics, including multi-objective and multi-product optimization (Dondo et al., 2013; Javanmard et al., 2014; Mokhtarinejad et al., 2015; Rahbari et al., 2019; Goodarzi et al., 2020; Tirkolaee et al., 2020; Shahabi-Shahmiri et al., 2021; Yu et al., 2016; Küçükoğlu and Ozturk, 2019; Qiu et al., 2021), multiple cross-docks (Maknoon and Laporte, 2017; Nasiri et al., 2018; Rahbari et al., 2019; Tirkolaee et al., 2020; Qiu et al., 2021; Shahabi-Shahmiri et al., 2021), multi-door facilities (Dondo et al., 2014; Dondo and Cerdá, 2015), and heterogeneous vehicle fleets (Wang et al., 2017; Baniamerian et al., 2019; Goodarzi et al., 2020; Qiu et al., 2021; Shahabi-Shahmiri et al., 2021; Huerta-Muñoz et al., 2022).

In a recent study conducted by Ghomi et al. (2023), a novel mixed-integer nonlinear optimization model was developed to address the complexities of cooperative logistics in the context of cross-docking vehicle routing problems. This research delved into the interplay between two distinct strategies: collaborative logistics (CL) and integration operations. The primary objective was to strategically allocate truckload goods, leveraging economies of scale by combining various less-than-truckload (LTL) products with varying weight-to-volume ratios. Ghomi et al. (2023) investigated this within the context of a three-tier supply chain structure involving suppliers, customers, and an intermediary terminal. Their study effectively demonstrated that partial cooperation between inbound carriers and outbound carriers offers advantages over both no-cooperation and full cooperation scenarios. This finding underscores the importance of adopting a balanced approach to cooperation in this complex logistical framework, resulting in significant benefits in terms of operational efficiency and cost-effectiveness.

Nasrollahi et al. (2023) introduced a pair of bi-objective multi-stage stochastic models aimed at designing an interconnected cross-docking distribution network. This innovative framework takes into account the presence of heterogeneous trucks and the uncertainty stemming from demand and supply capacity variables. The core objective function crafted by the authors focuses on minimizing the overall costs associated with distribution network configuration and reducing the cumulative shortage of products. To reconcile these objectives, the minimum deviation method was skillfully employed to harmonize individual goals, resulting in a consolidated normalized objective function. Nasrollahi et al. (2023) conducted a series of simulated problems; all addressed through the branch and bound method, to facilitate a comparative assessment of their proposed models. Specifically, the authors compared two distinct strategies. The first strategy involved the use of homogeneous trucks alongside individual cross-docks without interconnections, while the second strategy integrated heterogeneous trucks with linked cross-docks. Upon comprehensive analysis, the findings substantiated the superior efficiency of the second strategy, which includes heterogeneous trucks and linked cross-docks, when compared to the first strategy. Encouraged by these results, the authors proceeded to apply the second strategy in a practical context. They provided a tangible illustration through the design of an agri-food supply chain network, emphasizing the real-world applicability and potency of their proposed framework.

In their recent study, Liu and Li. (2023) identified persistent operational challenges within logistics centers, particularly the difficulty in effectively coordinating the transportation of goods. They specifically highlighted the challenge of synchronizing inbound transportation from suppliers to logistics centers with outbound replenishment transportation to convenience stores. This misalignment has resulted in a low utilization rate of cross-docking facilities. To address this issue, the authors propose an innovative solution leveraging blockchain technology to enhance cross-docking efficiency. Their approach introduces a novel mode of cross-docking implementation with a key technological component – smart contracts. These smart contracts create a dynamic foundation for negotiation transactions between suppliers and convenience stores. Liu and Li also developed a bilevel programming model for these negotiations, accompanied by a queuing model tailored for cross-docking operations scheduling. Additionally, they present an enhanced scheme for the particle swarm optimization (PSO) algorithm used to solve the proposed model. This scheme aims to improve computational accuracy and enhance the overall effectiveness of their solution framework.

Acevedo-Chedid et al. (2023) introduces an advanced transportation model that seamlessly integrates a cross-dock system into the delivery process from production facilities to markets. Their innovative approach centers on a mixed-integer non-linear optimization model, incorporating essential elements. These include a sophisticated vehicle routing model that meticulously accounts for time windows for both pick-ups and deliveries. The model also integrates optimal cross-dock center placements, a heterogeneous vehicle fleet with limited capacity, and intricate scheduling of product collections, arrivals, and departures. The primary objectives of this model are twofold: first, to efficiently reduce logistics costs, and second, to minimize the environmental footprint of operations. The findings of this study strongly emphasize the effectiveness of the cross-docking framework in facilitating the distribution of perishable goods. In their recent work, Akbari et al. (2023) introduced a comprehensive multi-objective model aimed at optimizing the design of a humanitarian supply chain network while concurrently addressing the associated vehicle routing challenges. An innovative aspect of their approach is the integration of a cross-dock system, which significantly enhances the operational efficiency of the network. To effectively apply this model in scenarios of substantial scale, they employed the Non-dominated Sorting Genetic Algorithm (NSGA-II). The primary objectives of their investigation encompass two key aspects. Firstly, their study aimed to minimize the cumulative costs associated with readiness and procurement activities before a disaster occurs. Secondly, it focused on reducing the negative experiences of individuals affected by disasters, particularly in terms of the efficiency of relief and treatment services. Through meticulous analysis, their findings emphasized a noteworthy relationship between cost fluctuations and their consequences. Specifically, they observed that an increase in costs was directly correlated with a higher ratio of patients to the total number of injuries. This cost escalation was also associated with an exacerbation of resource shortages, highlighting the intricate interplay between financial allocations and operational outcomes. For further reference, a summary of relevant papers is presented in Table 1.

2.1. Research gap

In today's dynamic market, adaptability is the key to survival in a highly competitive landscape. To thrive, businesses must create customized strategies that enable them to respond effectively to the unique characteristics of their products and the diverse markets they serve. This ability to tailor their approach sets them apart in the competitive arena.

While extensive research has explored the vehicle routing problem with time windows (VRPTW), its application within the realm of perishable products remains relatively limited. Although some efforts have been made to tackle this challenge, the integration of multiple-cross-docking systems, particularly suited for the swift and perishable product domain, remains an underexplored territory. The strategic adoption of multiple-cross-docking brings forth a myriad of advantages, including inventory reduction, enhanced operational efficiency, shortened delivery times, and improved control over distribution processes (Maknoon and Laporte, 2017; Nasiri et al., 2018; Rahbari et al., 2019; Tirkolaee et al., 2020; Qiu et al., 2021; Shahabi-Shahmiri et al., 2021; Theophilus et al., 2021). It is crucial to recognize that incorporating multi-cross-docking under conditions of uncertainty involves a multi-faceted planning endeavor, encompassing various activities such as unloading incoming shipments, consolidating products, and loading outgoing vehicles—a focal point of this study.

Considering the pivotal roles of cross-docks and transportation in enhancing the efficiency of extensive supply chain distribution networks, it is intriguing to explore other real-world factors, including reliability and pollution, in the design or redesign of these networks. Maximizing reliability translates to heightened customer satisfaction and an expanded market share, while pollution minimization contributes to the cultivation of environmentally conscious industries.

In response to the existing gap in the literature, our proposed study aims to develop a sustainable and efficient approach to managing perishable food supply chains by harnessing the potential of multiple-cross-docking within an environment of uncertainty. Our model employs mathematical optimization methodologies to intricately balance the objectives of minimizing pollution costs, maximizing customer satisfaction (reliability), and reducing distribution and shipping durations. This alignment is achieved while embracing the principles of multiple-cross-docking and routing optimization, all while considering the finite lifespan of products and temporal windows within a logical framework.

Our study will focus on the perishable product supply chain of Iran's Doosheh Dairy Company. Specialized considerations will encompass a heterogeneous fleet, time windows, multi-cross-docking, multi-door operations, and the unique handling requirements of perishable products; all heightened by the presence of uncertainty and split deliveries. Additionally, we will holistically address sustainability aspects, including CO2 emissions and fuel consumption, reflecting recent trends. To derive optimal solutions for this intricate problem, we will employ an advanced hybrid algorithm (MCGP-UF-GA) and benchmark its efficiency against other meta-heuristic algorithms, such as the Multi-Objective Simulated Annealing Algorithm (MOSA).

3. Problem statement

This section introduces a comprehensive modeling framework for optimizing a cross-docking system that handles both perishable and general products, utilizing a fleet of heterogeneous vehicles capable of split delivery. Fig. 2 illustrates the key components of this framework, which is designed to achieve several critical objectives: minimizing the total supply chain cost, reducing distribution-shipping times, and enhancing the overall reliability of perishable product supply.

To attain these objectives, the transportation process is meticulously designed to enable incoming vehicles to seamlessly transition into outgoing vehicles, thereby minimizing the overall completion time of all operational activities. Specifically, upon arrival at the warehouse, incoming vehicles are loaded with specific product types assigned to their routes while unloading any other products. Subsequently, these vehicles are reloaded with products of the same category that are already present in the vehicles. They then depart from the cross-dock facility, serving their designated destinations before returning to the cross-dock after completing their service cycle. This approach ensures that each vehicle serves its specified destinations in a single trip, optimizing both time and resources.

The framework employs two distinct types of vehicles: refrigerated and general-purpose vehicles. The selection and routing of these vehicles are optimized to minimize distribution-shipping times for all pick-up and delivery requests while concurrently minimizing the total supply chain costs. Furthermore, the framework places a strong emphasis on maximizing the reliability of perishable product supply, a pivotal factor in meeting consumer demands and ensuring product safety and quality.

By leveraging a combination of exact and heuristic methods, the proposed framework facilitates the identification of the most efficient

Table 1
Summary of scientific research.

source	objective	Cross-docks	Door	product	vehicle	scheduling	Routing	Inventory storage	Time windows	Pollution issues	Type of model
Vahdani et al., 2012	S	S	S	S	Ho	*	*				MIP
Dondo et al., 2013	M	S	M	S	Ho	*	*	*			MILP
Javanmard et al. (2014)	S	M	S	M	Ho	*	*	*	*		MIP
Ahmadizar et al. (2015)	S	M	S	M	He	*	*	*			MINLP
Afifi et al. (2016)	S	S	S	S	Ho		*		*		MIP
Maknoon and Laporte, 2017	S	M	S	S	Ho		*				MIP
Nasiri et al., (2018)	S	M	S	S	He		*	*	*		MIP
Küçükoğlu and Öztürk, 2019	S	S	S	M	Ho		*		*		MILP
Goodarzi et al. (2020)	M	S	S	M	He	*	*	*	*		MILP
Tirkolaee et al. (2020)	M	M	S	S	Ho		*		*	*	MILP
Qiu et al. (2021)	S	M	S	M	He		*	*			MILP
Shahabi-Shahmiri et al. (2021)	M	M	M	M	He	*	*	*	*		MILP
This study	**M**	**M**	**M**	**M**	**He**	*	*	*	*	*	**MINLP**

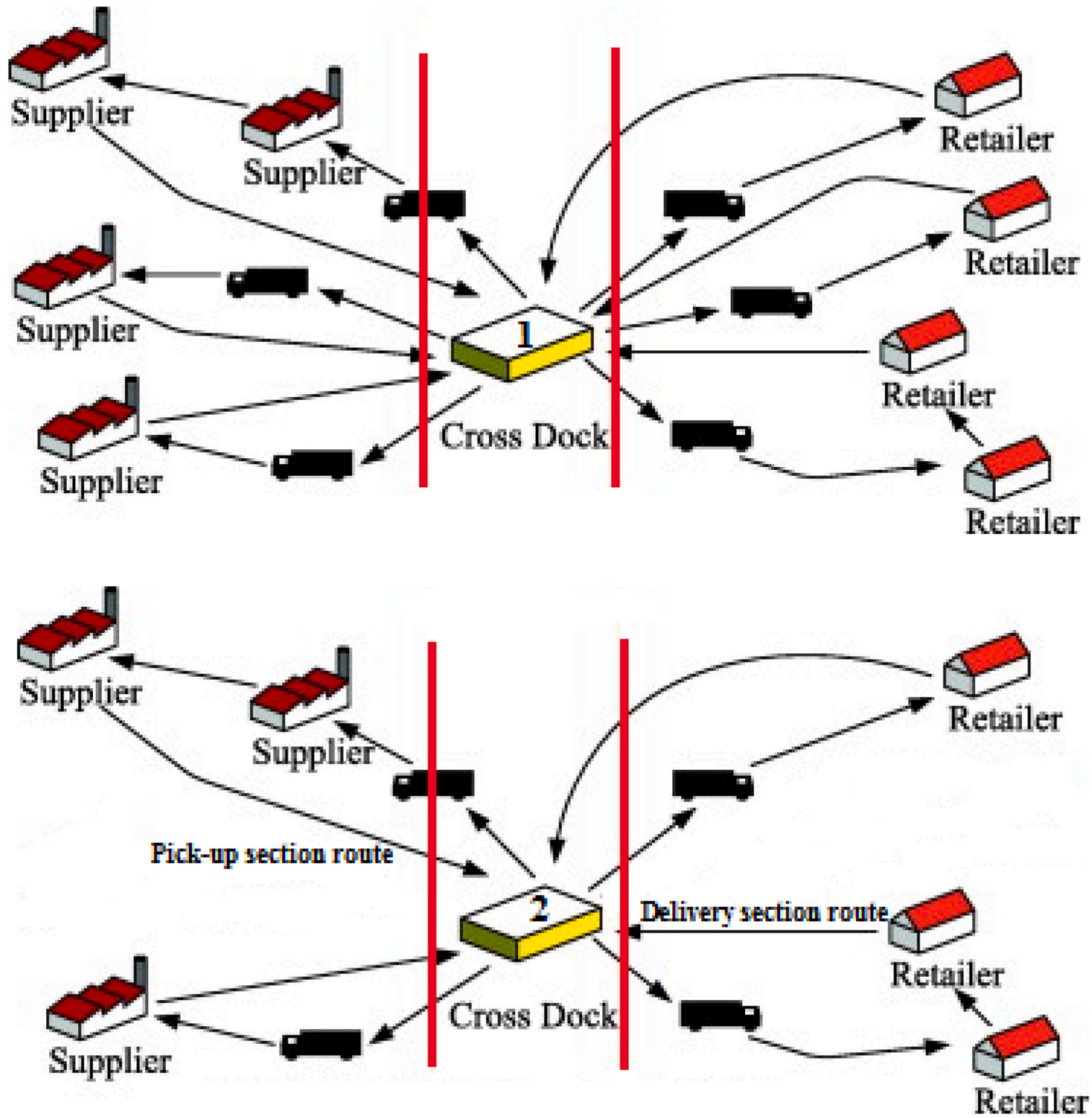


Fig. 2. Using cross-docking to supply a system on studied.

routes for the selected vehicles, ultimately enhancing the overall system efficiency. Additionally, it has the capacity to accommodate uncertainties in demand and supply through the utilization of robust optimization techniques. In summary, the presented modeling framework offers a promising approach for optimizing cross-docking operations involving both perishable and general products, efficiently managed by a fleet of heterogeneous vehicles with the capability for split delivery.

The modeling framework for the proposed problem, which involves heterogeneous vehicles and split delivery in a multiple-cross-docking system for perishable products, is illustrated in Fig. 2. This study focuses on optimizing the timing of heterogeneous vehicles within a multi-gate dock and vehicle routing. The primary objectives are to minimize the total supply chain cost and distribution-shipping time, taking into account all pick-up and delivery requests, while also maximizing the reliability of perishable product supply.

The transportation design is strategically crafted to enable the efficient utilization of incoming vehicles as outgoing vehicles, resulting in reduced completion times for all operational activities. This process involves incoming vehicles carrying specific product types assigned to particular routes, unloading other products, reloading with products of the same category already within the vehicles, and then proceeding to cross the warehouses as outgoing vehicles. Once they depart from the crossover warehouse, each vehicle serves its designated destinations only once and subsequently returns to the cross-dock, selecting the shortest route to their specified destinations.

The model employed in this study evaluates the cost-effectiveness of using incoming vehicles as outgoing vehicles based on their respective routes. Simultaneously, it addresses the allocation of vehicles to gates, vehicle timing, and vehicle allocation to destinations. The allocation of vehicles to destinations is particularly significant, as it ensures that each vehicle follows the shortest possible route to deliver products to their assigned destinations, aligning with the diverse objectives of this research. By assuming that incoming vehicles are allocated to specific destinations, the need for unloading and reloading products at the crossover warehouse is minimized, significantly reducing the total time required for cross-docking activities and distribution-shipping, consequently leading to cost reduction.

The proposed model is founded on several essential assumptions, each of which plays a crucial role in shaping the framework's parameters and constraints.

- **Temporal and Product Diversity:** The model accommodates various time periods and a diverse range of products, ensuring its applicability to dynamic real-world scenarios.
- **Predefined Cross-Dock and Customer Locations:** Similar to the approaches in studies by Dondo et al. (2014) and Dondo and Cerdá (2015), both the cross-dock and customer locations are predetermined, providing a structured foundation for routing optimization.
- **Capacity Constraints:** The cross-dock's capacity is constrained, considering both the number and size of goods, mirroring the principle established in Tirkolaee et al. (2020).
- **Demand Uncertainty:** The model acknowledges the presence of demand uncertainty for final products, aligning with the observations made in the work by Nasrollahi et al. (2023), which is crucial for robust supply chain management.
- ***Predefined Shipping Modes:*** Shipping modes, along with their fixed capacities, are predefined, drawing inspiration from the research conducted by Huerta-Muñoz et al. (2022), ensuring a realistic representation of the transportation system.
- ***Route Capacity Uncertainty:*** The capacities of transportation routes are susceptible to uncertainty, reflecting the dynamic nature of real-world logistics networks.
- *Restrictions on Material Movement:* As per the assumptions in Shahabi-Shahmiri et al. (2021) and Goodarzi et al. (2020), the model restricts the movement of materials between non-adjacent floors and surfaces on the same level, mirroring practical constraints in material handling.
- ***Consideration of Costs:*** Both variable and fixed costs, encompassing collection and transportation expenses, are taken into account, ensuring a comprehensive evaluation of supply chain expenses.
- ***Fixed Time Periods:*** Each time period is assumed to have a fixed duration, and processing is initiated only once all trucks have unloaded their cargo, in accordance with Shahabi-Shahmiri et al. (2021).
- ***Product-Vehicle Compatibility:*** The number of available products is assumed to surpass the number of accessible vehicles, ensuring efficient product-vehicle matching.
- ***Multiple Cross-Docking Points:*** Similar to the frameworks introduced by Nasiri et al. (2018) and Rahbari et al. (2019), the model accommodates the possibility of a single request being serviced through multiple cross-docking points, enhancing flexibility in supply chain operations.

These assumptions collectively form the foundation of the proposed model, enabling a comprehensive and adaptable approach to optimizing cross-docking operations in diverse logistical contexts.

3.1. Formulation of the model

In this section, we establish the foundational elements of our mathematical optimization model, which include the definition of key indexes, sets, parameters, and decision variables. Subsequently, we formulate the model by precisely defining its objectives and delineating the constraints that must be adhered to. This rigorous approach is essential to ensure clarity, precision, and effectiveness in addressing the specific optimization problem at hand.

Sets and indices	
C	Set of cross-docking.
R	Set of products.
T	Set of periods.
V	Set of vehicles.
P	Set of pick-up nodes.
D	Set of delivery nodes.
I,J	Set of nodes $i,j \in P \cup D \cup C$.
ID	Set of input dock door with index l.
OD	Set of output dock door with index u.
Parameters	
dis_{ij}:	Distance between pick-up/delivery to cross-docking.
sp_v:	speed of vehicle.
cv_v:	Capacity of vehicle.
tc_{ijvt}:	Transport cost unit based on distance with vehicle at time period.
ce_{ijvt}:	CO2 emission cost from transportation at time period.
cl_{ijt}, cu_{ijt}:	Cost of loading/unloading at time period.
l_r:	Lifespan of the products.
rl_c, ru_c:	Rate of loading/unloading in cross-docking.
de_{it}:	Demand of retailers at time period.
sc_i:	Suppliers capacity for pick-up.
β:	Rate of fuel consumption.
tst_{ivt}:	Time of service tardiness for retailers with vehicle at time period.
tse_{ivt}:	Time of service earliness for retailers with vehicle at time period.
tsl_{ivt}:	Time of service latest for retailers with vehicle at time period.
ts_{ivt}:	Time of service earliest for retailers with vehicle at time period.
tt_{lut}:	Time it took to carry the vehicle from unloading door to loading door at time period.
M:	Big number.
γ_{it}:	Indicator of failure rate at time period of suppliers, based on exponential distribution.
Decision variables	
LS_{ivt}:	level of service to retailers with vehicle at time period.
At_{ivt}:	Arrival time of vehicle to the retailers at time period.
Dt_{ivt}:	Departure time of vehicle to the retailers at time period.
μ_{clvt}, μ_{cuvt}:	$\begin{cases} 1 & \text{vehicle is assigned to dock doors from cross}-\text{dock at time period.} \\ 0 & \text{else} \end{cases}$
θ_{cvt}:	$\begin{cases} 1 & \text{vehicle is assigned to cross}-\text{dock at time period.} \\ 0 & \text{else} \end{cases}$
δ_{ijvt}:	$\begin{cases} 1 & \text{vehicle shiping for pick}-\text{up/delivers nodeaproduct at time period.} \\ 0 & \text{else} \end{cases}$
X_{ijvt}:	Amount of product transferred in the network at time period.
av_{ij}:	A variable used to eliminate sub-tours.

$$\text{Min } Z_1 = \sum_{i \in P\cup C} \sum_{j \in D\cup C} \sum_{v} \sum_{t} \delta_{ijvt}.tc_{ijvt}.\frac{dis_{ij}}{sp_v} + \sum_{i \in P\cup C} \sum_{j \in D\cup C} \sum_{v} \sum_{t} ce_{ijvt}.\beta.\frac{dis_{ij}}{sp_v}.X_{ijvt} + \sum_{i \in P\cup C} \sum_{j \in D\cup C} \sum_{v} \sum_{t} cl_{ijt}.rl_c.\theta_{cvt} + \sum_{i \in P\cup C} \sum_{j \in D\cup C} \sum_{v} \sum_{t} cu_{ijt}.ru_c.\theta_{cvt} \tag{1}$$

$$\text{Min } Z_2 = \sum_{i \in P\cup D\cup C} \sum_{v} \sum_{t} At_{ivt} \tag{2}$$

$$\text{Max } Z_3 = \sum_{i \in P\cup C} \sum_{j \in D\cup C} \sum_{v} \sum_{t} e^{\gamma_{it}.T}.X_{ijvt} \tag{3}$$

s.t.

$$\sum_{i \in D\cup C} \delta_{ijvt} = 1.\forall j, v, t \tag{4}$$

$$\sum_{j \in P\cup C} \delta_{ijvt} = 1.\forall i, v, t \tag{5}$$

$$\sum_{i \in C} \sum_{j \in C} \delta_{ijvt} = 0.\forall v, t \tag{6}$$

$$\sum_{j \in D\cup C} \sum_{t=\max\ (1,t'-l_r)}^{t+1} X_{jivt} - \sum_{j \in D\cup C} \sum_{t=\max(1,t'-l_r)}^{t+1} X_{ijvt} = \sum_{t} de_{it}.\forall i, v \tag{7}$$

$$\delta_{ijvt}.de_{it} \leq X_{ijvt} \leq \delta_{ijvt}.(cv_v - de_{it}).\forall i,j,v,t \tag{8}$$

$$\sum_{t}^{t+(l_r-1)} de_{it} \leq \sum_{t} X_{ijvt}.\forall i,j,v \tag{9}$$

$$X_{ijvt} \leq sc_i.\delta_{ijvt}.\forall i,j,v,t \tag{10}$$

$$\sum_{j\in P\cup C} X_{ijvt} \leq cv_v - \sum_{j\in P\cup C} X_{ijvt}.\forall i,v,t \tag{11}$$

$$au_{ij}+1 \leq au_{ji} + M\left(1-\delta_{ijvt}\right).\forall i,j,v,t \tag{12}$$

$$LS_{ivt} \leq \frac{\frac{1+0.15.(Dt_{ivt}-At_{ivt})^4}{cv_v} - (tst_{ivt}+tt_{lut})}{tsl_{ivt}-tst_{ivt}}.\forall i,l,u,v,t \tag{13}$$

$$LS_{ivt} \geq \frac{(tse_{ivt}+tt_{lut}) - \frac{1+0.15.(Dt_{ivt}-At_{ivt})^4}{cv_v}}{tse_{ivt}-ts_{ivt}}.\forall i,l,u,v,t \tag{14}$$

$$At_{ivt} \leq Dt_{ivt} + \sum_{i\in D\cup C} \frac{dis_{ij}}{sp_v}.\left(\frac{1+0.15.(Dt_{ivt}-At_{ivt})^4}{cv_v}\right) + M.\left(1-\delta_{ijvt}\right).\forall i,j,v,t \tag{15}$$

$$At_{ivt} \geq Dt_{ivt} + \sum_{i\in D\cup C} \frac{dis_{ij}}{sp_v}.\left(\frac{1+0.15.(Dt_{ivt}-At_{ivt})^4}{cv_v}\right) - M.\left(1-\delta_{ijvt}\right).\forall i,j,v,t \tag{16}$$

$$At_{ivt} \geq tst_{ivt} - M.(2-\mu_{clvt}+\mu_{cuvt}).\forall c,u,l,i,v,t \tag{17}$$

$$Dt_{ivt} \leq tse_{ivt} + M.(2-\mu_{clvt}+\mu_{cuvt}).\forall c,u,l,i,v,t \tag{18}$$

$$\sum_{l} \mu_{clvt} = \theta_{cvt}.\forall c,v,t \tag{19}$$

$$\sum_{u} \mu_{cuvt} = \theta_{cvt}.\forall c,v,t \tag{20}$$

The proposed model is designed to achieve several critical objectives within the context of optimizing the sustainable supply chain (SSC). These objectives are encapsulated in a set of key equations and constraints:

Objective 1: Minimizing Total Cost (Equation (1)).

The primary aim of the model is to minimize the total cost associated with the SSC. Equation (1) quantifies this cost reduction objective, considering various factors such as pollution costs, loading/unloading costs, and transportation costs.

Objective 2: Reducing Distribution and Shipping Time (Equation (2)).

In addition to cost reduction, the model strives to streamline the distribution and shipping processes. Equation (2) articulates this objective by focusing on minimizing the time required for products to move from suppliers to customers. This reduction in time enhances operational efficiency and customer satisfaction.

Objective 3: Maximizing the Reliability of Perishable Product Supply (Equation (3)).

Ensuring a reliable supply of perishable products is of paramount importance. Equation (3) quantifies the objective of maximizing reliability, taking into account factors that impact the consistency and timeliness of product delivery.

Customer Visitation Constraints: Equations (4) and (5) ensure that each customer is visited only once, optimizing the efficiency of service delivery. *Inter-Cross-Dock Visitation Constraint:* Equation (6) ensures that the assigned transport vehicle does not visit multiple cross-docks, streamlining the routing process. *Demand Satisfaction Constraints:* Equations (7)–(9) address the balance between demand and supply, ensuring that customer demand is met within the specified time horizon. *Load and Capacity Constraints:* Equation (8) defines the maximum load that can be transported between two nodes, while Equation (10) specifies the maximum capacity of each supplier. *Pick-up and Vehicle Capacity Relation:* Equation (11) establishes the relationship between maximum pick-up and vehicle capacity, facilitating efficient resource allocation. *Sub-Tour Elimination:* Equation (12) eliminates sub-tours, optimizing the routing of vehicles. *Service Level Constraints:* Equations (13) and (14) determine the level of service at the time of arrival and departure, contributing to customer satisfaction. *Node Arrival Time Estimation:* Equations (15) and (16) estimate the time required for each node to reach the vehicle, aiding in route planning. *Time Window Constraints:* Equations (17) and (18) define the upper and lower limits of the time window, ensuring timely deliveries. *Dock Door Allocation Constraints:* Equations (19) and (20) specify the allocation of transport means to dock doors within each cross-dock, enhancing operational efficiency.

As observed in constraints (13)–(16) within the model, a fusion of logic functions and time windows is introduced, driven by factors such as service level, vehicle capacity, and distance covered. This amalgamation renders the proposed model inherently nonlinear. The rationale behind incorporating such nonlinear combinations of logic functions and time windows can be delineated through the following justifications:

Firstly, the integration of time windows and logic functions confers a strategic advantage in the domain of supply chain and logistics optimization. This synergy empowers companies to meticulously schedule and execute diverse operations within predefined time slots. Consequently, this strategic approach yields heightened operational efficiency, reduced waiting times, and an elevated standard of service delivery. Particularly noteworthy is the embedded logic function within the time windows, which imparts dynamic adaptability to accommodate demand and supply fluctuations, facilitating the optimal allocation of resources. Consequently, this fusion optimizes resource utilization, minimizes delays, and fosters a harmoniously coordinated supply chain operation. Moreover, it is essential to recognize that cross-docking operations are subject to a plethora of real-world constraints that may not be easily encapsulated using linear methods alone. These constraints can encompass varying processing times, different transportation modes, fluctuating truck capacities, and the assignment of varying priority levels to different shipments. Non-linear combinations are better suited to capture the intricate interplay of these multifaceted constraints. Furthermore, time windows inherently define allowable time intervals during which specific activities can transpire. These time windows can often assume non-linear characteristics due to factors like varying priority levels, penalties for missed deadlines, and the dynamic nature of processing times. The adoption of non-linear combinations of logic functions and time windows serves to aptly reflect the significance of meeting precise time constraints and integrating penalties for their infringement.

In summary, the justification for using a non-linear combination of logic functions and time windows in cross-docking problems lies in the need to accurately model the intricate operations, constraints, and dynamics inherent in this logistics strategy. By adopting non-linear approaches, researchers and practitioners can develop more effective optimization models that account for the complexity of cross-docking operations and lead to better solutions.

3.2. Uncertainty model

This paper delves into the intricate realm of managing demand uncertainties, a facet inherently characterized by its unpredictability. Depending on the level and nature of access, diverse types of uncertainties emerge, each possessing unique properties classifiable within the framework established by Gholizadeh et al. (2022) (refer to Fig. 3). To scrutinize the policies employed by a dairy company, we employ stochastic distribution estimates, adeptly accommodating both epistemological and stochastic uncertainties. Our approach builds upon the pioneering works of Gholizadeh et al. (2020a,b), Nayeri et al. (2020),

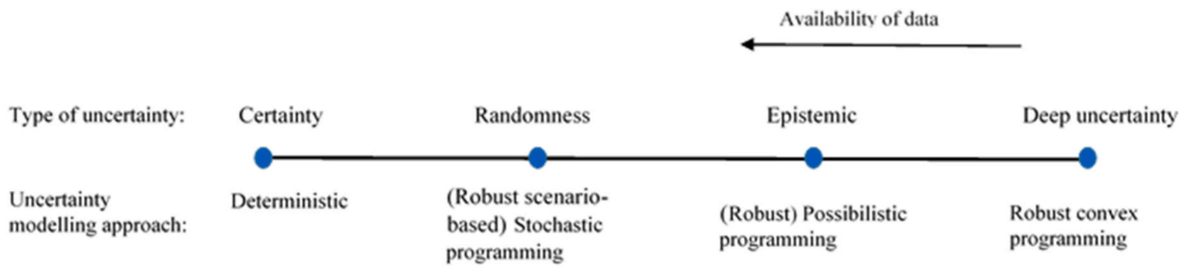


Fig. 3. Different approaches to uncertainty (Govindan and Gholizadeh, 2021).

$$\text{Min } Z1 = \sum_{s} P_s OBJ2_s + \lambda \sum_{s} P_s \left(OBJ2_s - \sum_{s'} P_{s'} OBJ2_{s'} + 2\theta_s \right) + \omega \sum_{s} P_s \delta_s \tag{21}$$

$$\text{Min } Z2 = \sum_{s} P_s OBJ3_s - \lambda \sum_{s} P_s \left(OBJ3_s - \sum_{s'} P_{s'} OBJ3_{s'} + 2\theta_s \right) \tag{22}$$

$$\text{Max } Z3 = \sum_{s} P_s OBJ1_s + \lambda \sum_{s} P_s \left(OBJ1_s - \sum_{s'} P_{s'} OBJ1_{s'} + 2\theta_s \right) \tag{23}$$

Gholizadeh and Fazlollahtabar, (2020), and Gholizadeh et al. (2022), all of which have significantly contributed to this field. Termed as a robust approach, our methodology generates solutions that closely approximate the optimal solution with a remarkable degree of precision. One of the primary merits of our approach is the utilization of a grading model. This model, in contrast to a fixed model, furnishes more realistic estimates, consequently enhancing the quality of decision-making processes. What sets our approach apart from others is its emphasis on scenario grading, a strategic facet that empowers us to fortify network resilience and bolster our predictive capabilities. Overall, our study presents a comprehensive exploration of demand uncertainties, enriched by the innovative grading model, which significantly enhances decision-making in comparison to conventional fixed models. This approach augments the robustness of the network and reinforces our capacity to foresee potential outcomes.

Scenario grading with uncertainty is a decision-making process that involves evaluating and ranking different scenarios or potential future outcomes in the presence of uncertainty. This approach is commonly used in fields such as risk management, financial planning, supply chain optimization, and strategic decision-making. The aim is to assess the potential impact of various scenarios under uncertain conditions and make informed choices based on their relative desirability or risk (Chaleshigar Kordasiabi et al., 2023). Scenario grading with uncertainty typically works including scenario generation, uncertainty consideration, grading and evaluation, risk assessment, ranking or prioritization, and decision-making. Scenario grading aims to assess the risk associated with each scenario. In scenario grading with uncertainty, the uncertainty associated with each scenario is explicitly recognized. This can involve quantifying uncertainty using probability distributions or other measures. Each scenario is evaluated based on predefined criteria, taking into account the potential benefits, risks, costs, and other relevant factors. The evaluation can include both quantitative and qualitative assessments, including economic conditions, market trends, technological advancements, and other relevant variables.

In the last section, I described adding the following constraint to the model:

$$OBJ1_s - \sum_{s'} P_{s'} OBJ1_{s'} + \theta_s \geq 0 \forall s \tag{24}$$

$$OBJ2_s - \sum_{s'} P_{s'} OBJ2_{s'} + \theta_s \geq 0 \forall s \tag{25}$$

$$OBJ3_s - \sum_{s'} P_{s'} OBJ3_{s'} + \theta_s \geq 0 \forall s \tag{26}$$

$$\theta_s \geq 0 \tag{27}$$

where λ, defines the weight of risk and ω, an infeasibility weight that is established by the decision maker.

The objective functions in this study aim to optimize the stability and efficiency of the model under different demand scenarios. Equation (21) presents the first objective function, which comprises three parts. The first and second parts, representing the mean and cost variance, respectively, are defined to ensure the model's stability and avoid over-optimization. The third part evaluates the model's suitability based on non-dominant values of the control constraints for each scenario. To address demand scenarios with the same mean and cost variance, we propose two additional objective functions, presented in Equations (22) and (23), respectively. To linearize these objectives, we use Equations (24)–(26). Finally, to limit unjustified amounts, Equation (27) introduces unsatisfied claims.

The significance of employing an integrated scenario-based approach and robust multiple cross-docking networks, as compared to other techniques previously explored in the existing literature, lies in their ability to enhance the efficiency, adaptability, and practicality of supply chain and logistics operations. For example, integrated scenario-based approach has adaptability to real-world variability, risk mitigation and decision resilience, and holistic optimization. On the other hand, robust multiple cross-docking networks have efficient handling and inventory reduction, dynamic response to fluctuations, and resource utilization optimization. However, compared to traditional techniques that often operate in isolation and make simplifying assumptions, the integrated scenario-based approach and robust multiple cross-docking networks offer several advantages including.

- Realism: Both approaches acknowledge the complexities and uncertainties inherent in real-world supply chains, providing more realistic solutions that are better aligned with practical situations.
- Adaptation: The integration of scenarios and cross-docking networks allows for adaptability to changing circumstances, making them more suitable for volatile market conditions and unexpected disruptions.
- Optimization Under Uncertainty: These approaches optimize with a broader perspective that accounts for uncertainty and risk, resulting in more resilient solutions.
- Holistic Benefits: The combined benefits of scenario-based planning and dynamic cross-docking enhance overall supply chain performance, leading to cost reduction, improved customer service, and reduced environmental impact.

In essence, the significance of using an integrated scenario-based approach and robust multiple cross-docking networks stems from their ability to provide sophisticated and flexible solutions that cater to the intricacies of modern supply chain challenges, resulting in improved efficiency, adaptability, and overall performance compared to more traditional techniques.

4. Solution approach

This article introduces a novel strategy for tackling multi-objective models through the utilization of the MCGP-UF technique, cleverly reformulated as a single-objective equivalent. To tackle the complexities posed by extensive problem domains, we have devised an adept and resourceful solution that leverages a hybrid methodology, amalgamating both Genetic Algorithm (GA) and MCGP-UF approaches. While prior research endeavors, such as the work by Razavi et al. (2020), have dabbled in similar hybrid methodologies, our method introduces a distinctive hybrid optimization protocol that takes into careful consideration the incorporation of binary variables. Our proposed approach embarks on a mission to present a pioneering solution to the multifaceted realm of multi-objective optimization—a challenge that resonates across a plethora of disciplines. Notably, our method capitalizes on the unique strengths of both GA and MCGP-UF, thereby fortifying the efficiency and efficacy of the overall optimization process. It is prudent to acknowledge that our proposed approach, although promising, is not impervious to limitations. Consequently, there exists a pressing need for subsequent research to rigorously evaluate its performance across diverse contexts. Nevertheless, we are confident that our approach contributes to the ongoing endeavors aimed at sculpting novel and refined optimization techniques, marking another stride towards the evolution of cutting-edge solutions.

4.1. MCGP-UF

In this study, we utilize the Multi-Choice Goal Programming, with Utility Function (MCGP-UF) method developed by Chaleshigar Kordasiabi et al. (2023) as one type of GP. This method has several advantages over other versions of GP, including the incorporation of expert opinions on various issues and the consideration of the preferential value of decision-makers. The MCGP-UF method is a type of GP that uses multiple criteria to evaluate alternative solutions and identify the optimal solution based on the decision-makers' preferences. The method can handle complex and conflicting criteria and allows for the integration of qualitative and quantitative factors in the decision-making process.

The corresponding model is presented below and is used to identify the optimal solution in the multi-criteria decision-making problem.

$$\begin{aligned}
& Min\sum_k \left[w_k^d.(d_k^+ + d_k^-) + w_k^{\xi}.(\xi_k^-)\right] \\
& S.t. \\
& \lambda_k \le \frac{U_{k,max} - y_k}{U_{k,max} - U_{k,min}} \quad \forall k \\
& f_k(X) + d_k^- - d_k^+ = y_k \quad \forall k \\
& \lambda_k + \xi_k^- = 1 \quad \forall k \\
& U_{k,min} \le y_k \le U_{k,max} \quad \forall k \\
& d_k^+, d_k^-, y_k, \lambda_k, \xi_k^- \ge 0 \quad \forall k \\
& \textit{Model constraint sets}
\end{aligned} \tag{28}$$

The proposed model includes several parameters and notations that are used to represent the different components of the optimization problem. Specifically, $U_{k,max}$ and $U_{k,min}$, represent the upper and lower bounds of the *kth* objective aspiration level, respectively. The decision variable y_k, is continuous, while d_k^+ and d_k^-, represent the positive and negative deviations of $f_k(X)$, from y_k. The parameter λ_k, represents the utility value, and ξ_k^-, is used to represent the normalized deviation of y_k , from $U_{k,min}$.

It is important to note that the model can be normalized, if needed, to ensure that the values of the different parameters are within a certain range. Normalization can be achieved by dividing the original parameter values by their respective maximum values. This will ensure that all the parameters are on the same scale and will not affect the optimization results.

Overall, the proposed model is designed to optimize the objective function while considering the different constraints and parameters. The different parameters used in the model are carefully chosen to ensure that the model is accurate and reflects the preferences and aspirations of the decision-makers. Further research may be needed to validate the effectiveness of the model under different conditions and to explore its potential applications in real-world problems, which is not included in this study.

$$Min\sum_k \left[w_k^d.\left(\frac{d_k^+ + d_k^-}{f_k^- - f_k^+}\right) + w_k^{\xi}.(\xi_k^-)\right] \tag{29}$$

In the above equation, for the minimization objective functions, $f_k^+ = \{\min f_k(X)\}$ and $f_k^- = \{\max f_k(X)\}$. ξ_k^-, Do not need to be normalized because of $0 \le \xi_k^- \le 1; \forall k$.

In the proposed equation, the objective functions are minimized by calculating the minimum and maximum values of $f_k(X)$, using the parameters ,$f_k^+ = \{\min f_k(X)\}$ and $f_k^- = \{\max f_k(X)\}$. Additionally, the parameter ξ_k^-, is used to represent the normalized deviation of y_k, from $U_{k,min}$, where $0 \le \xi_k^- \le 1; \forall k$.

It is important to note that the normalization of ξ_k^-, is not required because it is already restricted to a range of 0–1. This means that the parameter is already on the same scale as the other parameters used in the equation and does not require further normalization.

Overall, the proposed equation is designed to minimize the objective functions while considering the different constraints and parameters. The use of specific parameters such as f_k^+, f_k^-, and ξ_k^- is critical to ensuring the accuracy and effectiveness of the model.

4.2. GA

The utilization of meta-heuristic algorithms for optimizing logistics and supply chain networks has been the subject of extensive research, with contributions from various scholars such as Morais et al. (2014), Gholizadeh et al. (2022), Govindan and Gholizadeh (2021), and Razavi et al. (2020). Among these algorithms, the Genetic Algorithm (GA) has found common application in the domains of logistics and Vehicle Routing Problems (VRP) (Razavi et al., 2020; Gholizadeh et al., 2020a, 2022).

In our pursuit of enhancing solution flexibility, we propose an algorithm that harnesses the power of Variable Neighborhood Search (VNS) to generate potential solutions. Our systematic approach involves the exploration of the dynamic solution space, with the implementation of genetic algorithms for crossover, mutation, and fitness assessment of a subset of the initial population. This process aims to identify improved solutions across different scenarios. Furthermore, our GA employs a Roulette Wheel selection method for parent selection in the genetic operators.

The VNS procedure takes center stage in our search process, systematically replacing original solutions with improved alternatives in each scenario. This search commences with the smallest neighborhood and the lowest probability, progressively advancing toward larger neighborhoods with higher probabilities. This strategic approach empowers the algorithm to discover optimal solutions for complex problems, particularly in the context of VRP within cross-docking networks.

The core objective of this study is to introduce an algorithm capable of adapting VRP in cross-docks for logistics networks, accommodating various demand scenarios encompassing both pick-up and delivery. The algorithm is founded on multiple scenarios, thoroughly exploring the solution space to yield a variety of encryptions. Our approach initiates by generating a continuous solution, subsequently transformed into a feasible solution for the delivery process. Following this, the algorithm devises potential solutions for pick-up, ultimately resulting in a set of feasible routes that incorporate both pick-up and delivery tours. Leveraging the VNS, the algorithm selects the best feasible pick-up tours to complement the delivery tours.

Fig. 4 illustrates the chromosome representing the genetic makeup of the logistics network, comprising five suppliers, five customers, and three vehicles. This chromosome is divided into two parts, as previously mentioned: the first part corresponds to delivery genes, while the second part encompasses pick-up genes (see Fig. 5).

To enhance the performance of our algorithm, we employ a crossover operator with a specified probability denoted as P_c. In this study, our approach involves the random selection of the first pair of parents from a uniform distribution [0, 1] of two chromosomes, which will serve as the crossover operators. The crossover operation entails creating an offspring based on a compromise between the chromosomes of the selected parents. To illustrate this process, consider two parent chromosomes: Parent 1 with the sequence (1234|56,789) and Parent 2 with (3792|45,861), where the "|" symbol represents the cutting point. After applying the crossover, the resulting primary child of Parent 1 becomes (1234|45,861), while the primary child of Parent 2 becomes (3792|56,789). During this crossover process, the numbers (1, 4) from the primary child 1 and (7, 9) from the primary child 2, appearing both before and after the cutting points, are modified to ensure they do not repeat. As a result, the final child of Parent 1 becomes (7239|45,861), while the final child of Parent 2 becomes (3142|56,789).

Following the crossover process, a mutation operator was applied to rejuvenate the population. This involved a multi-point operation, which was carried out with a probability of P_m in. For each chromosome, a random interval [0,1] was selected using the mutation operator, followed by a random selection of a gene from a chromosome from multiple scenarios. The content of the selected gene was then changed. The two operator functions used in this study were derived from the research presented by Gholizadeh et al. (2022), which demonstrated their effectiveness in improving the algorithm's performance. Illustrated below Fig. 6 are the mutation operators: (a) Substitution, (b) Inversion, (c) Left Shift, and (d) Right Shift.

For the Substitution mutation (top-left), consider the parent gene as (123,456,789). Genes 4 and 7 are randomly selected, resulting in the child gene (123,756,489). For the Inversion mutation (top-right), genes 2 and 6 are randomly chosen from the parent, leading to the child gene becoming (125,436,789). For the Left-Shift mutation (bottom-left), genes 3 and 7 are randomly selected from the parent, resulting in the child gene (124,567,389). For the Right-Shift mutation (bottom-right), parent genes 3 and 7 are randomly chosen, leading to the child gene being (127,345,689).

4.3. Hybrid method

This study proposes a novel hybrid algorithm that combines the MCGP-UF method and the GA to solve a specific problem. The MCGP-UF parameters, including $U_{k,min}$, $U_{k,max}$, $f_k^+ = \{\min f_k(X)\}$ and $f_k^- = \{\max f_k(X)\}$, are calculated after generating the initial population in the GA. The MCGP-UF function is computed for each solution, and the chromosomes in the initial population undergo crossover and mutation operations until the stopping criteria are met.

To illustrate the proposed algorithm, the flowchart in Fig. 7 depicts the sequence of steps involved. The MCGP-UF method and GA are well-known optimization techniques in the field of evolutionary computing, and the rationale for their combination is thoroughly explained in previous research. The objective of the proposed hybrid algorithm is to achieve an optimal solution for the given problem. The fitness function and stopping criteria used in this algorithm are critical components that determine the efficiency and effectiveness of the algorithm. The details of these components are provided in the methodology section. Overall, the proposed hybrid algorithm has the potential to provide a robust solution to the problem at hand, and the approach can be generalized to other optimization problems.

Below is a step-by-step explanation of each part of the algorithm.

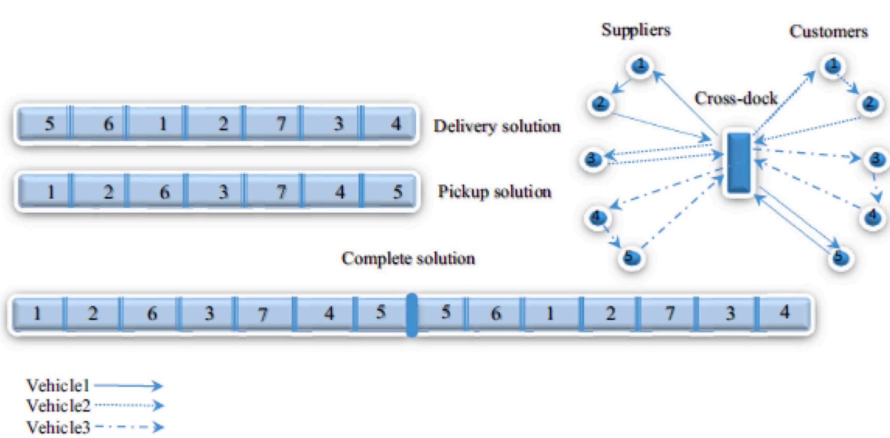


Fig. 4. Example of answer structure for GA.

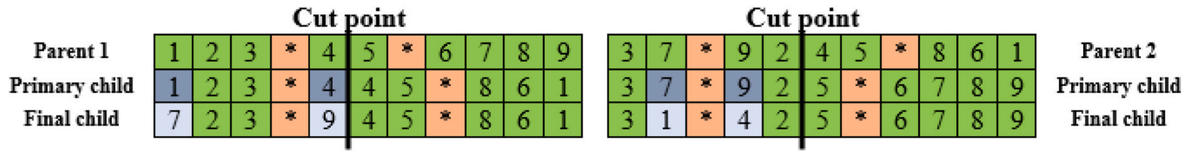


Fig. 5. Visualization of the crossover operator.

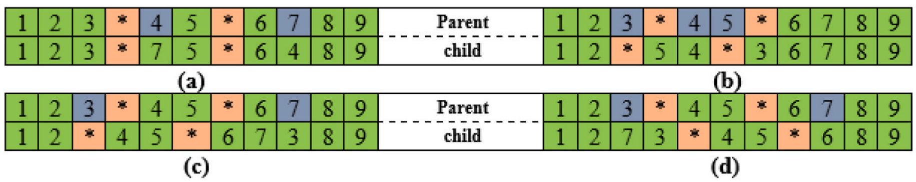


Fig. 6. Visualization of the mutation operator.

Step 1: Set Initial Parameters

In this step, defined the initial parameters for the algorithm. These parameters include Crossover Probabilities ($\mathscr{P}_c$), Mutation Probabilities ($\mathscr{P}_m$) , Population Size (N_{pop}) and Maximum Number of Iterations (M_{axIt}).

Step 2: Random Population Initialization

Generate an initial population of chromosomes, with each chromosome representing a possible solution to the optimization problem. It is crucial to ensure that these chromosomes adhere to the specific constraints and attributes of the problem. In this particular problem, focus on initializing the population with regard to the pick-up and delivery nodes, taking into account the unique characteristics of these nodes.

Step 3: Calculation of Each Objective Function

For each chromosome in the population, calculate the value of each objective function that you want to optimize. This typically involves evaluating how well each solution satisfies the goals and constraints of the problem.

Step 4: *Measuring* $U_{k,min}, U_{k,max}$, $f_k^+ = \{min\, f_k(X)\}$ *and* $f_k^- = \{max\, f_k(X)\}$.

This step involves using the MCGP-UF to find $U_{k,min}, U_{k,max}$, f_k^+ and f_k^- for each objective function (k). These values help quantify the trade-offs between different objectives.

Step 5: Evaluate Fitness Using MCGP-UF Method

Combine the information obtained in Step 3 and Step 4 to evaluate the fitness of each chromosome. This fitness value reflects how well a chromosome performs with respect to the objectives and constraints, incorporating the utility functions and goal programming.

Step 6: Check Terminal Condition

Determine whether the termination condition is satisfied. If the termination condition is met, end the algorithm. Otherwise, proceed to the next steps. These conditions may include the maximum number of iterations, the quality of the best solution discovered, and the computational time (CPU time) utilized during the optimization process.

Step 7: Tournament Selection

Set i= 1 to begin the iteration. Now, employ the tournament selection method with weight demand to choose two individuals, denoted as D_{ri} $^{\text{and}}$ $D_r{+}1_i$ which correspond to pick-up and delivery routes. This process is instrumental in identifying suitable candidate parents for the crossover operation.

Step 8: Crossover Operator

If a random number (Rand) is less than the crossover probability ($\mathscr{P}_c$), perform crossover on D_{ri} $^{\text{and}}$ $D_r{+}1_i$ to create new offspring.

Step 9: Mutation Operator

If Rand is less than the mutation probability ($\mathscr{P}_m$) , perform mutation on D_{ri} $^{\text{and}}$ $D_r{+}1_i$ to introduce small random changes.

Step 10: Evaluate Fitness of Offspring

Calculate the fitness of the newly created offspring D_{ri} $^{\text{and}}$ $D_r{+}1_i$.

Step 11: Initialize Subset for Variable Neighborhood Search

Prepare a subset of the population for the variable neighborhood search.

Step 12: Apply Variable Neighborhood Search

Apply a variable neighborhood search to the subset of the population to explore different neighborhoods and potentially improve solutions.

Step 13: Check if All Pick-up and Delivery Pairs Have Been Considered

If you have considered all pick-up and delivery pairs up to a limit (I $\leq$ R), proceed to Step 14. Otherwise, go to Step 15.

Step 14: Replace Population with Best Individuals from Mate Stage

Replace the population with the best individuals from the mate stage (i.e., offspring and potentially improved solutions from variable neighborhood search). Then, go back to Step 6.

Step 15: Select Two New Individuals

Increment I by 2 and return to Step 7 to select two new individuals using tournament selection for further genetic operations.

Repeat Steps 6 to 15 until the termination condition is met. The

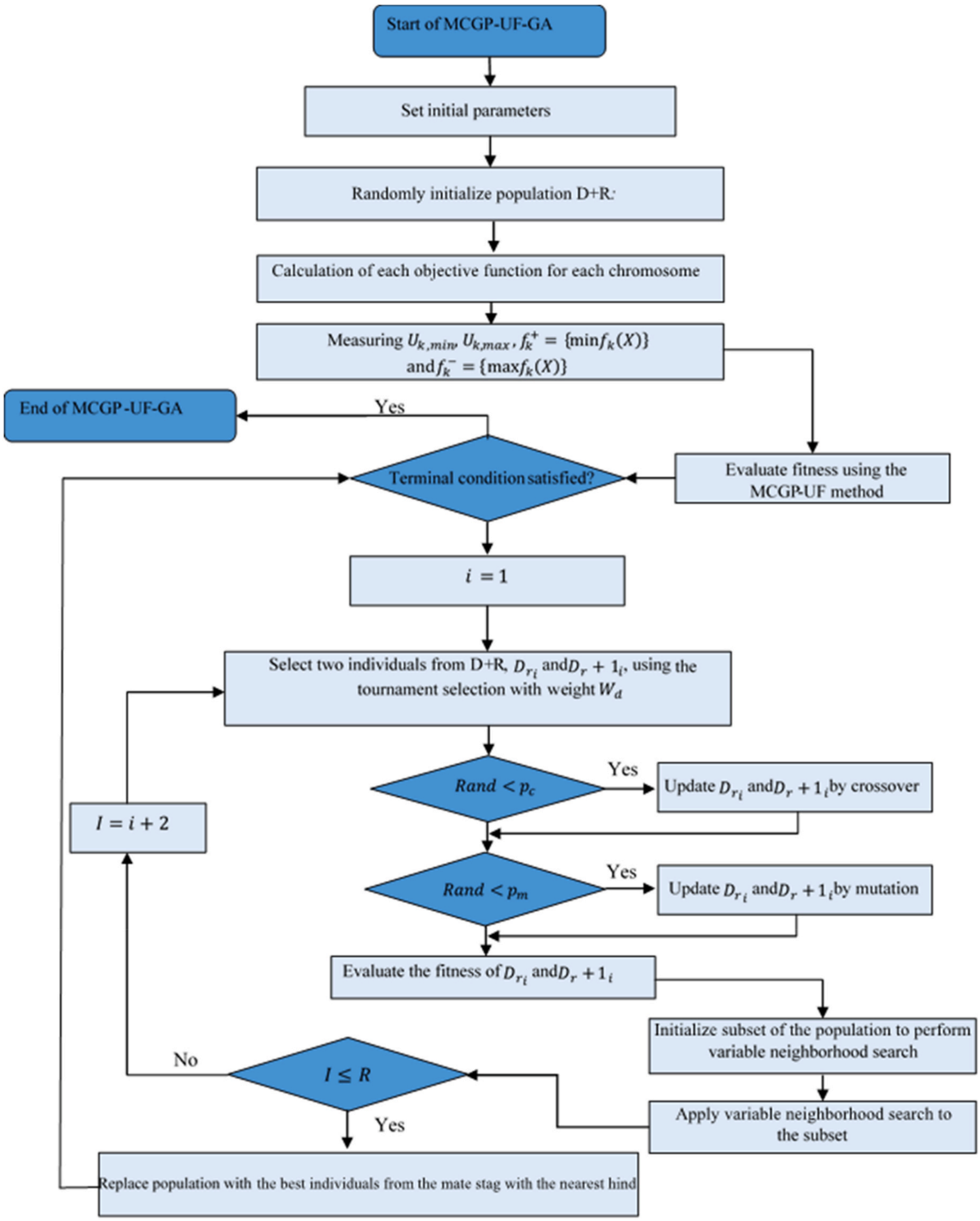


Fig. 7. The flowchart of MCGP-UF-GA.

algorithm aims to find an optimal solution by iteratively improving the population through genetic operators and variable neighborhood search while considering the multi-choice goal programming with utility function aspects.

4.4. Multi objective simulated-annealing algorithm (MOSA)

MOSA represents a metaheuristic optimization technique employed to tackle the complexities of multi-objective optimization dilemmas. Such scenarios entail the simultaneous optimization of numerous conflicting objectives, where enhancing one facet might necessitate trade-offs in others. Operating as a local search meta-heuristic, this algorithm adeptly averts entrapment in local optima, rendering it particularly suitable for nonconvex or discrete quandaries.

Moreover, its implementation simplicity, capacity for convergence, and proficiency in evading local optima render this algorithm a potent tool for enhancing optimal outcomes. The essence of MOSA lies in its pursuit of generating solutions that are non-dominated. It accomplishes this by deploying a straightforward probability function, which endeavors to generate solutions aligned with the Pareto optimal front. This function is strategically tailored to ensure uniform coverage of the objective space, striving to encompass as many nondominated and evenly distributed solutions as possible (Tirkolaee et al., 2020). This distinctive set of attributes has firmly established MOSA as an agile and dependable algorithm, setting it apart from its contemporaries in the realm of multi-objective optimization and positioning it as a preferred choice across a broad spectrum of optimization challenges. The fundamental structure of this algorithm commences with an initial solution and involves pivotal parameters such as the count of iterations per temperature (M), the outset temperature (T0), the rate at which temperature decreases (a), the ultimate temperature (Tend), and the Boltzmann constant (K). These parameters are initialized as the algorithm embarks on its search operations. Subsequently, the algorithm takes cognizance of a neighborhood solution space in relation to the initial solution. If the objective function value of the neighboring solution surpasses the current solution's objective value, the neighboring solution supplants the current one. Alternatively, if the objective value of the neighboring solution is lower, the disparity between the neighboring and initial solutions is computed. This difference is then assessed against a randomly generated number falling within the range of [0, 1]. Additionally, a comparison is performed by contrasting the probability of the exponential of the difference in objective values $exp\left(-\frac{\Delta}{KT}\right)$ against

Table 2
Values of parameters for various levels.

$$S/N = -10\log_{10}\left(\text{Objective Function}(Z_2)\right)^2 \quad (30)$$

Heuristic	Parameter	Level 1	Level 2	Level 3
GA	Crossover Probabilities ($\mathscr{P}_c$)	0.7	0.8	0.9
	Mutation Probabilities ($\mathscr{P}_m$)	0.1	0.2	0.3
	Population Size (N_{pop})	100	250	350
	Maximum Number of Iterations (M_{axIt})	200	400	500
	Iterations per temperature (M)	1	2	5
	Outset temperature (T0)	150	200	300
SA	Rate at which temperature decreases (a)	0.8	0.85	0.9
	Ultimate temperature (Tend)	1	2	5
	Boltzmann constant (K)	0.2	0.5	0.7

the randomly generated number. If this number is less than $exp\left(-\frac{\Delta}{KT}\right)$, the algorithm accepts the inferior solution. At each temperature level, a predetermined number of iterations is conducted before the temperature undergoes reduction. The equation for temperature reduction, known as

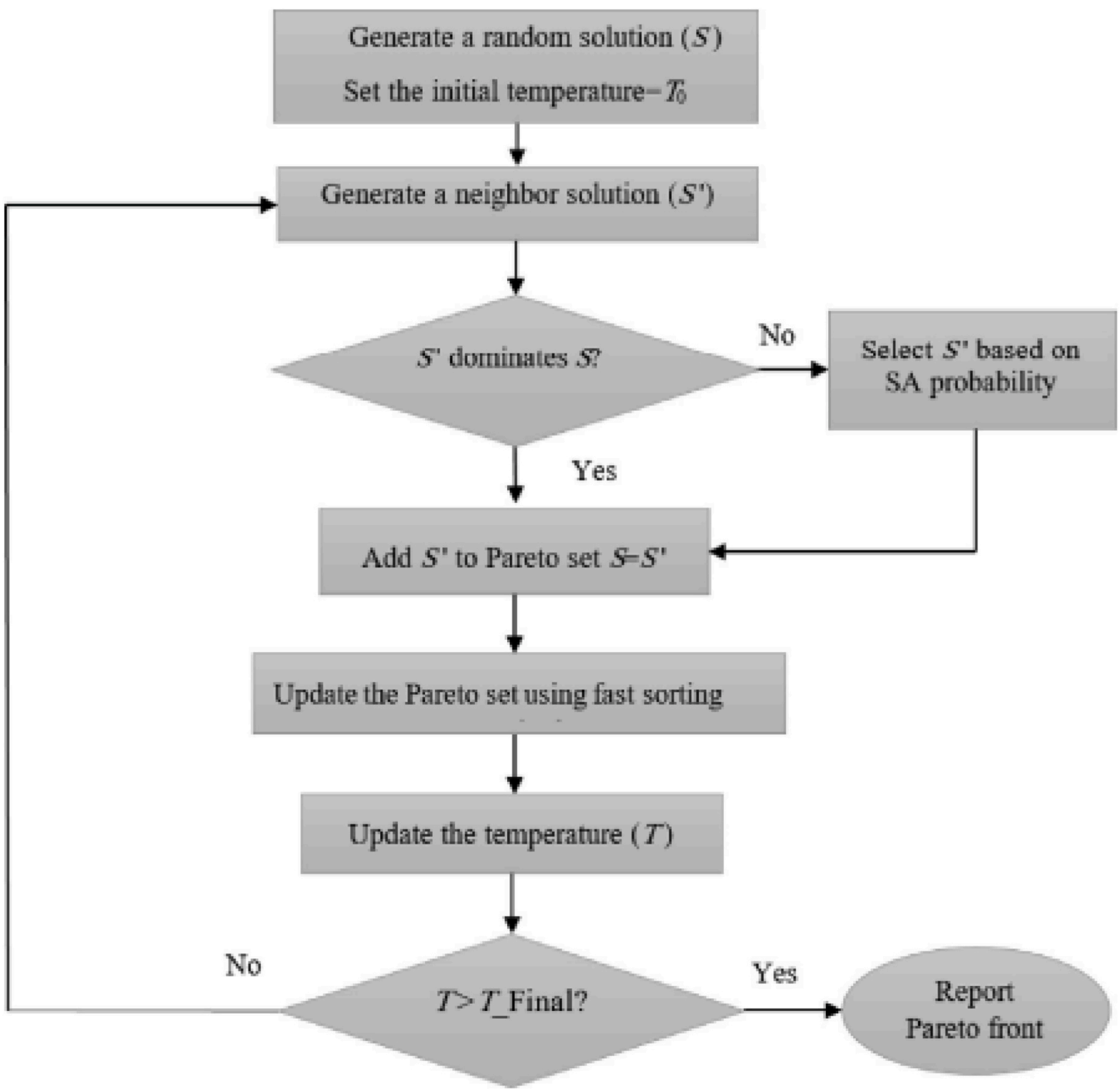


Fig. 8. The flowchart of MOSA.

annealing, is expressed as $\alpha T \rightarrow T$. The conclusion of the algorithm is determined by the achievement of the final temperature. The operational framework of the presented MOSA technique is influenced by the model introduced by Tirkolaee et al. (2020). To illustrate the MOSA algorithm, the flowchart in Fig. 8 depicts the sequence of steps involved.

4.5. Parameter setting

The proposed algorithm aims to solve a specific optimization problem using the Taguchi method, as outlined in Abdi et al. (2020), Govindan and Gholizadeh (2021), and Abdi et al. (2021). The Taguchi method is a well-known methodology for optimizing a process or system by identifying its key parameters and determining their optimal values.

To apply the Taguchi method to the proposed algorithm, the parameter levels are determined using Table 2, which outlines the various possible values of each parameter. Based on these values, the best signal-to-noise ratio (S/N) is selected. This ratio represents the quality of the output signal compared to the background noise and selecting the best S/N ratio is critical to achieving optimal results.

The selected S/N ratio is used to configure the proposed algorithm, as it determines the signal-to-noise threshold for accepting or rejecting candidate solutions. This threshold is a critical factor in the optimization process, as it ensures that only the most promising solutions are considered for further evaluation. The algorithm then proceeds to evaluate each candidate solution using the selected S/N ratio and other optimization criteria to identify the optimal solution.

Multi-criteria Decision-Making (MCDM) technique known as Simple Additive Weighting (SAW) is employed to aggregate measurements into a single solution, facilitating the selection of optimal parameter values. The SAW method can be delineated through a series of steps, as elucidated by Tirkolaee et al. (2020): **Step 1** involves ascertaining the nature of each index and categorizing it as positive or negative. Subsequently, in **Step 2**, the values derived for measurements in the decision matrix are subjected to descaling as per Equations (31) and (32):

$$\text{Negative criteria:} \quad n_{ij} = \frac{r_j^{min}}{r_{ij}} \quad \forall i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{31}$$

$$\text{Positive criteria:} \quad n_{ij} = \frac{r_{ij}}{r_j^{max}} \quad \forall i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{32}$$

In this context, r_{ij} signifies the positively normalized weight attributed to experiment i for measurement j.

Step 3 involves the incorporation of important coefficients, or the weights assigned to measurements, along with the normalized values from the decision matrix. Subsequently, the SAW score can be computed for each experiment using Equations (33) and (34).

$$\sum_{j=1}^{n} w_j = 1 \tag{33}$$

$$SAW_i = \sum_{j=1}^{n} w_j n_{ij} \quad \forall i = 1,2,\ldots,m \tag{34}$$

All measures are assigned equal and positive importance. As the normalized weights of experiments for measures are also positive, higher SAW values take precedence in the decision-making process. Consequently, based on the aforementioned discourse, it is necessary to solve a sample problem for every $3^4 = 81$ levels for GA and $3^5 = 243$ levels for SA. Nonetheless, subsequent to the implementation of the Taguchi design method, the L27 array is chosen as the appropriate experimental arrangement for parameter adjustments.

The experimental results are presented in Fig. 9, which displays the signal-to-noise (S/N) graphs for each algorithm. The optimal value of each algorithm parameter, determined using the Taguchi method, is $\mathscr{P}_c = 0.8$, $\mathscr{P}_m = 0.2$ and $(N_{pop}, M_{axlt}) = (250, 400)$ and $M = 5, T0 = 300, a = 0.85, Tend = 1, and\ K = 0.2$. The Taguchi method is a well-known approach for optimizing a process or system by identifying the key parameters and their optimal values. Based on the S/N analysis, the optimal parameter values identified by the Taguchi method are expected to result in the best overall performance for the proposed algorithm. These values represent the ideal balance between exploration and exploitation, ensuring that the algorithm can effectively search the solution space while avoiding premature convergence.

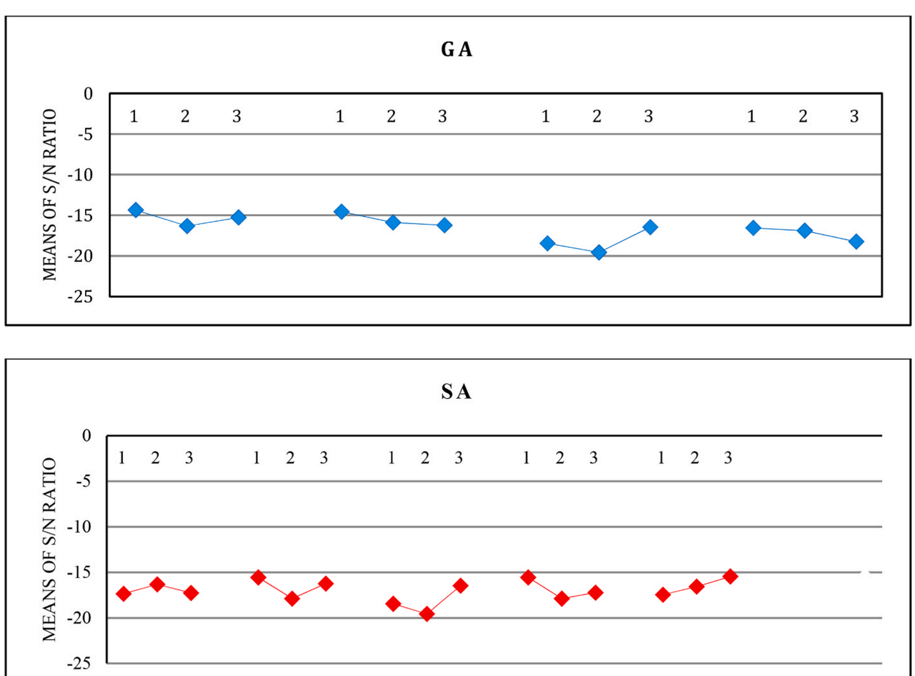


Fig. 9. Mean S/N ratio at each level for GA and SA parameters.

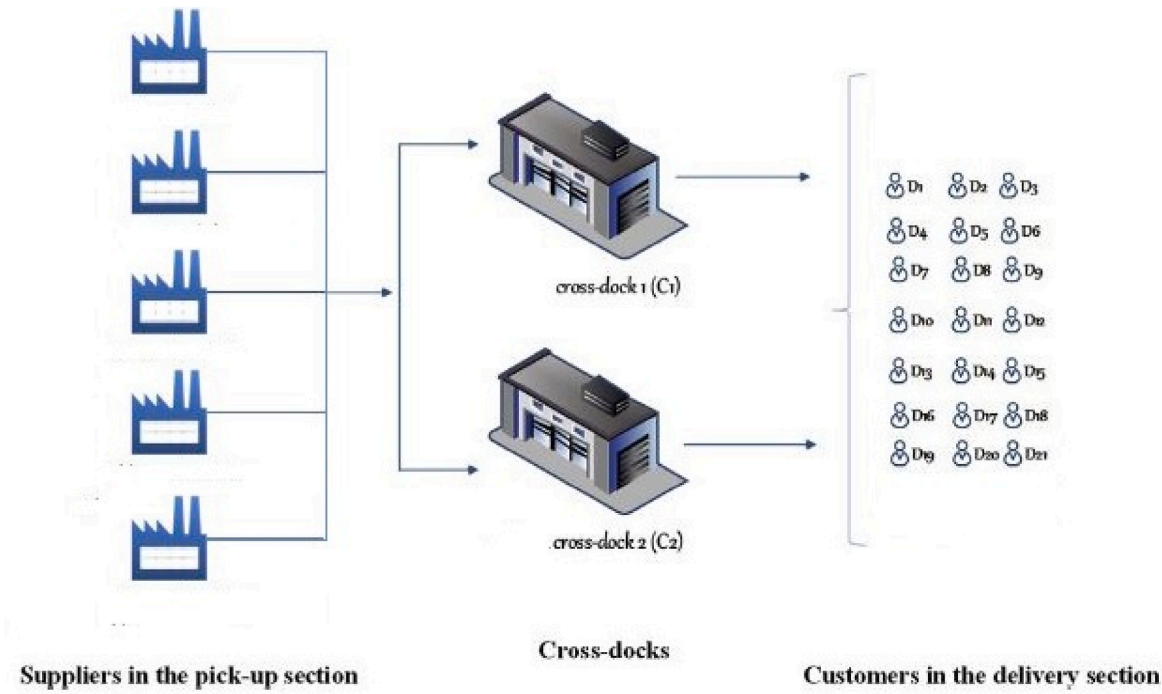


Fig. 10. The case study's supply chain network.

Table 3
Value of parameters.

Parameter	Corresponding random distribution	Parameter	Corresponding random distribution
dis_{ij}	U (5,20)	tst_{ivt}	U (50,150)
sp_v	U (30,100)	tse_{ivt}	U (30,120)
cv_v	U (100,260)	tsl_{ivt}	U (20,100)
tc_{ijvt}	U (5,20)	ts_{ivt}	U (150,350)
ce_{ijvt}	U (2,5)	tt_{lut}	U (10,20)
cl_{ijt}, cu_{ijt}	U (20,120)	M	1,000,000
l_r	U (1,4)	γ_{it}	1.5
rl_c, ru_c	0.35	de_{it}	U (10,100)
β	0.4	sc_i	U (1000,5000)

5. Case study

To demonstrate the effectiveness of the proposed model and approach, a case study was conducted in the supply chain of perishable products at Doosheh Dairy Company, one of the largest and most reputable dairy companies in Iran. The case study considered five suppliers, two cross-docks, and 21 retailers in Mazandaran province (refer to Fig. 10). The cross-dock facility is equipped with four reception dock doors and handles two types of vehicles, namely trucks and Nissan (refrigerated). The research team analyzed various problems of different sizes, using expert opinions and documents provided by Doosheh Dairy Company. Due to confidentiality concerns and a lack of data, the team generated random distributions to represent missing parameters, including demand.

The proposed model and algorithm were tested on a system with an 11th Gen Intel Core i7-11390H processor, 16 GB of memory, and a 1 TB SSD, running GAMS 2017; MATLABTM 2013 commercial software. Table 3 displays the random production of data from Doosheh Dairy Company, providing the values for the real data used in the analysis.

By analyzing the supply chain of a well-established company like Doosheh Dairy, the proposed approach was tested in a realistic and practical setting. The results demonstrate the effectiveness of the model and algorithm in optimizing the supply chain of perishable products, with the potential to enhance performance, reduce costs, and increase customer satisfaction. The case study provides valuable insights for researchers and practitioners interested in applying the proposed approach to other similar supply chains.

The input data for the case study is partitioned into various categories. For instance, Geographical Data encompasses details about the layout and placements of cross-docking facilities, dairy farms, distribution centers, and customer locations. This dataset comprises geographical coordinates (latitude and longitude) and inter-location distances. Inventory Data encompasses information about inventory levels of dairy products at distinct facilities, factoring in the perishable nature and product shelf life. Transportation Data delves into particulars concerning available transportation vehicles, encompassing capacities, speeds, costs, and regulatory stipulations. Demand Data provides insights into customer requisitions for dairy products, covering quantities and delivery time windows. Pollution Data encapsulates emissions data from diverse vehicle types, in addition to environmental regulations and constraints. Uncertainty Data pertains to variables impacted by uncertainties, such as demand variations and weather-induced travel time fluctuations. Operational Constraints encapsulate specific limitations affiliated with the dairy company's operations, like working hours and loading/unloading timeframes, along with cross-docking procedures.

To amass such data, avenues like interviews, surveys, on-site observations, company reports, and industry publications are harnessed. This compilation involves extracting information from credible sources like official reports from Doosheh Dairy Company, governmental publications tied to Iran's dairy industry, pertinent academic studies on dairy supply chain management, and esteemed industry journals. Subsequently, data analysis ensues, wherein relationships between diverse data variables are discerned through conventional techniques like correlation matrices, correlation plots, and statistical tests. Ultimately, the results gleaned from data analysis are integrated into the proposed model. It's noteworthy that in this study, authentic data is employed, gathered from sources, and presented as a uniform probability distribution due to the company's non-disclosure policy.

Table 4
Obtained result of robust optimization for the proposed methods.

No	Problem size								MCGP-UF				MCGP-UF-GA				Solution quality evaluation		
	C	*P*	*D*	*V*	*T*	*R*	*L*	*U*	OBJ1	OBJ2	OBJ3	CPU Time	OBJ1	OBJ2	OBJ3	CPU Time	GAP1%	GAP2%	GAP3%
1	4	5	5	2	2	2	2	2	1350.23	35.25	345.2	18.3	1350.23	35.25	345.2	18.3	0	0	0
2	4	6	5	2	3	2	2	3	2204.14	46.36	573.1	20.1	2204.14	46.38	573.1	18.8	0	0.043	0
3	6	8	5	3	3	2	3	3	3518.47	68.14	615.4	23.6	3542.47	69.03	625.12	19.5	0.682	1.306	1.579
4	6	8	8	3	4	2	3	4	5311.87	71.25	783.5	34.14	5431.17	72.34	795.14	19.2	2.246	1.530	1.486
5	8	10	8	3	6	3	4	4	7473.05	86.39	833.7	73.5	7563.36	87.45	848.5	21.4	1.208	1.227	1.775
6	8	10	10	4	8	3	5	4	9266.43	94.24	986.7	113.2	9456.05	96.32	996.1	22.3	2.046	2.207	0.953
7	8	15	15	4	10	3	6	5	12811.24	110.12	1083.7	205.7	12981.34	114.25	1109.15	22.8	1.328	3.750	2.348
8	10	15	20	4	12	5	10	5	15788.45	135.46	1286.9	398.5	16236.47	140.33	1316.5	21.9	2.838	3.595	2.300
9	10	18	25	5	15	5	10	10	19405.65	159.19	1590.8	836.1	20125.18	165.04	1630.22	24.6	3.708	3.675	2.478
10	15	20	30	5	20	5	10	15	23106.75	180.41	1944.1	1153.8	24001.15	187.11	2004.3	26.7	3.871	3.714	3.097

Table 5
Obtained result of deterministic optimization for the proposed methods.

No	Problem size								MCGP-UF				MCGP-UF-GA				Solution quality evaluation		
	C	*P*	*D*	*V*	*T*	*R*	*L*	*U*	OBJ1	OBJ2	OBJ3	CPU Time	OBJ1	OBJ2	OBJ3	CPU Time	GAP1%	GAP2%	GAP3%
1	4	5	5	2	2	2	2	2	1485.25	40.54	310.68	16.47	1485.25	40.54	310.68	16.5	0.0	0.0	0.0
2	4	6	5	2	3	2	2	3	2424.55	53.34	515.79	18.09	2424.55	53.34	515.79	16.9	0.0	0.0	0.0
3	6	8	5	3	3	2	3	3	3870.32	79.38	562.61	21.24	3910.13	81.61	568.23	17.6	1.0	2.8	1.0
4	6	8	8	3	4	2	3	4	5843.06	83.19	715.63	30.73	6004.11	86.19	726.36	17.3	2.8	3.6	1.5
5	8	10	8	3	6	3	4	4	8220.36	100.57	763.65	66.15	8544.34	103.08	780.45	19.3	3.9	2.5	2.2
6	8	10	10	4	8	3	5	4	10193.07	110.77	896.49	101.88	10593.32	114.22	913.52	20.1	3.9	3.1	1.9
7	8	15	15	4	10	3	6	5	14092.36	131.39	998.24	185.13	14380.12	132.96	1028.18	20.5	2.0	1.2	3.0
8	10	15	20	4	12	5	10	5	17367.30	161.38	1184.85	358.65	17930.14	164.28	1222.05	19.7	3.2	1.8	3.1
9	10	18	25	5	15	5	10	10	21346.22	189.80	1467.20	752.49	22136.43	196.82	1508.28	22.1	3.7	3.7	2.8
10	15	20	30	5	20	5	10	15	25417.43	215.18	1803.87	1038.42	25954.18	223.57	1867.01	24.0	2.1	3.9	3.5

5.1. A model validation study

This section provides information and discusses the validation and evaluation of a proposed model and algorithm using different methods. The primary focus is on comparing the performance of the proposed approach (MCGP-UF-GA) with another method (MCGP-UF) in terms of solution time and optimal gap. The goal is to provide insights into the effectiveness of the proposed approach and its practical implications. The proposed model and algorithm underwent validation through 10 tests, as presented in Tables 4 and 5. This step is crucial to ensure that the model performs consistently across different scenarios or instances. Validation helps in establishing the credibility and reliability of the proposed approach.

Two key metrics were used to evaluate the efficiency of the methods solution time and optimal Gap. Solution time refers to the time taken by each method to arrive at a solution. Faster solution times are generally preferred, as they lead to quicker decision-making and responsiveness. The optimal Gap refers to the difference between the solution obtained from the proposed approach $Hybrid_{sol}$, and $MCGP-UF_{sol}$,equations, divided by $MCGP-UF_{sol}$, and multiplied by 100. A smaller optimal gap indicates the closeness of the proposed approach's solution to the MCGP-UF approach's solution.

The results presented in Fig. 12 showcase the average gap percentages between the first, second, and third objective functions of the proposed approach. These gaps were 1.793%, 2.105%, and 1.602%, respectively. These figures represent the extent to which the proposed approach's solutions deviate from the optimal solutions of the MCGP-UF approach. Smaller gap percentages suggest higher solution quality. The fact that the proposed approach achieved an average gap percentage of less than 4% is significant. A gap of less than 4% is considered acceptable and indicates that the proposed approach consistently provides solutions that are close to the optimal solutions of the MCGP-UF method. This insight assures managers that the new approach is effective and can be relied upon for decision-making.

Fig. 11 demonstrates that the combined approach (MCGP-UF-GA) offers a significantly lower solution time compared to the exact method (MCGP-UF). This trade-off between speed and accuracy is crucial for managers to consider. While the combined approach might sacrifice some accuracy, the substantial reduction in solution time could be extremely beneficial in time-sensitive decision environments. The influence of problem complexity on the implementation time of the MCGP-UF model is highlighted. This suggests that for more complex problems, the solution process might take longer. Managers should be aware of this relationship and assess the feasibility of using the proposed approach for various problem scenarios. The analysis of average gap percentages across different objective functions (Tables 4 and 5) provides a comprehensive understanding of the approach's performance. Managers can identify which objectives are more challenging to

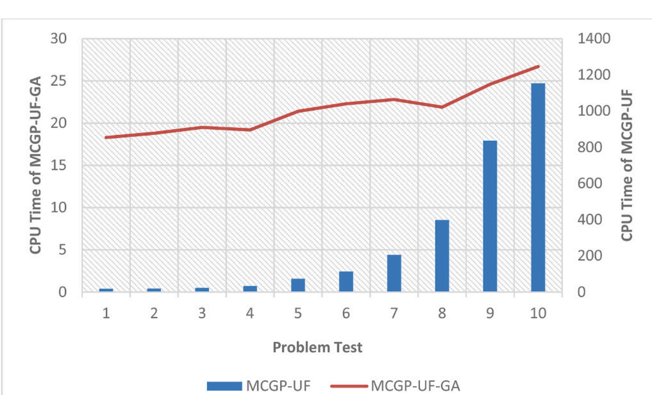


Fig. 11. Comparison of solution time.

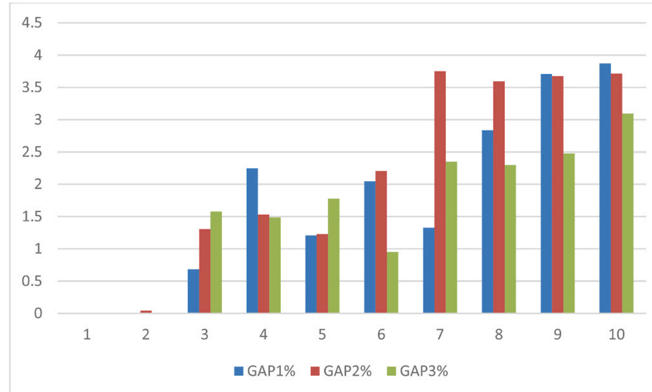


Fig. 12. Comparison gap.

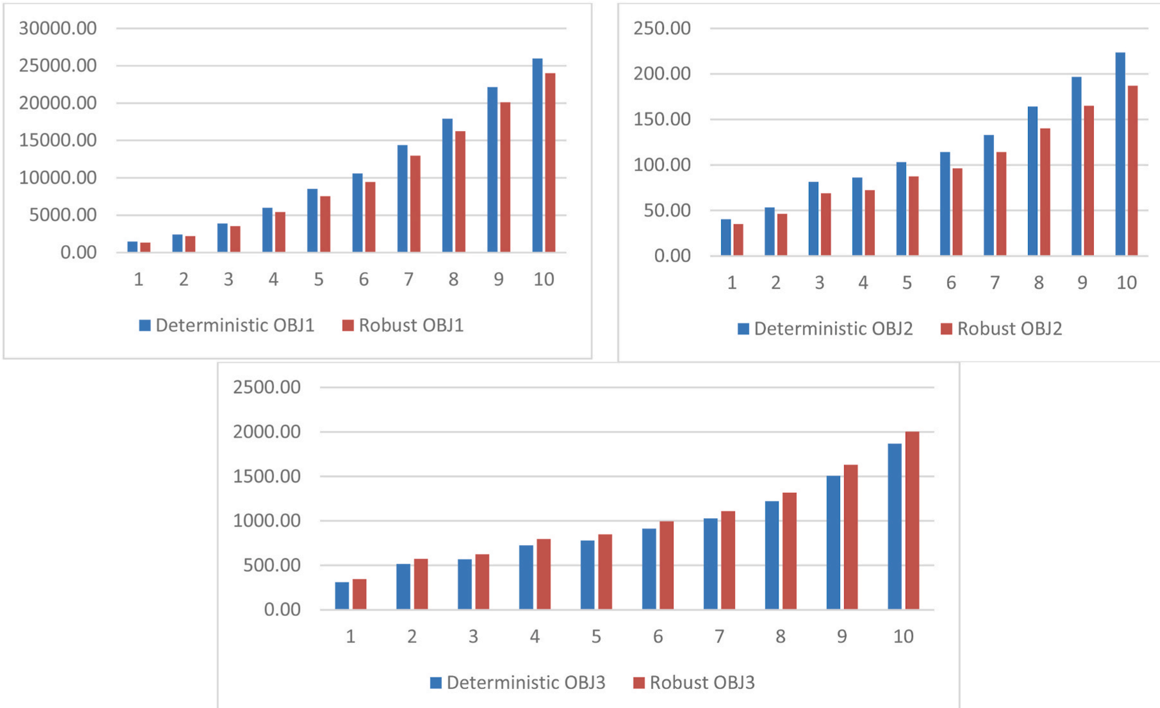
optimize and allocate resources accordingly.

In summary, the provided results indicate that the proposed approach is effective in solving the given optimization problem, achieving solutions with an acceptable gap percentage and reasonable solution times. However, managers need to consider the trade-off between solution speed and accuracy and account for the impact of problem complexity on implementation time.

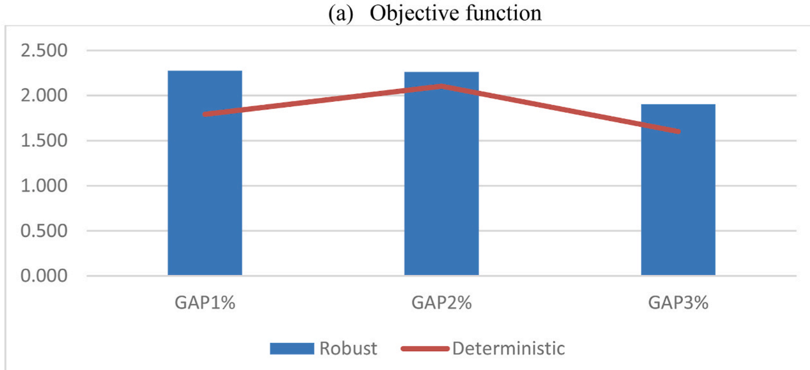
Objective Function Performance: The robust optimization approach outperforms the deterministic mode for all three objective functions. On average, there is an improvement of 10.17% for the first objective, 18.06% for the second objective, and 7.83% for the third objective, as depicted in Fig. 13 (a). This indicates that the robust approach is able to produce solutions that are generally better across a range of scenarios, accounting for uncertainties.

Average Optimal Gap: However, it's noted that the average optimal gap has increased by 17% compared to the deterministic mode, as depicted in Fig. 13 (b). The optimal gap refers to the difference between the optimal solution (found by the optimization algorithm) and the actual performance achieved under real-world conditions. This increase in the optimal gap implies that while the robust approach improves performance on average, it may not perform as well in the specific scenario where the optimal solution was derived. This discrepancy could be attributed to the inherent fluctuations caused by different demand scenarios, which the robust approach aims to mitigate.

According to the provided results: The robust optimization approach demonstrates its value by consistently outperforming the deterministic mode across various scenarios. This suggests that adopting a robust strategy can lead to more reliable and resilient outcomes when dealing with uncertain factors like demand fluctuations. The increase in the average optimal gap indicates a trade-off between average performance improvement and performance in the specific scenario for which the optimization was performed. Managers need to consider this trade-off when deciding between robust and deterministic approaches. The robust approach might be preferable when the focus is on overall better performance across diverse scenarios rather than optimizing for a single best-case scenario. The fact that the robust approach performs better suggests that considering uncertainty and variability in decision-making can yield better results. The fact that the solution time in the deterministic mode is less than in the robust mode, as shown in Table 5, highlights an important practical aspect of the decision-making process. Solution time refers to the amount of time required to find an optimal or near-optimal solution using a specific optimization approach. In this case, the deterministic mode is quicker in providing solutions compared to the robust mode. In summary, the inclusion of solution time information adds an additional layer of complexity to the decision-making process. While the robust mode exhibits better performance across diverse scenarios, the deterministic mode's quicker solution time can be advantageous in time-sensitive situations. Managers need to carefully



(a) Objective function



(b) Average GAP

Fig. 13. Comparison robust and deterministic.

Table 6
Pick-up process for cross-docking.

cross-docks	Vehicle	Tour	Collection of load	Release	Earliness	Tardiness
	Ne_1	To_7-To_4	$p_3^{35}-p_4^{33}-p_5^{55}$	$To_7^{2.7}$-$To_4^{2.6}$	$To_7^{0.5}$	$To_4^{2.6}$
C_1	Ne_3	To_2-To_7-To_1	$p_1^{15}-p_2^{63}-p_3^{35}$	$To_2^{0.87}$-$To_7^{2.22}$-$To_1^{2.41}$	$To_2^{7.3}$-$To_7^{3.5}$	$To_1^{4.2}$
	Tr_7	To_3	$p_1^{95}-p_2^{83}$	$To_3^{1.2}$	$To_3^{2.6}$	–
	Tr_9	To_1-To_3	$p_3^{27}-p_4^{19}-p_5^{36}-p_6^{25}$	$To_1^{4.2}$-$To_3^{0.89}$	$To_1^{0.5}$-$To_3^{3.5}$	–
	Ne_2	To_8-To_9-To_5	$p_1^{48}-p_2^{52}$	$To_8^{1.7}$-$To_9^{1.7}$-$To_5^{2.05}$	$To_9^{2.56}$-$To_5^{2.21}$	$To_8^{1.64}$
	Ne_4	To_5-To_6-To_4	$p_3^{37}-p_4^{33}-p_5^{27}$	$To_5^{3.2}$-$To_6^{1.82}$-$To_4^{1.25}$	$To_5^{9.8}$	$To_6^{4.05}$-$To_4^{1.32}$
C_2	Tr_5	To_5	$p_3^{63}-p_4^{51}$	$To_5^{2.85}$	$To_5^{3.78}$	–
	Tr_6	To_{10}	$p_5^{90}-p_6^{55}$	$To_{10}^{6.53}$	–	–
	Tr_8	To_3	p_2^{120}	$To_3^{3.5}$	–	–

Table 7
Delivery process for cross-docking.

cross-docks	Vehicle	Tour	Vehicle travel time	Deliver to unload
	Ne_1	To_{20}-To_{19}- To_{18}-To_{16}-To_{15}-To_{12}-To_9-To_7- To_8-To_6-To_2	12.23	$p_3^{51}-p_4^{35}-p_5^{61}-p_6^{15}$
C_1	Ne_3	To_5-To_{11}-To_1	10.08	$p_1^{49}-p_2^{71}$
	Tr_7	To_3	21.14	$p_1^{23}-p_2^{32}$
	Tr_9	To_{10}-To_{18}- To_{15}-To_{14}-To_{13}	10.05	$p_4^{10}-p_5^{15}-p_6^{10}$
	Ne_2	To_{16}-To_{17}-To_{12}	8.23	$p_1^{48}-p_2^{52}$
	Ne_4	To_{15}-To_{13}	6.3	$p_3^{40}-p_4^{30}-p_5^{20}$
C_2	Tr_5	To_{13}	4.4	$p_3^{33}-p_5^{15}$
	Tr_6	To_{19}- To_{18}-To_{17}	16.02	$p_4^{30}-p_5^{65}$
	Tr_8	To_{17}- To_{14}	9.45	p_2^{95}

assess the trade-offs between performance improvement and solution time based on the specific requirements of their decision-making context.

Tables 6 and 7 present the pick-up/delivery process for each of the studied cross-docks, where the level of products from each node is summarized by two types of vehicles, Nissan and trucks. For instance, Nissan (Ne1) 1 picks up 35 units of product 3, 33 units of product 4, and 55 units of product 5 at node 7, then moves to node 4, and finally to cross-dock C1.

Tables 6 and 7 likely provide information on the pick-up and delivery activities for various vehicles and nodes. The insights gained from the results, as presented in Tables 6 and 7, enable managers to make informed decisions and strategic changes in their supply chain management practices. Here are some insights that can be derived from these results.

- *Optimal Routes and Scheduling:* The data in the tables can help identify optimal routes and schedules for the pick-up and delivery process. Managers can analyze which routes and schedules result in the least time and cost to transport goods from nodes to the cross-dock and then to the final destinations.
- *Resource Allocation:* By understanding the distribution of product quantities among different vehicles, managers can optimize resource allocation. They can determine the right number of vehicles, their types (Nissan or trucks), and their capacities required to efficiently move products.
- *Node Efficiency:* The data can reveal the efficiency of different nodes in terms of product accumulation. Nodes with consistently high or low quantities of products can be analyzed further to understand the underlying reasons and make improvements accordingly.
- *Bottlenecks and Delays:* Analyzing the process can highlight potential bottlenecks and delays. If specific nodes consistently experience delays or congestion, managers can take corrective actions to alleviate these issues and ensure smoother operations.
- *Process Redesign:* If certain vehicles, nodes, or routes consistently show inefficiencies, the insights gained from the analysis can guide process redesign efforts to improve overall supply chain performance.
- *Customer Service Improvements:* Understanding the pick-up and delivery process can help enhance customer service by ensuring timely and accurate deliveries. Managers can identify areas where delays or errors are likely to occur and take steps to prevent them.

Model analysis involves the evaluation and comparison of different models or approaches based on various criteria or objectives. In our case, the model analysis aims to compare the performance of three approaches: the proposed approach, MCGP-UF-GA, the traditional approach, MCGP-UF, and the MOSA approach. The comparison is done based on multiple objectives. The results are presented in Table 8, which includes performance metrics time, and values for each approach across different problem instances.

The initial observation is that the proposed approach (MCGP-UF-GA) generally outperforms the other two approaches (MCGP-UF and MOSA) in terms of the value of each objective. This suggests that, on average, the proposed approach produces better results across a range of objectives compared to the other approaches. However, there are some instances (problems 5 and 8) where the MOSA approach has performed better in the cost objective. This indicates that while the proposed approach is superior in most cases, it's not universally better for all objectives in every problem instance. The results also reveal that the MOSA approach reaches the best solution sooner compared to both MCGP-UF-GA and MCGP-UF. This implies that MOSA might converge faster to good solutions, which can be a valuable consideration, especially in time-sensitive applications. The proposed approach, MCGP-UF-GA, showcases better performance across multiple objectives, signifying its effectiveness and versatility. This is an important insight for decision-makers, suggesting that this approach is likely to yield better outcomes in a majority of cases.

In conclusion, model analysis based on Table 8 provides valuable insights into the strengths and weaknesses of the three approaches across different objectives and problem instances. The proposed approach offers better results overall, but MOSA shows strengths in specific cases and faster convergence. These insights assist decision-makers in choosing the most suitable approach based on the particular objectives, constraints, and time considerations of the problem at hand.

5.2. Sensitivity analysis

5.2.1. The impact of demand on the problem

Demand uncertainty parameter analysis, in the context of this discussion, involves assessing the impact of variations in demand on the objectives or outcomes of a particular decision-making scenario can impact various aspects of a business or system. This type of analysis is crucial for businesses and organizations to understand how changes in demand levels might affect their operations, costs, profits, and other key metrics. In the provided excerpt, the focus is on evaluating the impact of demand changes on the objective functions of decision problems. The results provided are based on the sensitivity analysis of the impact of a 40% increase in demand on the three objective functions. Fig. 14

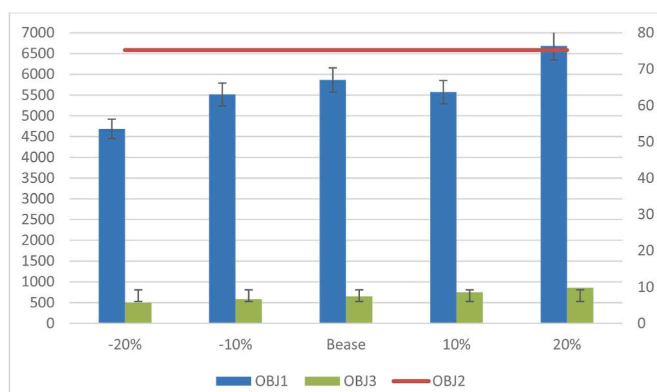


Fig. 14. The effect of demand on the problem.

Table 8
Results of computational experiments for problem instances.

	MCGP-UF				MCGP-UF-GA				MOSA			
No	OBJ1	OBJ2	OBJ3	CPU Time	OBJ1	OBJ2	OBJ3	CPU Time	OBJ1	OBJ2	OBJ3	CPU Time
1	1350.23	35.25	345.2	18.3	1350.23	35.25	345.2	18.3	1417.74	36.96	331.39	17.39
2	2204.14	46.36	573.1	20.1	2204.14	46.38	573.1	18.8	2215.16	47.77	555.91	17.86
3	3518.47	68.14	615.4	23.6	3542.47	69.03	625.12	19.5	3755.02	71.79	612.62	18.53
4	5311.87	71.25	783.5	34.14	5431.17	72.34	795.14	19.2	5811.35	73.72	755.38	18.24
5	7473.05	86.39	833.7	73.5	7563.36	87.45	848.5	21.4	7185.19	89.83	831.53	20.33
6	9266.43	94.24	986.7	113.2	9456.05	96.32	996.1	22.3	10023.41	101.14	946.30	21.19
7	12811.24	110.12	1083.7	205.7	12981.34	114.25	1109.15	22.8	13240.97	123.39	1042.60	21.66
8	15788.45	135.46	1286.9	398.5	16236.47	140.33	1316.5	21.9	16155.29	144.54	1224.35	20.81
9	19405.65	159.19	1590.8	836.1	20125.18	165.04	1630.22	24.6	20306.31	173.29	1597.62	23.37
10	23106.75	180.41	1944.1	1153.8	24001.15	187.11	2004.3	26.7	24721.18	198.34	1884.04	25.37

presents the results of the analysis.

Objective Function 1*: Minimizing Total Costs (Pollution, Loading/Unloading, Transportation):*

A 40% increase in demand leads to a 42.6% increase in this objective function. This indicates that as demand increases, the total costs associated with pollution, loading/unloading, and transportation also increase significantly.

Managing demand fluctuations and accurately forecasting demand is crucial for controlling costs. Rapidly increasing transportation and handling requirements due to higher demand can lead to higher pollution and operational costs. Strategies such as efficient route planning, inventory management, and demand forecasting can help mitigate these cost increases.

Objective Function 2*: Minimizing Distribution and Shipping Time:*

No change is observed in this objective function despite the 40% increase in demand. This suggests that the distribution and shipping time are not significantly impacted by changes in demand in this specific analysis.

The distribution and shipping time seem to be less affected by demand fluctuations in this scenario. This might be due to optimized routing and scheduling that can handle increased demand without significantly affecting delivery times.

Objective Function 3*: Maximizing Reliability of Perishable Product Supply:*

A 40% increase in demand leads to a 72.8% increase in this objective function. This indicates that the reliability of supplying perishable products is strongly impacted by changes in demand. Higher demand puts additional strain on the supply chain's ability to maintain reliable delivery of these products.

The higher increase in the reliability objective function implies that maintaining a consistent and reliable supply of perishable products becomes more challenging with increased demand. Managers should focus on enhancing supply chain robustness, possibly by investing in better cold chain infrastructure, inventory buffers, and backup plans to meet this increased demand while preserving product quality.

Managing demand fluctuations is key: The results emphasize the importance of effectively managing demand uncertainty. Accurate demand forecasting and planning are critical to preventing cost overruns and maintaining reliable supply, especially for perishable goods.

Environmental impact awareness: The analysis highlights that increased demand leads to higher transportation volume, which directly affects environmental impacts. This insight underscores the need to consider sustainability in demand management strategies.

Holistic supply chain optimization: While distribution and shipping time might remain stable, considering the interconnectedness of the objectives is crucial. Optimal decision-making should consider trade-offs between cost, reliability, and environmental impact to achieve holistic supply chain efficiency.

In conclusion, the sensitivity analysis of demand on the objective functions provides valuable insights for managerial decision-making. These insights help guide strategies to mitigate costs, maintain reliability, and reduce the environmental impact of transportation, all of which are essential for an efficient and sustainable supply chain.

5.2.2. Robustness analysis

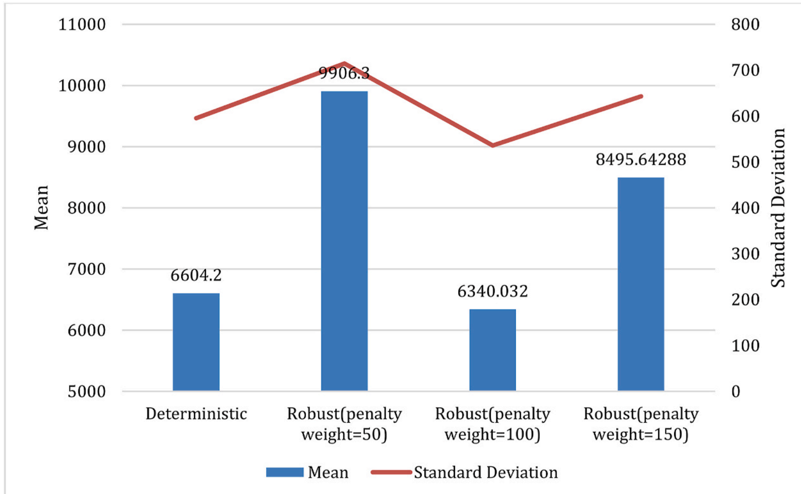
Model robustness analysis aims to assess how well a model performs under different conditions and uncertainties. The analysis involves several objective functions: cost, distribution-shipping time, and reliability of supply. The robustness of the model is evaluated based on the mean and standard deviation of these objective functions across different scenarios. For cost and distribution-shipping time, lower mean and standard deviation values indicate better robustness, as they suggest consistent and efficient performance. In managerial terms, this suggests that the proposed solutions are likely to perform consistently well across a range of scenarios. This stability is valuable for decision-makers as it reduces the risk of unexpected disruptions. On the other hand, for supply reliability, higher mean and standard deviation values are preferred, indicating a more reliable supply even in uncertain situations. This might seem counterintuitive at first. However, in this context, higher values indicate that the system is capable of accommodating and adapting to various uncertainties. This implies that the supply chain or process can handle disruptions or changes in conditions, which is essential for maintaining consistent performance. Six different realizations (scenarios or instances) are proposed to test the robustness of the optimization model. These realizations represent different sets of parameters, conditions, or uncertainties that the model may encounter in real-world situations. The model is solved for each of these realizations to observe how it performs under varying conditions.

The analysis further examines the impact of penalty weights on the model's performance. These penalty weights are used as an infeasibility factor, presumably to account for deviations from the optimal solution caused by uncertainties. It's likely that these weights introduce a trade-off between achieving optimal solutions and handling potential disruptions or deviations. The performance of the robust optimization model is compared against the deterministic model and evaluated across the different penalty weight settings. It shows that higher penalty weights indicate a stricter adherence to feasibility, potentially resulting in solutions that are less sensitive to uncertain conditions and the model prioritizes minimizing the impact of worst-case scenarios. Fig. 15 shows that the robust model with penalty weights of 100 and 150 outperforms the deterministic model, indicates the efficiency of the robust model. This means that, for these penalty weights, the robust model provides more stable and reliable solutions even in the face of uncertainties and deviations in these cases, leading to improved overall performance. However, when the penalty weight is reduced to 50, the deterministic model performs better than the robust model, an interesting trade-off between adherence to feasibility and flexibility. In this case, the deterministic model's solution is more favorable because it prioritizes other factors over robustness. This indicates that in scenarios with a lower emphasis on robustness, the deterministic model's optimal solutions are more favorable. This highlights the importance of understanding the decision context and the trade-offs between different objectives. Sometimes, a solution that sacrifices robustness in favor of other criteria might be more appropriate, depending on the specific circumstances.

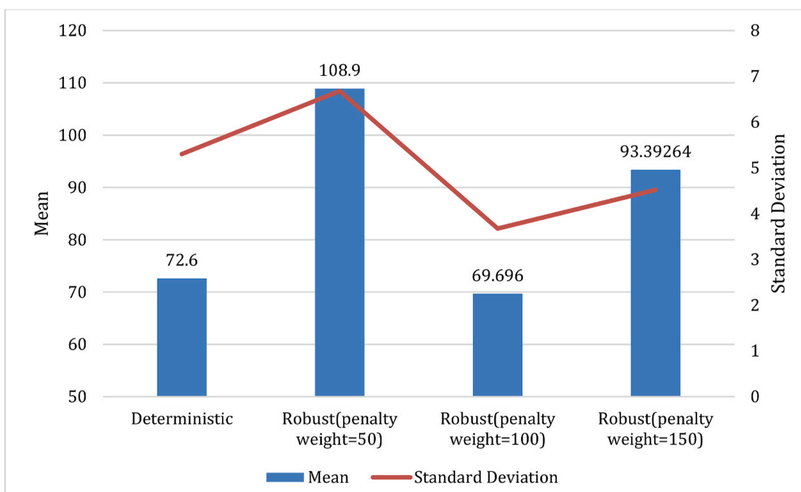
The conclusion drawn from this analysis is that the robust model demonstrates efficiency in handling worst-case scenarios and uncertainties by controlling deviations of the target functions. Optimal robustness conditions lead to improved performance in scenarios where deviations and uncertainties play a significant role. Overall, this robustness analysis provides insights into the trade-offs between optimal solutions and robustness in the context of the supply chain or distribution problem you're addressing. It suggests that the robust optimization approach is effective at balancing these trade-offs and achieving better performance under varying conditions.

5.2.3. IGD-metric analysis

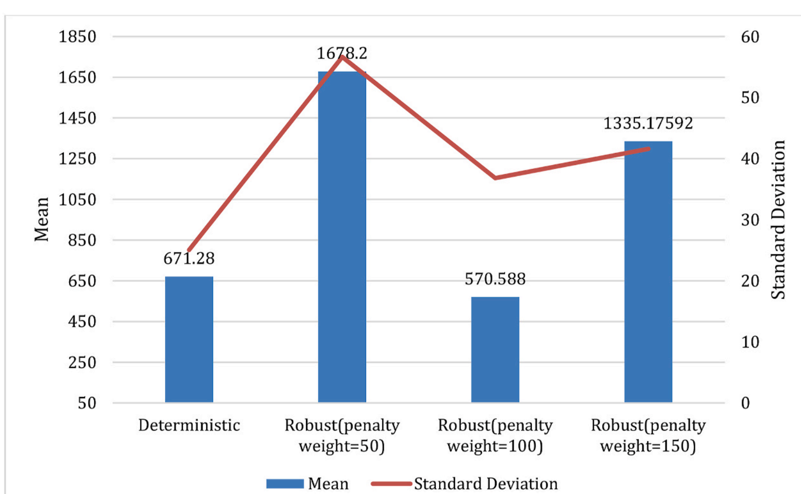
The Inverted Generational Distance (IGD) metric is a performance measure commonly used to assess the quality of solutions obtained from optimization algorithms, particularly in multi-objective optimization problems. It quantifies the closeness of a set of solutions generated by an algorithm to a reference set of optimal solutions. The main idea is to measure the average distance between each solution produced by the algorithm and its nearest neighbor in the reference set. The reference set consists of the true optimal solutions to the problem. The generated set is the set of solutions produced by the optimization algorithm being evaluated (in this case, the MCGP-UF-GA, MCGP-UF, and MOSA approaches). For each solution in the generated set, the distance to its closest solution in the reference set is calculated. This distance is typically a measure in the objective space, reflecting how far the generated solution is from an optimal solution. Common distance metrics used include Euclidean distance suitable measures based on the problem's characteristics. The IGD value is then calculated by averaging the



(a) First objective function



(b) Second objective function



(c) Third objective function

Fig. 15. The robustness analysis of models.

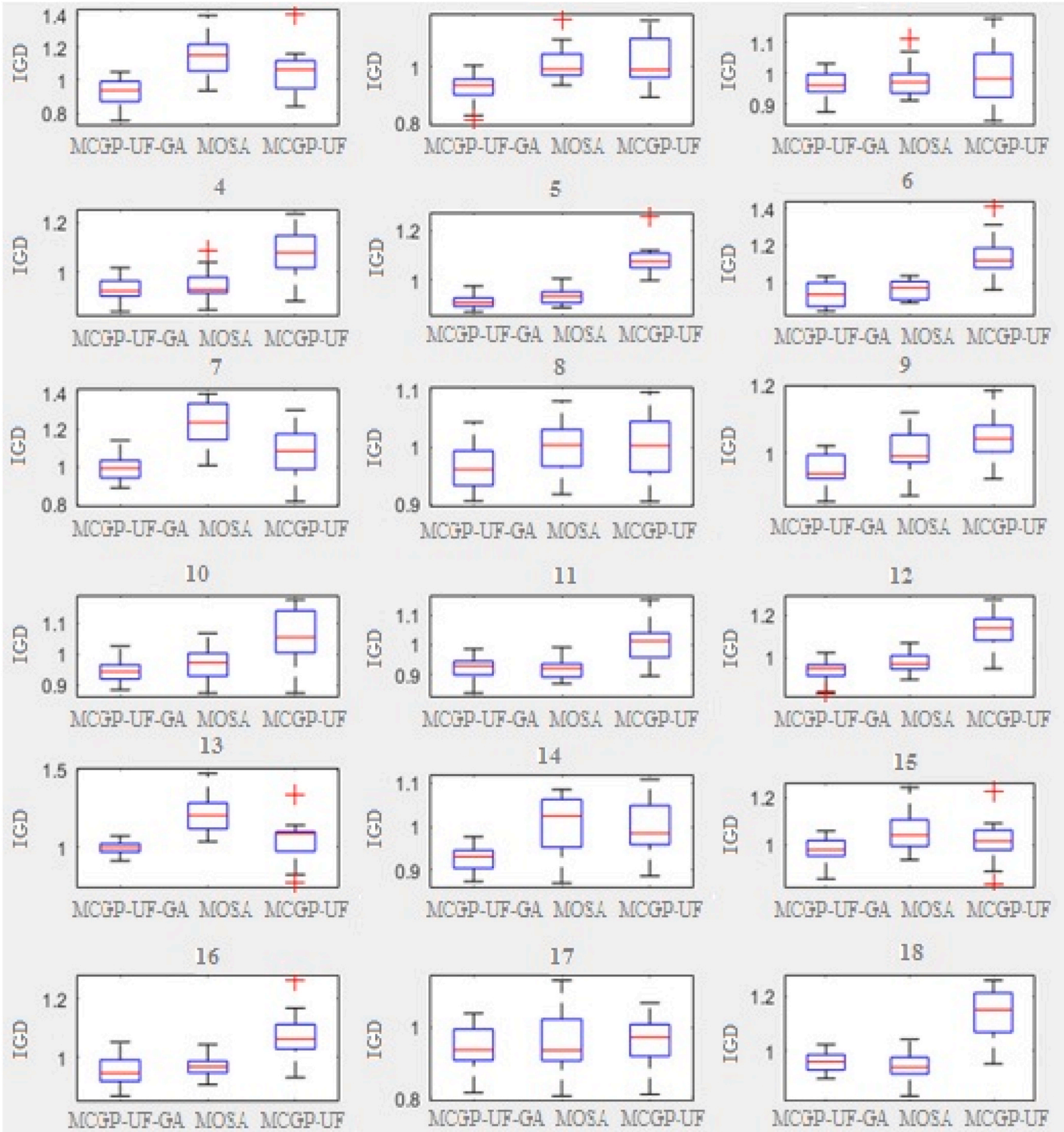


Fig. 16. Comparison of the proposed method.

distances of all solutions in the generated set to their nearest neighbors in the reference set. A lower IGD value indicates better performance because it means the generated solutions are closer to the true optimal solutions.

This section evaluated the efficiency of three different approaches (MCGP-UF-GA, MCGP-UF, and MOSA) using the IGD-metric on 18 different problems, as shown in Fig. 16. The study compared the performance of the three approaches in terms of their ability to approximate and distribute solutions effectively. The IGD metric allowed for a comprehensive evaluation of how close the solutions generated by each approach were to the reference set of optimal solutions. The results showed that the proposed approach, MCGP-UF-GA, outperformed both the traditional approach MCGP-UF and the approach MOSA. This conclusion is based on the observation that the IGD values obtained from MCGP-UF-GA were smaller, indicating that its generated solutions were closer to the optimal solutions than those produced by the other two approaches.

There were calculated mean and variance values for the IGD scores across the 18 problems. The proposed approach demonstrated both more focus and stability in its performance compared to the other approaches. The “more focused” performance suggests that the solutions generated by MCGP-UF-GA were consistently closer to the optimal solutions. The “more stable” performance implies that the proposed approach’s performance had less variability across different problem instances. The smaller IGD values obtained by the proposed approach indicate that its solutions were not only closer to the optimal solutions but also more evenly distributed across the objective space. This suggests that MCGP-UF-GA was able to provide a well-distributed set of solutions that covered a wide range of trade-offs between conflicting objectives. This suggests that the proposed approach is more effective in solving the optimization problem under consideration.

The proposed model is designed to enhance the efficiency of vehicle routing and scheduling. It achieves this by optimizing the routes taken by vehicles, ensuring they follow the most efficient paths and make the best use of their available time. Consequently, this optimization results in significant reductions in both transportation time and the time vehicles spend at cross docks. Moreover, the model focuses on evenly distributing shipments across the available vehicles. This balanced allocation minimizes the need for multiple trips or underused vehicles, ultimately leading to cost savings and shorter transportation durations. The load balancing aspect of the model is particularly valuable in terms of cost efficiency and quicker delivery times.

Furthermore, the system dynamically allocates resources, such as vehicles, in response to fluctuations in demand. This adaptability, driven by dynamic logic functions, maximizes operational efficiency by reducing downtime and idle periods of resources. Importantly, this efficiency also translates into reduced fuel consumption, delivering cost savings and environmental benefits simultaneously. The model leverages advanced algorithms and optimization techniques, providing it with the capacity to make well-informed, data-driven decisions. These capabilities surpass the limitations of manual or traditional methods and significantly improve the quality of decision-making. Furthermore, the model's ability to continuously learn and adapt ensures ongoing efficiency improvements over time.

Effective inventory management is another indirect key feature of the model. It prevents situations like stockouts and overstocking, which can lead to delays and increased expenses. By ensuring that the right amount of inventory is consistently available when needed, the model contributes to smoother operations. Consequently, the findings of this study provide professional justification in alignment with the aforementioned motivating factors.

5.3. Managerial insights

The envisaged framework for the management of perishable food supply chains through the integration of multiple cross-docking bears noteworthy administrative implications and advantages for entities operating within the food sector. This section elucidates the pivotal ramifications and advantageous outcomes that arise from the practical implementation of the proposed model. The subsequent elucidation outlines key implications and benefits associated with the proposed model.

Key implications.

- *Optimization of logistical expenditures and environmental impact:* This entails the reduction of costs related to transportation, loading/unloading operations, and pollution, concurrently diminishing carbon emissions stemming from the entire supply chain while curbing fuel consumption. This objective can be realized through the meticulous optimization of vehicle routes, the streamlining of waiting durations, and the adoption of energy-efficient transportation modes.
- *Minimization of delivery duration:* The adoption of a multiple-cross-docking approach, as delineated in the proposed model, serves as a direct avenue for companies to effectively eliminate superfluous handling. Furthermore, this model indirectly aids in the elimination of excessive storage demands. As a result, both inventory levels and delivery times are reduced, culminating in heightened product quality and an elevated degree of customer contentment.
- *Enhancement of oversight in distribution and shipping endeavors:* The envisaged model introduces a heightened level of efficiency and transparency in the management of distribution and shipping activities. This enables companies to exercise superior control over their supply chain, consequently mitigating the vulnerabilities associated with potential product spoilage or losses. Notably, the model's focus on minimizing distribution and shipping durations plays a pivotal role in controlling split deliveries and associated collision concerns.
- *Incorporating specific handling prerequisites for time-sensitive perishable goods:* The model takes into account the demand within a defined timeframe, ensuring that it aligns with the available supply or is not fulfilled by the time horizon. This approach encompasses designing logistics protocols that cater to the distinct handling needs of perishable items characterized by brief cycles. This entails measures like maintaining controlled temperature environments and streamlining handling times, all geared towards optimal performance.
- *Incorporation of time windows with logic function related to service level:* The integration of time windows with logic functions offers a strategic advantage in supply chain and logistics optimization. By incorporating this approach, companies can achieve more precise scheduling and execution of various activities within specific time frames. This advantage translates into improved operational efficiency, reduced waiting times, and enhanced overall service quality. Furthermore, the logic function embedded within the time windows enables a dynamic response to fluctuations in demand and supply, ensuring that resources are allocated optimally. As a result, this integration optimizes resource utilization, minimizes delays, and contributes to a well-orchestrated and synchronized supply chain operation.

Benefits.

- *Enhanced Operational Efficiency:* The proposed model empowers organizations to streamline their logistical procedures, resulting in optimized operations. It achieves this by minimizing distribution and shipping durations, eliminating unnecessary storage and handling, reducing waiting intervals, and ultimately elevating the overall quality of service. This comprehensive approach directly contributes to heightened operational efficiency within the supply chain.
- *Enhanced Retailer Satisfaction:* The proposed framework elevates retailer contentment through a reduction in delivery timelines and an augmentation in product quality according to lifespan. These improvements foster heightened loyalty and increased sales, thereby bolstering the overall satisfaction of retailers.
- *Adaptable Reaction to Demand and Supply Variability:* In light of uncertain demand, the model involves curtailing handling durations and ensuring the optimal allocation of resources, including the allocation of vehicles to cross-docking facilities. The suggested model enables companies to optimize the utilization of resources, mitigates delays, curbs pollution-related expenses, and contributes to the seamless coordination and synchronization of supply chain activities.
- *Enhanced competitive edge and market share:* Through the enhancement of operational efficiency, product excellence, and retailer contentment, the introduced model has the potential to elevate a company's competitive standing and expand its market share.
- *Favorable Environmental and Societal Impacts:* The suggested model yields a positive influence on the environment through the reduction of carbon emissions cost, thereby fostering a more sustainable and inclusive food ecosystem.

6. Conclusions

Cross-docking serves as a pivotal mechanism in enhancing the operational efficiency of extensive supply chain distribution networks. In contrast to conventional warehousing practices, cross-docks adopt a characteristic of minimal or negligible inventory retention. Instead, incoming vehicle cargoes are promptly transferred via multi-crossdocking procedures to outgoing vehicles. This distinctive approach significantly curtails inventory holding expenses while concurrently expediting the transit time from suppliers to end-customers. Simultaneously, the pursuit of cost-efficient transportation is achieved through meticulous route planning, while being mindful of the ecological repercussions of vehicular transit, particularly concerning CO2 emissions. Coupled with these efforts, the optimization of customer contentment by bolstering supply reliability and reducing distribution and shipping durations contributes to the establishment of a more sustainable supply chain management paradigm. It is these compelling rationales that served as the impetus for the authors to introduce and explore the concept of reliable pollution scheduling and routing within the framework of robust multiple cross-docking networks, all under the purview of sustainable development principles. In this vein, an advanced Multi-Objective Mixed-Integer Programming (MOMIP) model was meticulously devised to formulate the problem. This model was grounded in real-world assumptions and aimed to concurrently minimize total costs encompassing pollution, transportation, and loading/unloading, while maximizing supply reliability and minimizing distribution and shipping lead times.

Given the inherent complexity of the problem, acknowledged as NP-hard, an innovative hybrid algorithm christened MCGP-UF-GA was engineered. This algorithm was subsequently benchmarked against MOSA to showcase its prowess in addressing the problem. Parameter fine-tuning for the proposed algorithm was executed utilizing the Taguchi design method. Through a battery of tests encompassing diverse problem instances, the algorithms' performances were evaluated. For smaller problems, the goal programming method, an exact approach, was also employed via GAMS software with the CPLEX solver. Furthermore, a statistical examination was conducted to gauge the optimization capabilities of MCGP-UF-GA, MOSA with respect to individual objectives. Lastly, to validate the practicality and applicability of the proposed methodology, a real-world case study was undertaken in Iran, thereby providing tangible insights into the potential real-world impact of the developed approach.

To establish a cohesive connection between the research contributions and the numerical outcomes, it can be asserted that the synthesis of sustainable development through the optimization of total costs, supply reliability, and distribution and shipping lead times within the context of the pollution-routing problem in robust multiple cross-docking networks is notably absent from the existing literature. The numerical results were devised to effectively elucidate the intricate interplay between these three pivotal objectives. The empirical evaluation of these concepts was conducted through the generation and systematic analysis of solutions. To achieve this, a case study was executed, wherein the MCGP-UF-GA algorithm, identified as the optimal solution tool, was employed. The outcomes encompassed not only the elucidation of optimal route planning in the delivery and pick-up domains but also the reporting of objective function values. Notably, a sensitivity analysis was performed, yielding insights into the relationships between the respective objectives. Specifically, it was discerned that the first and third objective functions display a direct dependency on the demand parameter. Consequently, this analytical approach empowers management to assess available resources in response to fluctuations in demand within real-world scenarios.

6.1. Discussions on limitations

This study grappled with several limitations and factors that warrant attention. An important limitation pertains to the uncertainty inherent in perishable goods. Conventional scheduling and routing models may fall short of fully accounting for this uncertainty, potentially leading to suboptimal solutions. Another noteworthy constraint arises from the dynamic nature of demand for perishable goods. The demand landscape can exhibit significant dynamism, posing a challenge for static scheduling and routing models that might struggle to adapt swiftly. This could result in underutilization of resources and failure to meet delivery windows. The intricate network structures within the context of perishable goods supply chains present another limitation. The complexity is compounded by the presence of diverse vehicle types and time constraints, rendering the scheduling and routing problem more intricate. Additionally, the limited shelf life of perishable goods underscores the need for meticulous inventory management. Overestimating demand or inefficient routing can trigger food wastage and financial setbacks. The availability and accuracy of data constitute yet another significant consideration. The efficacy of optimization techniques hinges on the quality and availability of data encompassing demand predictions, vehicle capabilities, road conditions, and perishable goods attributes. Inaccurate data can lead to unrealistic outcomes. Operational constraints encountered in practical cross-docking operations further contribute to the complexity. These constraints encompass delivery and pickup time windows, vehicle capacity limitations, and facility-related restrictions. Integrating these constraints into optimization models can introduce added intricacy. Furthermore, the challenge of real-time adaptation cannot be overlooked. Traditional optimization models may struggle to respond effectively to dynamic shifts due to inherent limitations. To surmount these limitations, researchers and practitioners should contemplate advanced optimization techniques, incorporate real-time data and adaptive strategies, and devise resilient decision-support systems. Moreover, fostering interdisciplinary collaboration among multiple stakeholders is pivotal to crafting comprehensive solutions that strike a balance between efficiency, reliability, and quality within the realm of perishable food supply chains.

6.2. Future research

Looking ahead, potential avenues for future research could involve the integration of constructive heuristics alongside expansive large neighborhood search methodologies as evidenced by Cen et al. (2023). This augmentation holds the promise of elevating the efficacy of the hybrid meta-heuristic algorithm proposed herein. This enhancement, in turn, stands to yield solutions of heightened optimality for analogous challenges within the same domain. Furthermore, it's crucial to underscore that the proposed algorithm exhibits considerable potential as an invaluable solution paradigm for akin inquiries in this field. Its applicability transcends the confines of the dairy industry, holding the capacity to offer advantageous insights into diverse predicaments across various sectors. To address this recommendation, researchers are encouraged to delve into the realm of advanced optimization algorithms within forthcoming research pursuits. Our intention is to initiate an inclusive discourse within the manuscript, highlighting the paramount importance of adopting a spectrum of sophisticated optimization techniques. This spectrum encompasses customized heuristics, metaheuristics, hyperheuristics, adaptive algorithms, and island algorithms. Notably, these techniques have been substantiated to deliver efficacious solutions across a panorama of domains, including online learning, as illustrated by Zhao and Zhang. (2020) with their online-learning-based evolutionary many-objective algorithm; scheduling, as evidenced by Dulebenets (2021) and Kavoosi et al. (2019a, 2019b) who introduced the adaptive polyploid memetic algorithm and universal island-based metaheuristic approach, respectively; and multi-objective optimization, as outlined by Pasha et al. (2022), Rabbani et al. (2022) and Tirkolaee et al. (2020), Sahebi et al. (2023) among other notable references.

Kropat et al. (2016), Özmen et al. (2017), Yerlikaya Ozkurt et al. (2016), Kalayci and Purutçuoğlu Gazi. (2022), and Savku and Weber (2018)'s research primarily revolves around modeling, computational techniques, and the management of hybrid systems across temporal domains, along with the study of networks and systems. Their proposed approaches hold potential for future research within this domain. By seamlessly incorporating these references, our aim is to establish a robust bedrock for substantiating the effectiveness and versatility of advanced optimization algorithms in effectively tackling intricate decision problems. This incorporation serves to fortify the scholarly underpinnings of our research and provides a comprehensive framework for addressing complex real-world challenges.

CRediT authorship contribution statement

Farid Taheri: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **Ali Falahati Taft:** Writing – review & editing, Supervision, Investigation.

Declaration of competing interest

❖ None of the authors of this paper has a financial or personal relationship with other people or organizations that could inappropriately influence or bias the content of the paper.

❖ It is to specifically state that "No Competing interests are at stake and there is No Conflict of Interest" with other people or organizations that could inappropriately influence or bias the content of the paper.

Data availability

The data that has been used is confidential.

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