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The Optimization of an Integrated Forward and Reverse Logistics Network Based on Routing and Cross-Docking Strategy

Fatemeh Kangi[1], Seyed Hamid Reza Pasandideh[2,*], Esmaeil Mehdizadeh[1], Hamed Soleimani[1,3]

[1] Department of Industrial Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran; f.kangi@yahoo.com; emqiau@yahoo.com; hd_soleimani@yahoo.com.

[2] Department of Industrial Engineering, Faculty of Engineering, Kharazmi University, Tehran, Iran; pasandid@yahoo.com.

[3] School of Mathematics and Statistics, University of Melbourne, Melbourne, Parkville, VIC 3010, Australia; hd_soleimani@yahoo.com.

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Abstract

In recent years, expanding the concept of social responsibility, increased environmental considerations, economic incentives, and governmental pressure on manufacturers for waste management have caused organizations to focus on developing closed-loop supply chains (CLSC) and reverse logistics (RL) processes. Adopting these approaches will enable organizations to simultaneously meet economic, social, and environmental goals and consider the manufacturing cycle from supply and production to product reuse. Hence, this study deals with an optimization model within the framework of a multi-echelon, multi-product, and multi-period CLSC with hybrid facilities where cross-docking strategy and vehicle routing with soft time windows have been included. In the problem defined as a MILP model, decisions are made simultaneously at three strategic, tactical, and operational levels. Furthermore, to tackle the NP-hard problem and achieve near-to-optimal results in a reasonable time, two meta-heuristic algorithms, NRGA and MOPSO, are developed, and the algorithms' parameters are tuned using the Taguchi method. Finally, the computational results are examined by the performance measures and statistical analysis. The sensitivity analysis is performed regarding the impacts of demand and rate of returned products on the objective functions' values.

Keywords: Closed-loop supply chain, Hybrid facilities, Cross-docking delivery strategy, Vehicle routing, Time windows, Multi-objective optimization, De Novo programming.

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1 | Introduction

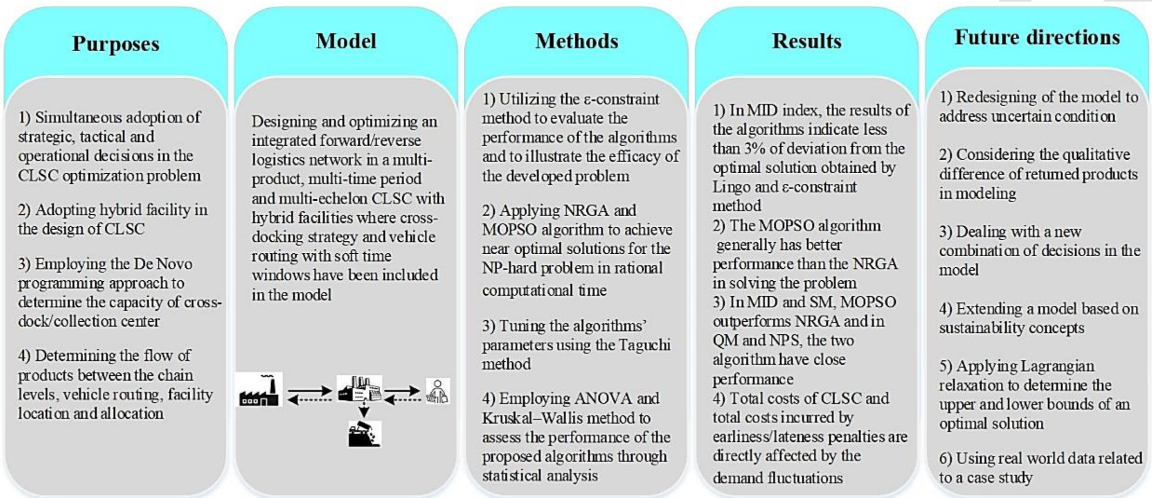
In recent years, environmental and social concerns have compelled countries to pay special attention to Reverse Logistics (RL) to reuse second-hand goods and prevent environmental damage [1]. As a result, in many countries, mandatory laws and regulations have been made to collect scraped and returned products. On the other hand, the profitability of reusing second-hand goods has encouraged companies to develop and manage RL networks; thus, the novel concept of a Closed-Loop Supply Chain (CLSC) has emerged. In related literature, a CLSC refers simultaneously to the forward logistics (i.e., supply, production, and distribution of products) and the RL (i.e., reuse of second-hand products that consumers no longer require) [2]. Over the past decades, CLSC and the integration of forward and RL have become fascinating subjects for research purposes [3], [4], [5], [6].

Today, logistics operations contribute significantly to the price of products and services; hence, optimizing these activities can provide companies with competitive advantages and substantially affect customer satisfaction and cost reduction. The physical distribution of products is one of the most important logistics processes in supply chains. Logistics companies with high transfer rates have started adopting the cross-docking strategy due to reduced required storage space, acceleration of the inventory turnover, liquidity enhancement, and service level improvement through on-time deliveries [7]. Indeed, the cross-docking strategy is a modern warehousing approach in which the two operations, namely storage and selection of products, have been omitted compared to the conventional approach [8]. The cross-docking strategy aims to integrate the shipments of different dimensions but the same destination to complete the capacity of trucks while reducing transportation costs and thereby leading to profit gains for companies [9].

Besides applying an appropriate warehousing strategy as a vital element of logistics operations [10], making an efficient decision on vehicle routing is crucial to transportation and logistics systems [11]. As a result of the prominent role of transportation optimization in the supply chain's success, a great deal of studies have been carried out regarding the Vehicle Routing Problem (VRP) in the literature [12], [13], [14]. The main reason for the importance of vehicle routing in RL is that inefficient transportation activities may restrict the economic success arising from the recycling or recovering of products. The VRP aims to act upon mathematical and optimization models to minimize the number of vehicles, penalty for violating soft time windows, total travel time, total travel distance, and transportation costs while satisfying customers. According to [15], the adoption of vehicle routing and cross-docking strategy enables organizations to determine the optimal set of routs traveled by vehicles to serve the transportation needs between pickup and delivery points.

Although some of the previous research studies have addressed the employment of a cross-docking strategy in CLSCs, to the best of our knowledge, these works have considered the cross-dock as either a distribution center in forward flow or a collection center in reverse flow of the supply chain with a predetermined specific capacity. Hence, this study's main contribution is to emphasize the role of cross-dock as a hybrid facility that plays the role of cross-dock in forward flow and the role of collection centers in reverse flow. On the other hand, De Novo programming is used as an "optimal system design approach" to determine its capacity. Moreover, even though the adoption of strategic, tactical, and operational decisions in the CLSC optimization problems have been thoroughly examined, there has not yet been an emphasis on the decisions on the facility location of the hybrid cross-dock/collection center (as a strategic decision) and vehicle routing (as an operational decision) in one integrated model in any of these studies.

The present study provides a developed version of the CLSC model introduced by Kangi et al. [16]. In that paper, a bi-objective MILP model was proposed to optimize a multi-period, multi-product, and multi-echelon CLSC where location, allocation, outsourcing, and cross-docking delivery strategy were included in one integrated model. The authors have considered strategic and tactical decisions and answered how transportation cost discounts offered by 3PL companies may influence the flow of products from manufacturers to retailers. Consequently, our research study seeks to specify the flow of products between the chain levels, vehicle routing, facility location, and allocation and set the maximum capacity of the hybrid cross-dock/collection facility to minimize the total costs of CLSC (i.e., the costs relevant to establishing of hybrid cross-dock/collection center, production, recovery, transportation, using vehicles) and the total penalty of soft time windows violations. To solve the proposed NP-hard problem, NRGA and Multi-Objective Particle Swarm Optimization (MOPSO) are employed, whose parameters are adjusted by the Taguchi method to improve the precision of solutions. The model's and meta-heuristic algorithms' efficiency is evaluated by solving problems in different scales. Furthermore, some comparison measures and statistical analysis are applied to



examine the performance of the proposed algorithm. The framework of the study is graphically illustrated in *Fig. 1*.

Fig. 1. The framework of the study.

The model presented in this paper is derived from the structure of fast-changing industries such as electronic devices or garments. Due to the short life cycle of such products, adopting a cross-docking strategy is a suitable policy for inventory reduction. In these supply chains, decisions like remanufacturing, repairing, recycling, and disposing are taken to manage end-of-life products. In the electronic and clothing industries, products are produced by manufacturers and shipped to cross-dock. Cross-dock is an internet distribution center consolidating and classifying shipments according to their destinations. In addition, retailors can place an online order for their required products, and they can return the imperfect products or the products that do not satisfy them as well as expected. Then, the returned products go through a process in which the repairable and the scraped products are transported to the collection center. The scraped products with serious defects and their recovering, recycling, or repairing are costly or even impossible. They are sent to the disposal center (for electronic devises) or put up for auction at a very low price (for clothing). Furthermore, repairable/recoverable products for repairing, recycling, or modification are shipped to the manufacturers, entering the chain once more.

In short, this paper aims to address the following questions:

- *How the integration of strategic, tactical, and operational decisions can lead to the prevention of sub-optimality?*
- *What approach can be adopted to determine the capacity of hybrid facilities?*
- *What are the appropriate solution methods to search for near-to-optimal results for the proposed multi-objective*

optimization model?

– *How the values of objective functions are affected by changes in demand?*

– *What techniques are proper for the performance evaluation of proposed algorithms within a comparative framework?*

The reminder of the paper is as structured in the following. A review of the literature on multi-objective optimization and vehicle routing in CLSC is provided in Section 2. Section 3 is dedicated to describing the suggested CLSC problem and mathematical formulation. The proposed solution methods and the algorithms' parameter tuning technique are explained in Section 4. In Section 5, computational results achieved from solving some problems are presented to assess the behavior of the developed model and solution methods. Moreover, the examination of the obtained results is carried out through some comparison measures and statistical analysis. The results of the sensitivity analysis are given in Section 6. The managerial implications of the paper are discussed in Section 7. Finally, the overall conclusion and further research directions are presented in Section 8.

2 | Literature Review

In recent years, implementing CLSC as a solution for sustainable development and profitability growth of organizations has expanded. According to the literature review, concepts of CLSC and RL have been used in various fields such as vehicle routing [17], [18], [19], sustainability [20], [21], pricing [22], [23], environmental considerations [24], [25], [26], outsourcing [16], [27], [28], inventory control [29], [30], [31], production planning [32], [33] and queuing system [34], [35].

Based on the features of the discussed problem, this section reviews the literature on multi-objective optimization and vehicle routing in CLSC. Then, the paper's main contributions are discussed by focusing on the research gap.

2.1 | Multi-Objective Optimization in CLSC

In recent years, the application of multi-objective optimization in CLSCs has attracted the attention of researchers. The main reason for having such an interest is that this powerful problem-solving tool can cope with optimization problems in which more than one objective function is to be improved.

Du and Evans [36] analyzed a two-objective RL network for postal sales services, which minimizes the total costs and delay of the service cycle. For optimizing the problem, a hybrid solution method based on a scatter search algorithm, dual simplex method, and ε-constraint technique is developed. The numerical results indicated an interactive relationship between the two objectives. Amin and Zhang [37]studied a CLSC network of multiple plants, collection centers, and demand points. The authors first formulated a MILP model to minimize the total chain costs in a multi-product single-period facility location problem. Then, to consider environmental factors, maximization of the use of environmentally friendly materials and clean technologies was added to the primary model, and the weighted sums and ε-constraint techniques were applied to solve the extended model. Devika et al. [20] presented a multi-objective MILP model for a multi-tier CLSC network the following year. In this problem, the objective functions were defined as minimizing total chain costs, total environmental effects, and maximizing social interests. Three novel hybrid meta-heuristic methods based on ICA and the VNS algorithm were employed to find the Pareto optimization solutions. In another study, Asl-Najafi et al. [38] addressed an inventory-location problem in a multi-product CLSC to optimize strategic and tactical decisions under facility disruption risks (i.e., unavailability). In addition, the effects of the returned products in RL on the ordering pattern of distribution centers and the demands of retailers in forward logistics were analyzed, and a hybrid meta-heuristic approach was applied to cope with the considered problem.

Moreover, Vahdani and Mohammadi [34] proposed a bi-objective CLSC problem under uncertainty in the iron and steel industry. For this purpose, they suggested a multi-priority queueing system with multiple service providers for parallel processing operations. A novel hybrid method based on interval programming, probabilistic planning, robust optimization approach, and fuzzy multi-objective programming was adopted to solve the problem, where minimization of the total costs and the maximum mean waiting times of products in the queue were considered as key objectives.

Chen et al. [39] investigated the problem of designing a CLSC network with economic and environmental considerations in the solar power industry. A deterministic multi-objective model was constructed to design this network that deals with capacity expansion and recycled components and considers the total cost and carbon dioxide emissions as the main objectives. In research by Rezaei and Kheirkhah [40], a comprehensive model was suggested to develop a sustainable CLSC according to economic, environmental, and social requirements. The developed model aims to minimize total costs and environmental impacts while maximizing social interests. In another study, Mohammadpour Tosarkani and Hassanzadeh Amin [41] utilized a fully fuzzy programming method to evaluate uncertainty's impacts on a multi-echelon battery CLSC.

To cope with the green factors, the proposed model was extended to a bi-objective problem that maximizes the network profitability and the green performance of the plants and the battery recovery centers. Nayeri et al. [42] elaborated a multi-objective optimization model to configure a sustainable CLSC, considering sustainability criteria and uncertainty of parameters. The proposed model intends to simultaneously minimize the supply chain's financial, environmental, and social effects while addressing strategic and tactical decisions. A fuzzy robust optimization method and the goal programming approach were adopted to deal with uncertainty and solve the proposed model. Pant et al. [43] developed an optimization model for a paper industry under uncertainty, aiming to maximize the supply chain surplus while minimizing carbon content (by decreasing the number of vehicles between different network tiers). In this CLSC model, sustainability was achieved by reducing the next-period demand by repairing some of the collected products and decreasing the supplier demand for raw materials by utilizing recycled or usable products from the recycling center. Salehi-Amiri et al. [44] introduced a MILP model for optimizing the costs and job employment opportunities in the context of CLSC for the avocado industry. According to the sensitivity analysis of the most important parameters of the proposed model, demand had the greatest effect on the supply chain. Furthermore, Khosravi Rastabi et al. [45] modeled a dynamic redesigning multi-level, multi-period, and multi-product CLSC network with capacity planning where returned products and customers' demand are uncertain. They addressed the decisions related to the facility location, capacity allocation, and different flows in the network and proposed an accelerated Benders decomposition algorithm to solve the model.

In a recent study, Ahmed et al. [46] presented a multi-objective mixed-integer linear programming model to configure and optimize a multi-echelon, multi-product, and multi-period tire CLSC. The study proposed a novel decision-making method based on Spherical fuzzy logic to calculate the weighting factors of suppliers with a focus on qualitative criteria. Aimed at optimizing the total profit and social benefits, Keshavarz-Ghorbani and Pasandideh [47] presented a bi-objective mathematical model for a multi-period CLSC concerning pricing, advertising, supplier selection, production planning, inventory control, and network configuration decisions. This paper assessed the durability of a company's product portfolio under internal competition among older and new generations, and a multi-generational distribution's effects on production planning and pricing strategies have been investigated. Kazi Wahadul et al. [48] successfully applied three heuristics (MOGA, NSGA-II, and MOBO) and an updated choice function-based hyper-heuristic for optimizing a multi-objective nonlinear model in a closed loop green supply chain with disruption risk. The proposed model minimizes total supply chain costs while mitigating CO_2 emissions and industrial waste. Yousefi et al. [49] proposed an optimization model for aggregate production planning in a CLSC under uncertain conditions. They have adopted the LP-metric method to tackle the multi-objective problem, where minimizing costs, maximizing the quality of manufactured products, and both the supplier's and customer's satisfaction are considered the main objectives.

In the problem discussed here, the costs associated with transportation operations and the total penalty of soft time windows violations are interconnected, and lateness penalties are lowest whenever products are shipped by more, faster vehicles. Furthermore, the costs incurred by earliness penalties will be reduced if more vehicles are allocated to routs such that orders related to closer routs are shipped by one vehicle to serve retailors in a predefined time interval. Thus, there is a contrast between using fewer and slower vehicles to reduce transportation costs and shipping products with more and faster vehicles to decrease total earliness/lateness penalties. Therefore, due to the conflicting nature of the proposed objective functions, NRGA and MOPSO are employed to solve the mentioned problem.

2.2 | Vehicle Routing in CLSC

The purpose of VRP, which is of great importance in transportation systems and logistics, is to determine the optimal routs traveled by certain vehicles to serve customers. Routing is also important in CLSC and RL because inefficient transportation activities limit the economic success of the revival of products.

Dethloff [50] extended a heuristic algorithm for the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) in RL and compared the discussed problem with other studies in the VRP literature. In research by Blanc et al. [51], a VRP with replaceable delivery spots in a CLSC is investigated. The proposed problem is solved by a heuristic algorithm that generates a set of possible routes and selects an optimal combination. Later on, Alshamrani et al. [52] suggested a model for the blood distribution operations of the American Red Cross in which the design of the delivery route and the best pickup scenarios are addressed simultaneously. A heuristic greedy algorithm was employed to solve the developed model, and a modified Or-opt algorithm was then adopted to achieve a more optimal solution. In another study, Kim et al. [17] studied a vehicle routing approach for recycling the end of life electronic appliances in South Korea. They intended to determine the delivery or collection routes of every vehicle at the lowest cost in a way that the distance of transportation of end-of-life products collected by local authorities and the distribution centers of the main manufacturers to four local recycling centers. Kassem and Chen [18] presented a MILP model to optimize a VRPSPD problem in a closed-loop logistic network. Since then, in many practical VRPs, products are picked up and delivered within a specific time interval; in this study, a time window was considered for transportation routes, and the objective function was formulated to minimize all transportation costs. A heuristic method was utilized to solve the NP-hard problem and find high-quality solutions, and a simulated annealing algorithm was then adopted to improve the initial solutions. Hu et al. [19] studied a VRPSPD problem with uncertain pickup and deterministic delivery in a CLSC. The proposed problem considers the incompatibility between products of pickup and delivery and aims to minimize transportation costs, incompatibility, and the number of customers visited twice. A two-step method based on the VNS algorithm was employed to solve the model. Considering the sustainability aspects and quantitative discounts, Ebrahimi [53] designed a CLSC network under uncertainty for the tire industry. This research developed a multi-objective stochastic model for supplier selection, routing, facility location, and allocation. This model intends to minimize the total costs and effects of environmental emissions and maximize the responsiveness of the integrated network in both forward and reverse flows. The ε-constraint method was utilized to solve the proposed model, and the sensitivity analysis was conducted to evaluate the model's performance. Govindan et al. [54] suggested a hybrid supplier selection, demand allocation, and vehicle routing approach with a heterogeneous transportation fleet in a multi-product CLSC. The proposed mathematical model considers an inventory–allocation–routing problem under uncertainty and minimizes cost and shortage simultaneously. Furthermore, a fuzzy solution approach is proposed to incorporate uncertainty in the model and convert the multi-objective model into a single-objective one.

Navazi et al. [55] proposed a multi-objective model for a sustainable CLSC, concentrating on perishable products. The developed location-routing-inventory problem considers multi-compartment trucks, simultaneous pickup and delivery, technology selection, and urban traffic risks, intending to minimize the total costs and the environmental side-effects while maximizing the utility of main network stakeholders (including customers, supply chain personnel, and the local community affected by the supply chain activities). The two evolutionary algorithms with a new customized solution representation were used to solve the developed model for large-sized problems. The year after, Tavana et al. [56] developed a comprehensive multi-objective model to design a multi-product, multi-period, and multi-echelon CLSC network with location-inventory-routing, demand uncertainty, supplier selection, cross-docking, time window, order allocation, and simultaneous pickup and delivery. This study involved the proposed model's economic, environmental, and social objectives. Then, an intelligent simulation method was applied to generate the supply chain data, and a fuzzy multi-objective solution approach was used to solve the problem. Govindan et al. [57] elaborated a bi-objective mixed-integer linear programming model for optimizing operational and strategic decisions in a multi-period and multi-product CLSC network. The proposed location-inventory-routing problem aims to manage the production, distribution, and inventory planning in the wire and cable industry, where the carbon tax policy is implemented to decrease emissions as well as scheduling processes to reduce the waiting time for vehicles, as included in the model. A scenario-based approach was applied to overcome the uncertainty of demand, and an augmented ε-constraint method was employed to achieve an optimal solution. Pedram et al. [58] formulated a mixed-integer programming model for designing a CLSC network with routing decisions and uncertain parameters in another study. The authors extended a hybrid fuzzy stochastic method as a solution approach to overcome the complexity and uncertainty of parameters, where minimizing the total costs is considered the key objective.

The problem addressed in this study relates to the VRP mentioned above literature, aiming to incorporate the vehicle routing concept with soft time windows into the proposed optimization model and minimize the total costs incurred by earliness/lateness penalties.

2.3 | Research Gaps

A brief review of some related literature on the CLSC is provided in Table 1 to deal with the research gap.

The main limitation of research centered around the issue of cross-docking strategy in CLSC is that they have presumed a fixed and predetermined value for cross-dock capacity and have considered this facility as a distribution center in forward flow [40] or as a collection center in reverse flow [59]. Thus, considering cross-docking as a hybrid facility that acts as a cross-dock in forward flow and as a collection center in reverse flow is one of the contributions of the present study where the capacity of cross-dock/collection facility as a decision variable is determined through the De Novo programming approach. Furthermore, reviewing the existing literature illustrates that no attempts have been made to simultaneously study vehicle routing with a soft time window and cross-docking strategy in CLCS and integrate them into one model.

The main contributions of the current research are as follows:

- *Applying a cross-docking strategy to improve the performance of CLSC.*
- *Adopting a hybrid facility (cross-dock/collection center) in the design of CLSC to reduce the costs related to construction and maintenance as well as minimize environmental pollution.*
- *Employing the De Novo programming approach to determine the cross-dock/collection center capacity.*
- *Making strategic, tactical, and operational decisions simultaneously.*

3 | Problem Description

In this problem, in addition to designing an integrated forward/ RL network, decisions are made at three levels: strategic decisions (determination of location and capacity of hybrid cross-dock/collection center), tactical decisions (optimal flow between facilities), and operational decisions (vehicle routing). As a result, the strategic decisions on the network design can be integrated into tactical and operational decisions to prevent sub-optimality. In the forward flow of the discussed problem, products are produced and transported from manufacturers to cross-dock. The established cross-dock is considered a hybrid facility that acts as a cross-dock in the forward flow and a collection center in the reverse flow. Its capacity is determined through the De Novo programming approach. On the other hand, in the reverse flow, returned products are sent to the collection center, where recoverable products and scrapes are detected and separated.

Reference	Model Characteristics						Decision Variables	Objective		Method
	Flow	Hybrid Fac.	Period	Product	Cross.	Example		No.	Des.	
[36]	CLSC	No	Si	Mu	No	Test problem	Loc/Alloc	Mu	↓Total costs ↓Total tardiness	Scatter search, Dual simplex ε-constraint
[17]	RL	No	Si	Si	No	Consumer electronic goods	Alloc/Route	Si	↓Distance vehicles travel for RL	Heuristic method
[37]	CLSC	No	Si	Mu	No	Copier remanufacturing	Loc/Alloc	Mu	↓Total costs ↑Environmental factors	Weighted sums ε-constraint
[20]	CLSC	No	Si	Si	No	Test problem	Loc/Alloc	Mu	↓Total costs ↓Environmental impacts ↑Social benefits	GAMS software Metaheuristics
[38]	CLSC	No	Mu	Mu	No	Refrigerator industry	Loc/Alloc/Inv	Mu	↓Total costs ↓Total travel time	ε-constraint GAMS software Metaheuristics
[34]	CLSC	Yes	Si	Mu	No	Test problem	Loc/Alloc	Mu	↓Total costs ↓Waiting time in services	Interval-stochastic robust optimization Metaheuristic Lower bound procedure GAMS software
[25]	CLSC	No	Si	Mu	No	Copiers industry	Loc/Alloc	Mu	↓Total costs ↓CO2 emissions	ε-constraint
[39]	CLSC	No	Si	Si	No	Solar cell industry	Loc/Alloc	Mu	↓Total costs ↓CO2 emissions	Branch & bound CPLEX software Metaheuristic
[59]	RL	No	Si	Mu	Yes	Test problem	Alloc	Si	↓Total costs	CPLEX software
[53]	CLSC	No	Si	Mu	No	Tire industry	Loc/Alloc/Route/SS	Mu	↓Total costs ↓Environmental emission ↑Responsiveness	ε-constraint
[40]	CLSC	No	Si	Si	Yes	Test problem	Loc/Alloc	Mu	↓Total costs ↓Environmental impacts ↑Social benefits	GAMS software Metaheuristics

Table 1. A brief review of CLSC literature.

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Reference	Model Characteristics						Decision Variables	Objective		Method
	Flow	Hybrid Fac.	Period	Product	Cross.	Example		No.	Des.	
[41]	CLSC	No	Mu	Mu	No	Battery	Loc/Alloc/TPS	Mu	↑Total profit ↑Environmental compliance	Scatter search, Dual simplex ε-constraint
[21]	CLSC	No	Mu	Si	No	CFL light bulb	Alloc/Inv/Price	Mu	↓Total costs ↓Environmental impacts ↓Social impacts	
[54]	CLSC	No	Si	Mu	No	Automotive parts industry	Alloc/Route/SS	Mu	↓Total costs ↓Shortage	
[42]	CLSC	No	Si	Mu	No	Tanker industry	Loc/Alloc/SS	Mu	↓Total costs ↓Environmental impacts ↑Social impacts	
[43]	CLSC	No	Mu	Si	No	Test problem	Loc/Alloc	Mu	↑Supply chain surplus ↓CO2 emissions	
[44]	CLSC	No	Mu	Mu	No	Avocado industry	Loc/Alloc	Mu	↓Total costs ↑Job employment	
[16]	CLSC	Yes	Mu	Mu	Yes	Test problem	Loc/Alloc/TPS	Mu	↓Total costs ↓Total processing times	
This paper	CLSC	Yes	Mu	Mu	Yes	Test problem	Loc/Alloc/Route	Mu	↓Total costs ↓ Total penalty for soft time window violations	

Fac. (facility), Cross. (cross-dock), Des. (description), RL (reverse logistic), CLSC (closed loop supply chain),
Si (single), Mu (multi), Loc (location), Alloc (allocation), Inv (inventory), Route (routing), SS (supplier selection), TPS (third party selection), Price (pricing).

Table 1. Continued.

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The recoverable products are transported to manufacturers, while scraped products that cannot be recycled or recovered are transported to the disposal center. In the problem discussed here, vehicle routing is performed assuming there are soft time windows. In soft time windows, it is possible to provide retailers with services slightly outside the predefined interval. In other words, in addition to a specific time window, a service interval is defined for each retailer, and penalties are imposed for services that violate this interval. The developed optimization model is employed to determine the vehicles servicing each demand point and routes chosen to provide demand points with services so that the total travel time, number of vehicles, penalty for violating soft time windows, and transportation costs are minimized.

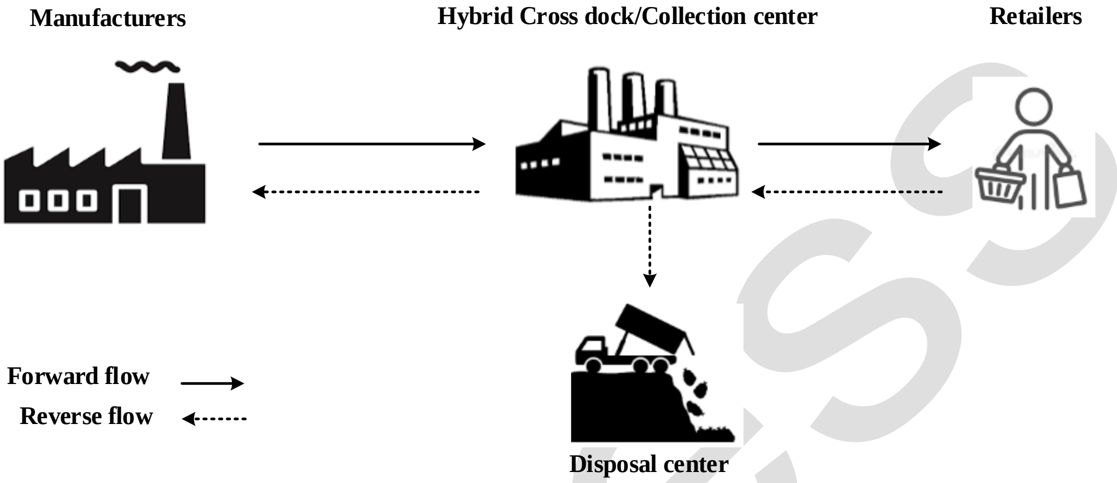

Fig. 2. The structure for the considered CLSC network.

3.1 | Assumptions and Notations

3.1.1 | Assumptions

The mathematical model formulation includes the following assumptions:

- *Each manufacturer has a limited production capacity and produces a family of products.*
- *There is only one available disposal center with an infinite capacity.*
- *The quality of recovered products is equal to the quality of new products.*
- *Shortage is not allowed, and the retailers' demand for different products has to be completely satisfied.*
- *Transportation is performed through the heterogeneous transportation fleet, while vehicles differ in speed, cost, and capacity.*
- *The VRP with soft time windows in services provided for retailers is considered.*
- *The operations of pickup and delivery of both new and returned products are carried out simultaneously with the same vehicle (VRPSPD).*
- *All parameters of the problem are assumed to be known and fixed values.*

The indices, parameters, and decision variables used for the problem formulation are as follows:

3.1.2 | Indices

i: Index of manufacturers, $i \in \{1,2,\ldots,I\}$.

j: Index of retailers, $j \in \{1,2,\ldots,J\}$.

c: Index of potential locations for hybrid cross-dock/collection center, $c \in \{1,2,\ldots,C\}$.

l: Index of transportation vehicles, $l \in \{1,2,\ldots,L\}$.

m : Index of product's family types, $m \in \{1,2,\ldots,M\}$.

n: Index of product types, $n \in \{1,2,\ldots,N\}$.

t : Index of planning periods, $t \in \{1,2,\ldots,T\}$.

3.1.3 | Parameters

DE_{jt}^{nm} :Demand for product n of family type m at retailer j in period t.

MC_{it}^{nm} :Production capacity for product n of family type m at manufacturer i in period t.

VC_l :Transportation capacity of vehicle l.

C_{ijlt} :Transportation cost for shipping products from node i to node j by vehicle l in period t.

CR_{lt} :Cost of use (rent) of transportation vehicle l in period t.

τ_1 :Unit penalty for lateness.

τ_2 :Unit penalty for earliness.

ST_{it} : Service time for node i in period t.

T_{ijl} : Transportation time required for shipping products from node i to node j by vehicle l.

PC_{it}^{nm} :Production cost per unit of product n of family type m at manufacturer i in period t.

RC_{it}^{nm} :Recovery cost per unit of product n of family type m at manufacturer i in period t.

EC_{ct} :Establishing the cost of hybrid cross-dock/collection center in candidate place c in period t.

$[a_{it}, b_{it}]$:Lower and upper bound of the time window for the node i in period t.

TA^{nm} : Time spent on consolidation and classification of each unit of product n of family type m at cross-dock.

α_i^{nm} :The fraction of returned product n of family type m produced at manufacturer i.

β_i^{nm} :The fraction of returned product n of family type m produced at manufacturer i, which is recoverable.

γ^{nm} :Weight/volume of each unit of product n of family type m.

M :Large positive number.

3.1.4 | Decision variables

Q_{ijt}^{nm} :Quantity of product n of family type m transported from manufacturer i to retailer j in period t (units).

SC_c :Maximum capacity of hybrid cross-dock/collection center located at candidate place c (units).

AL_{ilt} :Loading amount of vehicle l from cross-dock in the process of providing node i with services in period t.

L_{ilt} :Loading amount of vehicle l when leaving node i in period t (units).

A_{ilt} : The time that vehicle l arrives in node i in period t.

R^{nm}_{it} : Quantity of product n of family type m recovered at manufacturer i in period t (units).

RP^{nm}_{jit} : Quantity of product n of family type m returned from retailer j to manufacturer i in period t (units).

W^{nm}_{t} : Quantity of product n of family type m wasted in period t (units).

D^{nm}_{lt} : Quantity of product n of family type m transported from collection center located at candidate place to disposal center by vehicle l in period t (units).

TD_{it} : The amount of lateness of vehicles in the process of providing node i with services in period t.

ED_{it} : The amount of earliness of vehicles in the process of providing node i with services in period t.

X_{ijlt} :1, if arc (i, j) is traveled by vehicle l in period t, 0, otherwise.

X'_{it} :1, if node i has an input/output (reception/transmission) in period t, 0, otherwise.

V_{clt} :1, if a product is transported from the collection center located at candidate place c to the disposal center by vehicle l in period t, 0, otherwise.

Z_i :1, if candidate place i is selected for opening a hybrid cross-dock/collection center, 0, otherwise.

Y_{lt} :1, if vehicle l is used in period t, 0, otherwise.

S_{ilt} :Slack variable for eliminating sub-tours.

3.2 Objective Funcions

The first objective function aims to minimize the total costs of the considered CLSC network consisting of the opening cost of the hybrid cross-dock/collection center, production cost, recovery cost, transportation cost, and cost of using vehicles.

$$Min(TC) = \sum_{c\in C}\sum_{t\in T} SC_c . EC_{ct} + \sum_{n\in N}\sum_{m\in M}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} Q^{nm}_{ijt} . PC^{nm}_{it} + \sum_{n\in N}\sum_{m\in M}\sum_{i\in I}\sum_{t\in T} R^{nm}_{it} . RC^{nm}_{it} + \sum_{i\in I}\sum_{j\in J}\sum_{l\in L}\sum_{t\in T} C_{ijlt} . X_{ijlt} + \sum_{l\in L}\sum_{t\in T} CR_{lt} . Y_{lt}. \quad (1)$$

The second objective function is to minimize the total penalty of soft time window violations in all demand nodes.

$$Min(TED) = \sum_{i\in\{I\cup J\}}\sum_{t\in T} (\tau_1 TD_{it} + \tau_2 ED_{it}). \quad (2)$$

3.3 Constraints

All constraints of the proposed model are presented as follows:

$$\sum_{i\in I} Q_{ijt}^{nm} \ge DE_{jt}^{nm} \quad \text{for all } n,m,j,t. \tag{3}$$

$$\sum_{j\in J} Q_{ijt}^{nm} \le MC_{it}^{nm} + R_{it}^{nm} \quad \text{for all } n,m,i,t. \tag{4}$$

$$(Q_{ijt-1}^{nm}\,\alpha_i^{nm}) - 1 \le RP_{jit}^{nm} \le Q_{ijt-1}^{nm}\,\alpha_i^{nm} \quad \text{for all } n,m,i,j,t>1. \tag{5}$$

$$(\sum_{j\in J} RP_{jit}^{nm}\,\beta_i^{nm}) - 1 \le R_{it}^{nm} \le \sum_{j\in J} RP_{jit}^{nm}\,\beta_i^{nm} \quad \text{for all } n,m,i,t. \tag{6}$$

$$W_t^{nm} = \sum_{i\in I}\sum_{j\in J} RP_{jit}^{nm} - \sum_{i\in I} R_{it}^{nm} \quad \text{for all } n,m,t. \tag{7}$$

$$D_{lt}^{nm} \ge W_t^{nm} - ((1-\sum_{c\in C} V_{clt})M) \quad \text{for all } n,m,l,t. \tag{8}$$

$$\sum_{i\in\{I\cup C\cup J\}}\sum_{l\in L} X_{ijlt} = X'_{jt} \quad \text{for all } j\in\{I\cup J\},t. \tag{9}$$

$$\sum_{n\in N}\sum_{m\in M} R_{it}^{nm} + \sum_{j\in J}\sum_{n\in N}\sum_{m\in M} Q_{ijt}^{nm} \le X'_{it}M \quad \text{for all } i,t. \tag{10}$$

$$\sum_{i\in I}\sum_{n\in N}\sum_{m\in M} RP_{jit}^{nm} + \sum_{n\in N}\sum_{m\in M} DE_{jt}^{nm} \le X'_{jt}M \quad \text{for all } j,t. \tag{11}$$

$$\sum_{i\in\{I\cup J\cup C\}} X_{ijlt} = \sum_{i\in\{I\cup J\cup C\}} X_{jilt} = 0 \quad \text{for all } j\in\{I\cup J\cup C\}. \tag{12}$$

$$X_{ijlt} + X_{jilt} = 0 \quad \begin{array}{ll} \text{for all } i\in I & \text{for all } j\in J, \\ \text{for all } i\in I & \text{for all } j\in DC, \\ \text{for all } i\in J & \text{for all } j\in DC. \end{array} \tag{13}$$

$$X_{ijlt} \le Z_i \quad \text{for all } i\in C, j\in\{I\cup J\}. \tag{14}$$

$$\sum_{i\in C} Z_i = 1. \tag{15}$$

$$X_{ijlt} \le Y_{lt} \quad \text{for all } i,j\in\{I\cup J\cup C\}. \tag{16}$$

$$S_{jlt} > S_{ilt} + 1 - (1-X_{ijlt})M \quad \begin{array}{l} \text{for all } i\in\{I\cup J\cup C\}, \\ \text{for all } j\in\{I\cup J\}. \end{array} \tag{17}$$

$$L_{ilt} \ge \sum_{j'\in I} AL_{j'lt} - (1-Y_{lt})M \quad \text{for all } i\in C. \tag{18}$$

$$AL_{ilt} \ge \sum_{n\in N}\sum_{m\in M} \gamma^{nm} R_{it-1}^{nm} - (1-\sum_{j\in\{I\cup C\}} X_{jilt})M \quad \text{for all } i\in I. \tag{19}$$

$$AL_{ilt} \ge \sum_{n\in N}\sum_{m\in M} \gamma^{nm} DE_{it}^{nm} - (1-\sum_{i\in\{J\cup C\}} X_{jilt})M \quad \text{for all } i\in J. \tag{20}$$

$$L_{ilt} \ge L_{jlt} + \sum_{j'\in J}\sum_{n\in N}\sum_{m\in M} \gamma^{nm} Q_{ij't}^{nm} - \sum_{n\in N}\sum_{m\in M} \gamma^{nm} R_{it-1}^{nm} - (1-X_{jilt})M \quad \begin{array}{l} \text{for all } j\in I, \\ \text{for all } i\in\{I\cup C\}. \end{array} \tag{21}$$

$$L_{ilt} \ge L_{jlt} - \sum_{n\in N}\sum_{m\in M} \gamma^{nm} DE_{it}^{nm} + \sum_{i'\in I}\sum_{n\in N}\sum_{m\in M} \gamma^{nm} RP_{ii't-1}^{nm} - (1-X_{jilt})M \quad \begin{array}{l} \text{for all } j\in J, \\ \text{for all } i\in\{J\cup C\}. \end{array} \tag{22}$$

$$L_{ilt} \le VC_l \quad \text{for all } i\in\{I\cup J\cup C\}. \tag{23}$$

$$A_{ilt} \ge A_{jlt} + ST_{jt} + T_{jil} - (1-X_{jilt})M \quad \begin{array}{l} \text{for all } i,j\in\{I\cup C\}, \\ \text{for all } i,j\in\{J\cup C\}. \end{array} \tag{24}$$

$$A_{jlt} \geq A_{ilt} + \sum_{i' \in I} \sum_{j' \in J} \sum_{n \in N} \sum_{m \in M} Q_{i'j't}^{nm} \cdot TA^{nm} + T_{ijl} \quad \text{for all } i \in C, \text{ for all } j \in J. \tag{25}$$

$$\sum_{l \in L} (X_{iDClt} + X_{DCilt}) \geq 2 - (1 - Z_i) \cdot M \quad \text{for all } i \in C, \text{ for all } t \in T. \tag{26}$$

$$\sum_{n \in N} \sum_{m \in M} W_t^{nm} \leq VC_l - (1 - \sum_{i \in C} X_{iDClt}) \cdot M \quad \text{for all } l, t. \tag{27}$$

$$TD_{it} \geq A_{ilt} - b_{it} - (1 - \sum_{j \in \{I \cup C\} or \{J \cup C\}} X_{jilt}) \cdot M \quad \text{for all } i \in I \text{ or } J. \tag{28}$$

$$ED_{it} \geq a_{it} - A_{ilt} - (1 - \sum_{j \in \{I \cup C\} or \{J \cup C\}} X_{jilt}) \cdot M \quad \text{for all } i \in I \text{ or } J. \tag{29}$$

$$X_{jilt}, X'_{it}, Y_{lt}, Z_i, V_{clt} \in \{0,1\} \quad \text{for all } i, j, c, l, t. \tag{30}$$

$$L_{ilt}, AL_{ilt}, A_{ilt}, Q_{ijt}^{nm}, RP_{jit}^{nm}, W_t^{nm}, D_{lt}^{nm}, SC_c, R_{it}^{nm}, TD_{it}, ED_{it} \geq 0 \ \& \ \text{Integer} \quad \text{for all } i, j, c, l, t. \tag{31}$$

Objective (1) indicates minimizing the total costs of CLSC (including the cost of establishing a hybrid cross-dock/collection center, production, recovery, transportation, and utilization of vehicles). *Objective (2)* states the minimization of total costs incurred by earliness/lateness penalties of soft time windows violations. *Constraint Set (3)* guarantees that the demands of customers are met. *Constraint Set (4)* ensures that the manufacturer's production capacity and recovered products are adequate to satisfy customers' demands. *Constraint Sets (5)-(7)* represent the quantity of returned products from customers, recovered products at manufacturers, and wasted products, respectively. *Constraint Set (8)* indicates that the quantity of wasted products in a specific period can be less than the total quantity of products transported from the collection center to the disposal center. In other words, the wasted products of several periods can be collected in a collection center and transferred to the disposal center at once. According to *Constraint Set (9)*, a vehicle should enter the relevant node a vehicle should enter the relevant node if a manufacturer or retailer has a transmission or reception at a particular period. *Constraint Set (10)* determines whether a manufacturer has an input/output (reception/transmission) in a period. *Constraint Set (11)* is similar to the *Constraint Set (10)* but refers to the existence/non-existence of the retailer's reception/transmission. *Constraint Set (12)* ensures that if a vehicle enters a node in a period, it should leave. *Constraint Set (13)* states that there is no direct flow between manufacturers and retailers, manufacturers and disposal centers, and retailers and disposal centers. *Constraint Set (14)* guarantees that a vehicle can only exit from the active established cross-dock. *Constraint Set (15)* assures that exactly one hybrid cross-dock/collection center can be established. *Constraint Set (16)* determines the vehicles utilized in each period. *Constraint Set (17)* guarantees that sub-tours are eliminated.

Constraint Set (18) determines the loading amount of each vehicle when leaving the cross-dock. *Constraint Set (19)* determines the loading amount of each vehicle from the collection center to provide each manufacturer with recoverable products.

Similarly, *Constraint Set (20)* determines each vehicle's loading amount from cross-dock to satisfy each retailer's demands. *Constraint Sets (21)* and *(22)* determine the vehicle load when it leaves a manufacturer and cross-dock, respectively. *Constraint Set (23)* guarantees that the load of each vehicle never exceeds its transportation capacity. *Constraint Set (24)* specifies the arrival of a vehicle to route nodes. *Constraint Set (25)* guarantees that the transfer of vehicles from cross-dock to retailers can be conducted only when all vehicles have reached the cross-dock and all products have been classified. *Constraint Set (26)* indicates that a vehicle can transport scraped products to the disposal center. *Constraint Set (27)* ensures that the vehicle capacity allocated for transporting scraped products to the disposal center is not exceeded. *Constraint Sets (28) and (29)* calculate the amount of earliness and lateness of vehicles in the process of providing manufacturers and retailers with services. *Constraint Sets (30)* and *(31)* guarantee the binary restrictions and non-negativity integrality.

4 | Solution Methodology

The problem of designing and planning CLSC is NP-hard, as illustrated by [60] and [61]. In addition, it has been proven that solving VRP is NP-hard in nature [62], and Tavakkoli-Moghaddam et al. [63] specifically studied the VRP with time windows and proved that the problem belongs to the class of NP-hard. Therefore, the problem studied in this paper is NP-hard due to the investigation of a CLSC problem as well as referring to vehicle routing with time windows. As a result, two well-known meta-heuristics, namely NRGA ([64], [65], [66]) and MOPSO ([67], [68], [69]), are applied to achieve near-optimal solutions for the given problem in rational computational time.

To evaluate the proposed algorithms' performance and illustrate the developed problem's efficacy, the ε-constraint method is used to optimize the model in small-sized problems. The results of LINGO software for the MID index denote that the near-optimal solutions achieved from the proposed algorithms have less than 3% deviations from the optimal solutions.

4.1 | The Non-Dominated Ranked Genetic Algorithm

The Non-Dominated Ranked Genetic Algorithm (NRGA) resembles the NSGA-II structure. Their only difference lies in the selection operation and the strategy of sorting the population in the next generation [70]. In this algorithm, all solutions of the non-dominated fronts are sorted such that the first front has the best solutions in the population. After ranking the fronts, solutions within each front are ranked based on the crowding distance. The highest rank is allocated to the solution with the greatest crowding distance. Thus, each solution has a two-layered rank. The first rank indicates the rank of a non-dominated front inside with existing solutions, whereas the second rank denotes the solution rank based on the crowding distance within that front. Applying the comparative operator for the two given solutions i and j in the population is such that a comparison is drawn among the ranks of the non-dominated fronts within which these solutions exist. If the rank of the front within which the ith solution exists is higher, the ith solution will then be more likely to be selected for reproduction in the next generation. If both solutions exist within the same non-dominated front, the solution with a greater crowding distance will have a higher chance of selection. Accordingly, a non-dominated front should first be determined, and

$$P_i = \frac{2 * rank_i}{N_f * (N_f + 1)} = \frac{rank_i}{\sum_{i=1}^{P} rank_i}. \tag{32}$$

within that front, a solution is then selected. The probability of selecting the ith non-dominated front is calculated through *Eq. (32)*:

where $rank_i$ and N_f denote the rank of the ith front and the number of fronts specified in sorting non-dominated fronts, respectively. Evidently, the solutions within the better fronts will have higher probabilities of being selected. The selection probability of the jth solution existing within the ith non-dominated front is calculated through *Eq. (33)*:

$$P_{ji} = \frac{2 * rank_{ji}}{N_j * (N_j + 1)} = \frac{rank_{ji}}{\sum_{j=1}^{P} rank_{ji}}. \tag{33}$$

where N_j and $rank_{ji}$ indicate the number of solutions existing within the ith front and the rank of the jth solution within the ith front based on the crowding distance, respectively. According to this equation, the solutions with more crowding distances have higher selection probabilities.

Due to the key role of a solution representation in reflecting the characteristics of an optimization problem, designing a proper format for representation is crucial when applying meta-heuristic algorithms. In this study, the solution representation consists of four parts for determining the location of the hybrid cross-dock/collection center, allocation of retailors' demands to the manufacturers, and allocation of product transportation from each manufacturer to the cross-dock and from collection center to disposal center. Furthermore, the innovative approach proposed by [63] represents vehicle routing.

The first part (LCN) is a vector with real values in the range of [0, 1] and the length of the number of potential locations. The maximum value in the vector will specify the location for opening the hybrid facility. The second part (DMN) is a five-dimensional matrix (I, J, N, M, T) with real values in the range of [0, 1]. The manufacturer that satisfies the retailer's demand for each product of each family type in each period will be specified in this part. The third part (I2C) is a three-dimensional matrix (I, L, T) with real values in the range of [0, 1]. This part specifies vehicles for transporting products from each manufacturer to cross-dock in each period. The fourth part (C2W) is a two-dimensional matrix (L, T). The vehicle with the highest value is chosen for shipping products from the collection center to the disposal center. For the representation of vehicle routing, one node (i), which has not been served so far, is selected randomly, and a new vehicle (l) is sent from the depot to this node with maximum capacity. Then, the closest node to node i (like node j) is found such that if vehicle l is transferred from node i to node j, the constraints related to soft time windows and vehicle capacity are not violated. If such a node is found, vehicle l will be dispatched from node i to j; otherwise, the vehicle will return to the depot. This procedure is repeated until the vehicle l is returned to the depot and all nodes are served.

```
Specify the location of hybrid facility with the highest value in LCN
For tt: 1 to T
While DE_jt^nm is not equal to 0 for all indices for t=tt
Specify ii, jj, nn, mm related to the member with the highest value in {DMN | t=tt},
Specify l1 relevant to transportation from manufacturers to cross-dock with the highest value in
{I2C | c=cc, i=ii, t=tt),
Specify l2 relevant to transportation from cross-dock to disposal center with the highest value in
(C2W c=cc, i=ii, t=tt},
Q_ijt^nm = min(MC_it^nm, DE_jt^nm, VC l_1, VC l_2),
Update MC_it^nm, DE_jt^nm, VC l,
End while
End for
```

Algorithm 1. The pseudo-code relevant to the product's flow from manufacturer to retailer.

The location of hybrid facility and the flow of products from manufacturers to retailers and disposal center is formed through the parts of representation relevant to facility location and allocation. Besides, by applying the representation part related to vehicle routing, we can show what vehicles and routes are chosen to provide demand points with services.

This algorithm uses the Ranked-Based Roulette Wheel Selection (RRWS) for parent selection. The roulette wheel operator is designed so that the better population members have higher probabilities for reproduction and formation of the next generation. Furthermore, aimed at generating better offspring and improving solutions quality [71], the crossover operates according to a guiding matrix. The guide matrix is composed of binary values and is applied for each part of the solution representation following its scale. As a result, there is a corresponding member in the guide matrix for every chromosome member. If the relevant value of the guide matrix equals 1, the values of those corresponding members in the solution representations are swapped between the two parents, and a new offspring is generated.

On the contrary, that member remains unchanged in both parents. Moreover, a mutation operator is applied for all parts of the solution representation to inhibit the algorithm from falling into the trap of local optima and help a wider search for feasible solutions [71]. To this end, one individual is randomly selected from the population and the values of its near-randomly selected genes are randomly re-created. To clarify this matter, a graphical example of the suggested crossover and mutation operators is illustrated in *Figs. 3* and *4*, respectively. The searching process will be stopped when a predetermined number of iterations is met.

Consider that:
ris a set of nodes that have not been served so far, r⊂V-{1},
1 stands for the depot,
L_0 is a set of vehicles which has not been used, $L_0 \subset L$,
VC_l is the capacity of vehicle l,
UC is a counter for the used capacity of a current vehicle,
VC_{max} is the maximum capacity in the fleet ($VC_{max} = max_{l \in L_0}\{VC_l$) and
Vand L are a set of nodes and a set of fleets, respectively.
Letr=V-{1} and UC=0,
Choose node i at random (i∈r) and let UC = DE_i
Allocate vehicle $l \in L_0$, to node i where $VC_l = VC_{max}$,

- Find a node j at random where j∈r and generate a service time ST_{it}.
  Then, transfer vehicle l to node j to serve in which constraints (23), (28), and (29) have not been violated.
- IF node j is not found, THEN dispatch vehicle l to depot AND let l=l^*
  Where$|VC_r$ −UC$|$=$min_{l \in L_0}\{|VC_l - UC|\}$ AND set $L_0 = L_0$ -$\{l^*\}$ ELSE let r=r-{j} AND UC = UC+DE_j

Repeat until vehicle l returns to the depot,
Repeat Steps until r = Ø
End

Algorithm 2. The pseudo-code relevant to vehicle routing [63].

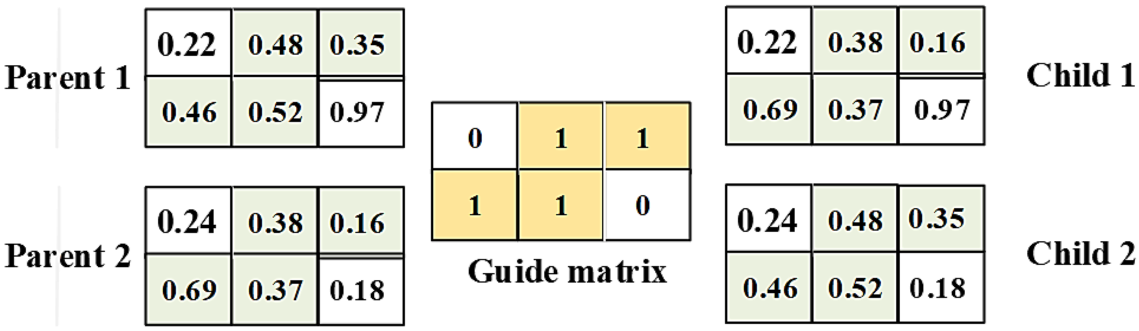

Fig. 3. A sample of crossover operator.

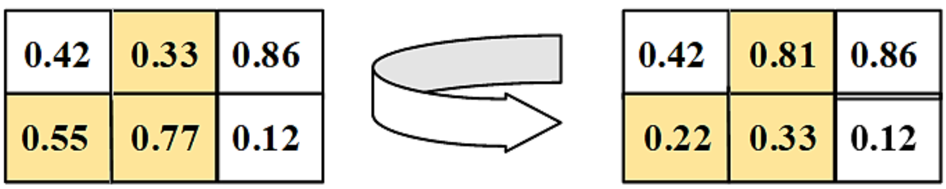

Fig. 4. A sample of mutation operator.

4.2 | The Multi-Objective Particle Swarm Optimization Algorithm

The Particle Swarm Optimization (PSO) algorithm as the first intention of simulating social behavior is proposed by Eberhart and Kennedy [72]. In the PSO algorithm, the first step is to generate a specific number of particles at random positions and velocities, where each particle is tantamount to a potential solution. These particles start moving over a virtual D-dimensional search space to change their positions. In each iteration, based on the current position of a particle and its distance from the best position found by the particle so far and its adjacent particles, the velocity and new position are calculated through *Eqs. (34)* and *(35)*, respectively. Then, according to the objective function, a fitness value is allocated to particle positions, and the best personal and global positions are changed if necessary. This procedure continues until the stopping condition is met. Eventually, the best position all particles find will be presented as the solution.

$$v_{ij}^{t+1} = w \times v_{ij}^{t} + C_1 \times r_1 \times (Pbest_{ij}^{t} - x_{ij}^{t}) + C_2 \times r_2 \times (Gbest_{ij}^{t} - x_{ij}^{t}). \quad (34)$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1}. \quad (35)$$

where v_{ij}^{t} and x_{ij}^{t} stand for the velocity and current position of the i[th] particle in the j[th] dimension at t[th] iteration, respectively. In addition, w is the inertia weight, C1 and C2 are acceleration constants of the particle's motion towards the optimum point and r_1 , and r_2 are uniform random numbers $U(0,1)$.

In MOPSO, a set of non-dominated solutions is considered the repository set, and the members of this set provide an approximation of the real Pareto frontier of the optimization model. The initial particles' solutions are copied and kept in the repository according to the dominant sorting and crowding distance. Based on this algorithm, if the termination condition is not met, according to the domination relation between the current best position and the new position of the particle, the best personal and global positions are updated in the repository set to use in successive generations.

In this research, the functions' evaluation procedure, solution representation, and stopping criterion for the MOPSO algorithm are similar to those of NRGA addressed in subsection 4.1.

4.3 | Algorithms Parameter Tuning

The selection of the algorithm's parameters has a noticeable effect on a meta-heuristic's performance and the accuracy of its results. Taguchi methodology, as a popular design of experiments method ([16], [55], [73], [74], [75]), can assess many parameters with a small number of observations. In this method, to tune the parameters of the proposed solution methods, the Signal-to-Noise (S/N) ratio is used as follows [76]:

$$S/N \ \text{ratio} = -10\log_{10}\left(\frac{\sum_{i=1}^{n} y_i^2}{n}\right). \quad (36)$$

where n stands for the number of experiments and y_i is the solution point in ith experiment.

In this paper, according to the number of algorithm parameters and their levels, the orthogonal array L27 is chosen for both NRGA and MOPSO algorithms. Next, using the MID index and generating five problems with different dimensions, meta-heuristic algorithms are run two times under the Taguchi plan. Then, the proper levels of parameters are determined by applying the results in Minitab software and utilizing the average of the S/N ratio for each algorithm. The average S/N ratio obtained by different NRGA and MOPSO parameter levels is depicted in *Figs. 5* and *6*, respectively. As the maximum value of the S/N ratio is more desirable [77], the best values of the parameters are specified according to the maximum value of the S/N ratio.

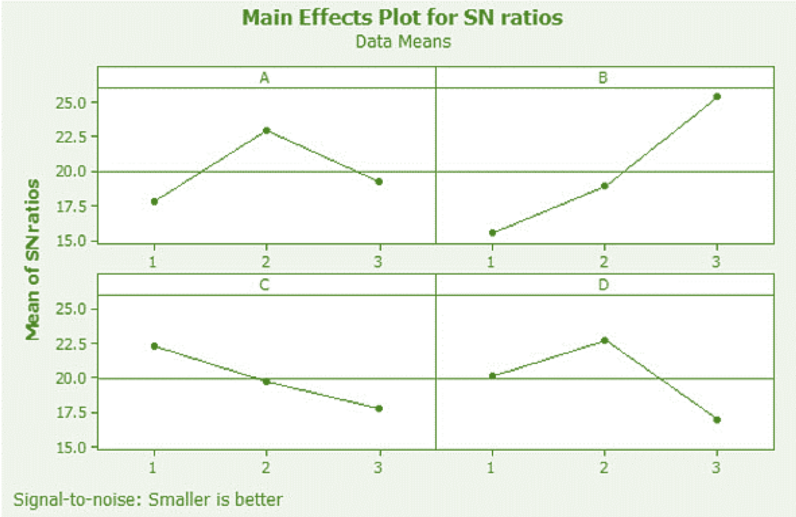

Fig. 5. Average S/N ratio levels for NRGA's parameters.

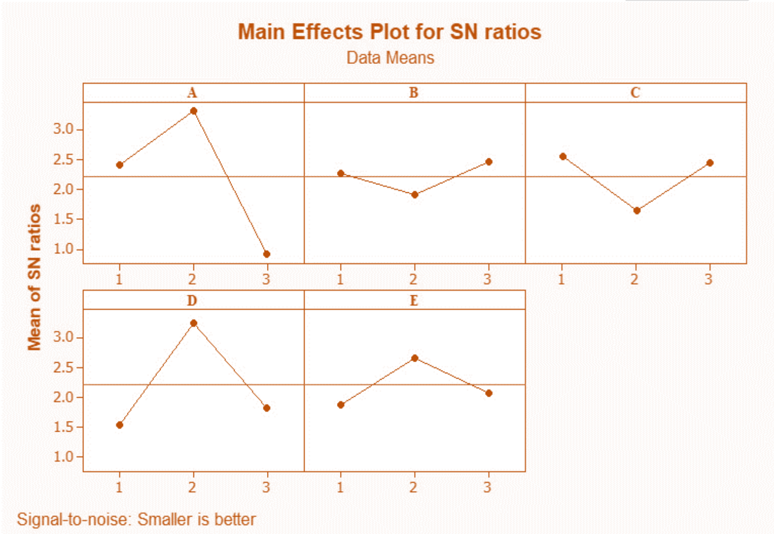

Fig. 6. Average S/N ratio levels for MOPSO's parameters.

Based on the results achieved through the utilization of the Taguchi method, the best values of NRGA parameters are 150, 200, 0.85, and 0.05 for pop size, iteration, crossover, and mutation rate, respectively. On the other hand, the best values of MOPSO parameters are 100, 200, 0.75, 1.5, and 1.5 for pop size, iteration, inertia weight, $C1$, and $C2$, respectively. The optimum level of the parameters is presented in *Tables 2* and *3*.

Table 2. Parameters and their levels for NRGA.

Parameters	Symbols	Levels			Value Tuned
		Level 1	Level 2	Level 3	
Pop size	(A)	100	150	200	150
Iteration	(B)	100	150	200	200
Crossover rate	(C)	0.85	0.9	0.95	0.85
Mutation rate	(D)	0.03	0.05	0.1	0.05

Table 3. Parameters and their levels for MOPSO.

Parameters	Symbols	Levels			Value Tuned
		Level 1	Level 2	Level 3	
Pop size	(A)	50	100	150	100
Iteration	(B)	100	150	200	200
Inertia weight	(C)	0.75	0.8	0.85	0.75
C1	(D)	1.0	1.5	2.0	1.5
C2	(E)	1.0	1.5	2.0	1.5

5. Computational Results and Discussions

This section evaluates the developed model's behavior and the proposed meta-heuristics performance using different problems of various sizes. Furthermore, qualitative and quantitative comparison measures and statistical analysis assess the computational results. The developed solution methods are coded in MATLAB.

Table 4. Size and level of problems.

Problem Levels	Problem Size (I, C, J, L, M, N, T)	
Small scale	P1. (2, 2, 5, 2, 2, 2, 3)	P6. (4, 3, 10, 2, 2, 2, 3)
	P2. (2, 2, 7, 3, 2, 2, 3)	P7. (5, 2, 5, 2, 2, 2, 3)
	P3. (3, 3, 10, 2, 2, 2, 3)	P8. (5, 2, 7, 3, 2, 2, 3)
	P4. (3, 2, 5, 2, 2, 2, 3)	P9. (6, 3, 10, 2, 2, 2, 3)
	P5. (4, 2, 7, 3, 2, 2, 3)	P10. (6, 3, 10, 3, 2, 2, 3)
Medium scale	P11. (7, 4, 15, 3, 2, 3, 5)	P16. (11, 5, 30, 3, 3, 3, 5)
	P12. (7, 4, 20, 4, 2, 4, 5)	P17. (13, 4, 15, 3, 2, 3, 5)
	P13. (9, 5, 30, 3, 3, 3, 5)	P18. (13, 4, 20, 4, 2, 4, 5)
	P14. (9, 4, 15, 3, 2, 3, 5)	P19. (15, 5, 30, 3, 3, 3, 5)
	P15. (11, 4, 20, 4, 2, 4, 5)	P20. (15, 5, 30, 4, 3, 4, 5)
Large scale	P21. (16, 6, 50, 5, 3, 5, 10)	P26. (20, 9, 100, 5, 4, 5, 10)
	P22. (16, 6, 75, 7, 3, 7, 10)	P27. (22, 6, 50, 5, 3, 5, 10)
	P23. (18, 9, 100, 5, 4, 5, 10)	P28. (22, 6, 75, 7, 3, 7, 10)
	P24. (18, 6, 50, 5, 3, 5, 10)	P29. (24, 9, 100, 5, 4, 5, 10)
	P25. (20, 6, 75, 7, 3, 7, 10)	P30. (24, 9, 100, 7, 4, 7, 10)

Since there are no benchmarked problems for the suggested mathematical model in the CLSC literature and applying the ORLIBARARY site is not worthwhile because of the changes like the subject, 30 experimental problems are generated in small, medium, and large scales, including the different number of manufacturers, potential locations for the construction of cross-dock/collection center, retailers, vehicles, a family of products, product types and planning periods (see *Table 4*). Moreover, the values of the input parameters are designed randomly based on the assumptions illustrated in *Table 5*. To omit the uncertainty from the results obtained in different runs, test problems have been solved five times considering different random parameters, and the average of the results is reported. To confirm the efficiency of the developed meta-heuristic algorithms, comparisons of their results with those obtained by Lingo software have been provided for small-sized problems.

Table 5. Parameters ' range in test problems

Parameter	Random Generation Function
Demand (DE)	U [50, 150]
Production capacity (MC)	U [200*J/I, 200*J/I+275*J/I]
Transportation capacity (VC)	U [200*N*J/I, 200*N*J/I+275*N*J/I]
Service time (ST)	U [20, 40]
Transportation cost (C)	U [1000, 2500]
Cost of use (rent) of vehicle (CR)	U [10000, 15000]
Transportation time (T)	U [20, 60]
Production cost (PC)	U [80, 100]
Opening cost of hybrid facility (EC)	U [5, 30]
Recovery cost (RC)	U [20, 30]
Consolidation time (TA)	U [0.08, 0.11]
Penalty for lateness (τ_1)	U [3, 6]
Penalty of earliness (τ_2)	U [5, 10]
Bounds of time window $[a,b]$	U [30, 120]
Fraction of returned product (α)	U [0.02, 0.04]
Fraction of recoverable product (β)	U [0.25, 0.8]
Weight/volume of each unit of product (γ)	U [0.5, 3]

5.1. Comparison Measures

In single-objective optimization problems, according to the objective type (i.e., maximum or minimum), a solution is selected as the best solution in the last repetition of the algorithm. However, in multi-objective optimization, a set of solutions is generated that specify the algorithm's performance in diversity and convergence. In this study, five metrics are employed to evaluate the performance of the multi-objective meta-heuristic algorithms.

$$MID = \frac{\sum_{i=1}^{n} c_i}{n}. \tag{37}$$

Mean ideal distance (MID) ([78]). This metric calculates the average distance between Pareto frontier members and an ideal point through the following equation:

where n is the number of Pareto optimal solutions and c_i the distance between the non-dominated solution's value and the ideal point; the lower value of this measure indicates the better performance of the algorithm.

Spacing measure (SM) ([79]). This measure is set to determine how much the Pareto solution is spread uniformly in the solution space.

$$SM = \sqrt{\frac{1}{n-1}\sum_{i=1}^{|n|}(d_i - \bar{d})^2}. \qquad (38)$$

In this relation, $\bar{d}$ is the average of all $d_i s$ where d_i can be calculated as follows:

$$d_i = \min_{k \in Q \wedge k \notin i} \sum_{m=1}^{M} \left| f_m^i - f_{m-1}^k \right|. \qquad (39)$$

The algorithm with the lower value of SM performs better.

Number of Pareto solutions (NPS) ([80]). This metric counts the total number of Pareto optimal solutions in the Pareto set. As the number of Pareto solutions increases, the algorithm performs even better.

Quality metric (QM) ([81]). This metric generates a combination Pareto set among all non-dominated solutions, and the percentage of non-dominated solutions associated with each algorithm is computed. The algorithm with a higher amount of this measure performs better and is, therefore, more desirable.

In addition, computational times in seconds are another index for the performance evaluation of developed meta-heuristic algorithms.

5.2 | Computational Results

The computational results of the NRGA and MOPSO regarding five performance measures (MID, SM, NPS, QM, and time) and for different problems' sizes (small, medium, and large) are presented in *Table 6* and *Fig. 7.*

Problem Size	#P.	MID		SM		NPS		QM		Time
		NRGA	MOPSO	NRGA	MOPSO	NRGA	MOPSO	NRGA	MOPSO	NRGA
Small	P1.	0.9575	0.6325	1.36006	0.7475	10	6	0.6338	0.6062	76.614
	P2.	0.8034	0.0415	1.3823	1.3980	2	7	0.0700	0.8783	87.318
	P3.	1.0388	0.9893	0.5930	1.0250	4	9	0.4733	0.5099	86.021
	P4.	0.7995	0.5598	1.7206	0.3053	7	11	0.9298	0.0999	82.316
	P5.	0.3518	0.5031	0.9222	1.1840	3	7	0.9252	0.5132	96.019
	P6.	1.6937	0.1246	1.4277	1.0709	3	6	0.3311	0.7406	103.542
	P7.	1.2070	0.7338	1.6429	1.1722	12	11	0.9020	0.3203	106.978
	P8.	1.3392	0.3731	1.7892	0.6923	4	4	0.7742	0.6124	125.081
	P9.	1.2372	0.9400	0.7483	0.7586	11	11	0.7300	0.5294	122.099
	P10.	1.7166	0.4473	1.0645	1.2959	11	9	0.2560	0.9767	123.011
Medium	P11.	0.3223	0.3134	1.2779	0.3547	7	5	0.5499	0.2313	141.659
	P12.	1.0249	0.2274	0.4406	1.2151	7	12	0.4531	0.3263	155.512
	P13.	0.9745	0.3834	1.4839	0.3862	11	8	0.3342	0.5286	153.946
	P14.	0.3985	0.9646	1.1064	0.6668	9	4	0.0959	0.6337	154.090
	P15.	0.8605	0.8687	1.6656	1.2103	4	6	0.8592	0.6072	155.141
	P16.	1.2853	0.2065	0.2738	0.8278	12	8	0.9068	0.3515	168.108
	P17.	0.5930	0.7667	1.1870	0.8468	10	9	0.0171	0.5833	168.298
	P18.	0.4772	0.6676	1.5273	0.5540	5	7	0.6085	0.5584	159.755
	P19.	1.4367	0.4682	1.1797	0.7024	4	6	0.9304	0.6991	169.502
	P20.	1.9435	0.5999	0.8046	1.530	4	10	0.7543	0.1846	168.739
Large	P21.	1.2274	0.1312	0.7696	1.4843	7	5	0.7889	0.1164	178.514
	P22.	1.5371	0.0687	1.2283	1.0776	2	4	0.9633	0.7579	174.733
	P23.	1.4911	0.0976	1.2704	0.6772	8	12	0.1377	0.9217	190.377
	P24.	0.2244	0.7560	0.9294	0.9013	7	3	0.9717	0.4517	167.204
	P25.	1.3486	0.6511	0.0464	0.7717	9	7	0.8024	0.3810	174.327
	P26.	1.5561	0.8676	1.7228	0.2333	12	11	0.4731	0.7530	179.358
	P27.	1.0041	0.5349	0.9128	1.0170	2	10	0.2922	0.4236	189.000
	P28.	0.8631	0.1350	1.6777	0.8336	6	9	0.7038	0.3672	175.747
	P29.	1.2668	0.1417	1.6049	0.9814	10	7	0.4169	0.7421	180.660
	P30.	0.3125	0.3603	0.1993	1.2620	12	11	0.7076	0.7780	183.150

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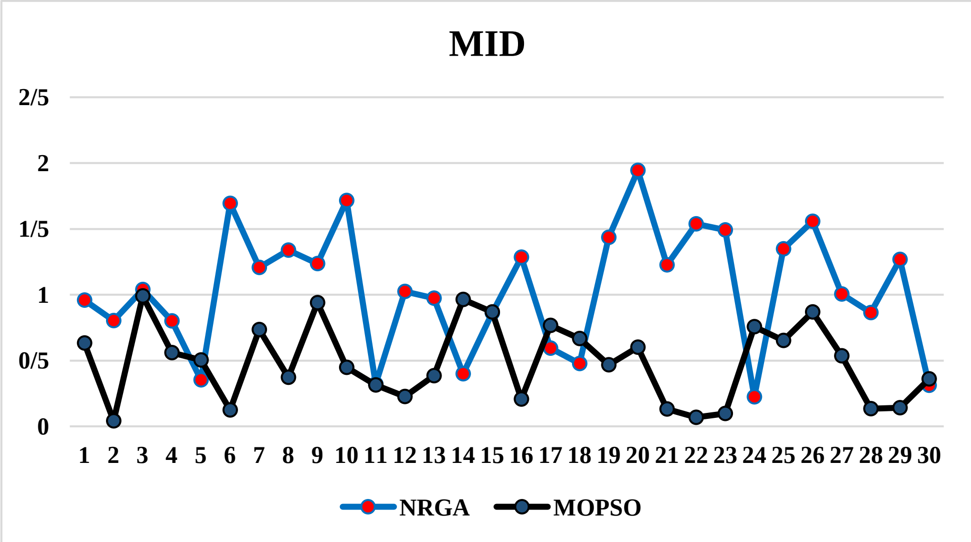
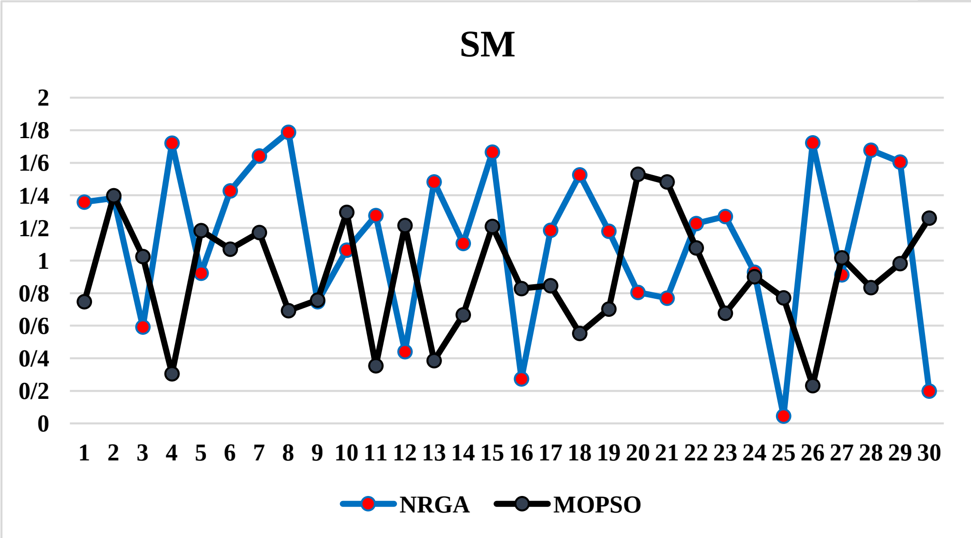
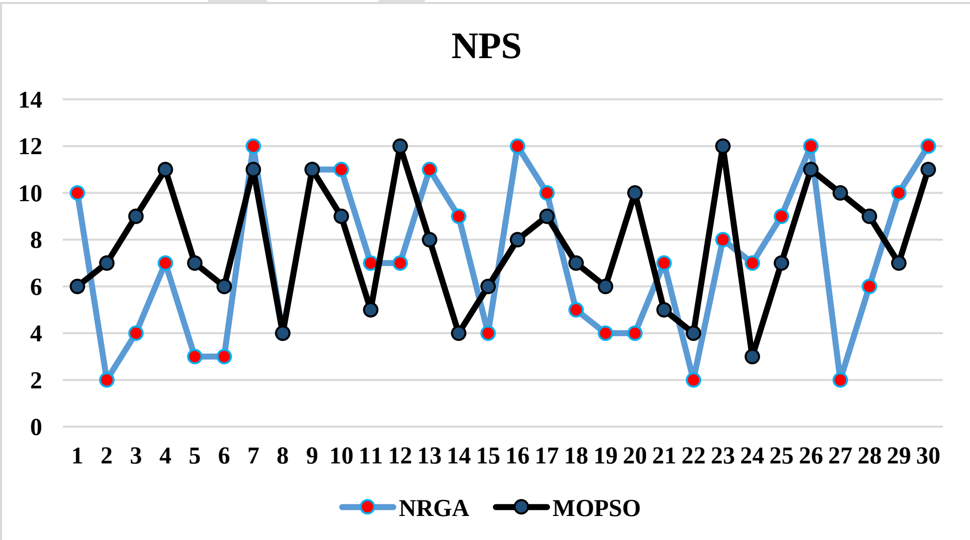
Table 6. The obtained metrics for algorithms' performance (MID, SM, NPS, QM, and time).







https://doi.org/10.22105/jarie.2023.368851.1510

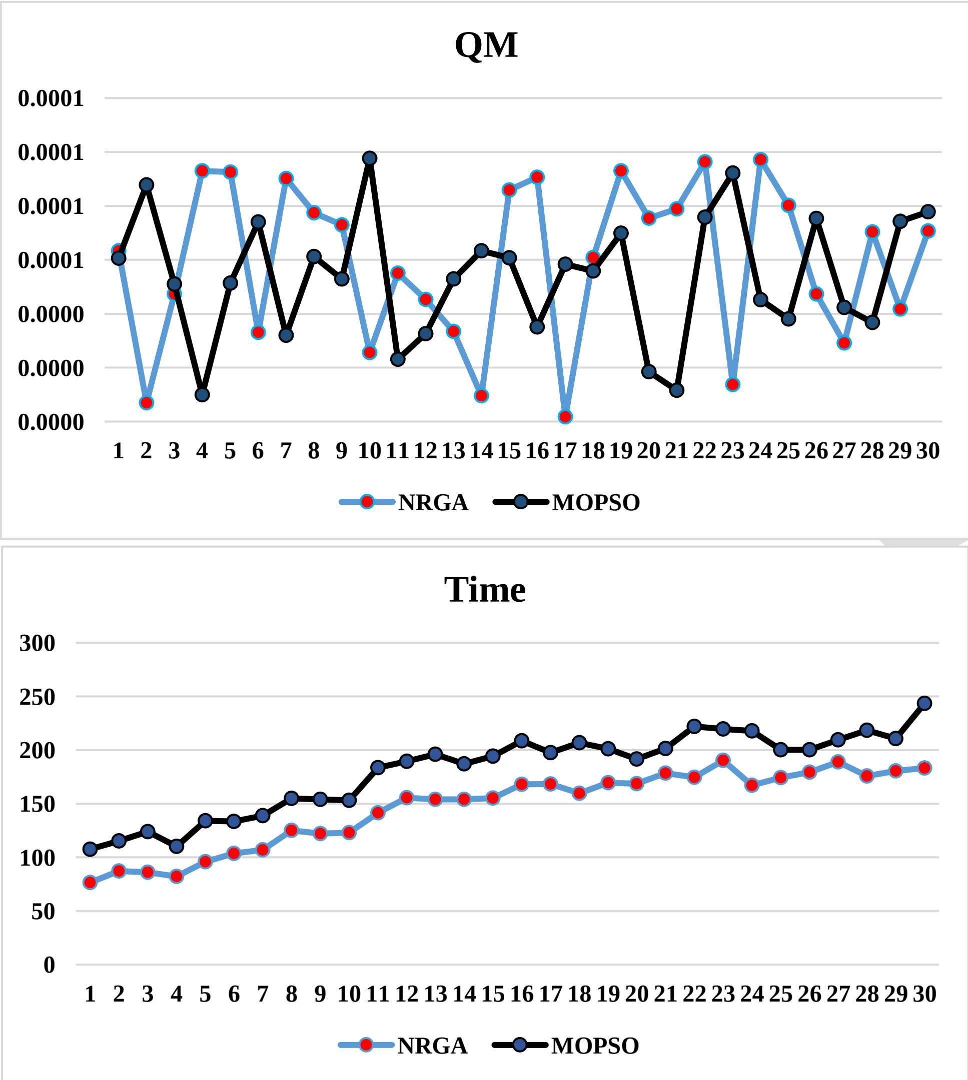


Fig. 7. Graphical compression of the algorithms' performance measures.

As seen in *Fig. 7*, the MOPSO algorithm outperforms the NRGA by taking MID and SM into account, and the performance gap between these two algorithms in terms of MID measure is less in medium-sized problems. Regarding QM and NPS, the two algorithms have yielded close performance with no significant differences in results. Moreover, computational time is the only metric that indicates the better performance of the NRGA than that of the MOPSO. In both algorithms, the value of this performance measure has increased as the problem scales increased.

According to the ANOVA results (*Tables 7-10*), which are the output of Minitab software, the p-values for MID, SM, NPS, and QM are equal to 0.000, 0.042, 0.401, and 0.437, respectively, which indicate that the results of the two algorithms are not equal in terms of MID and SM when alpha is considered to be 0.05. The MOPSO outperforms NRGA, considering these indices. In addition, as discussed earlier, there is no remarkable difference between the performance of the meta-heuristics concerning the NPS and QM metrics. Based on *Algorithm 3*, the Kruskal–Wallis test results indicate that compared to MOPSO, NRGA has less computational time to tackle problems of different sizes.

Table 7.
ANOVA results for MID criterion

Source	DF	SS	MS	F-Test	P-Value
Factor	1	4.669	4.669	30.74	0.000
Error	58	8.808	0.152		
Total	59	13.476			

Table 8. ANOVA results for SM criterion.

Source	DF	SS	MS	F-Test	P-Value
Factor	1	0.765	0.765	4.32	0.042
Error	58	10.268	0.177		
Total	59	11.033			

Table 9. ANOVA results for NPS criterion.

Source	DF	SS	MS	F-Test	P-Value
Factor	1	6.67	6.67	0.72	0.401
Error	58	540.33	9.32		
Total	59	547.00			

Table 10. ANOVA results for QM criterion.

Source	DF	SS	MS	F-Test	P-Value
Factor	1	0.0431	0.0431	0.61	0.437
Error	58	4.0849	0.0704		
Total	59	4.1281			

Algorithm 3. Kruskal-Wallis test on computational time.

Kruskal-Wallis Test on Time

Algorithm	N	Median	Ave Rank	Z
NRGA	30	157.6	22.4	-3.58
MOPSO	30	195.1	38.6	3.58
Overall	60		30.5	

H=12.80 DF=1 P=0.000

6 | Sensitivity Analysis

This paper conducts a sensitivity analysis on demand and rate of returned product parameters, where changes range from -20% to +20%.

Since the demand parameter is propounded as one of the most effective components of the supply chain's structure, it will be desirable to know what changes may occur in the total costs and total earliness/lateness penalties if retailers' demand varies. The results of the analysis based on the changes in demand for problem P4 and applying the MOPSO algorithm are presented in *Table 11* and *Fig. 8*.

Objective Functions	Demand's Change Interval

Table 11. Results of sensitivity analysis on demand.

	-20%	-10%	0%	10%	20%
Total cost	452,455	487,209	675,231	864,243	987,262
Total penalty	123	170	284	365	386

Fig. 8. Sensitivity analysis on the demand.

The results obtained from the sensitivity analysis on demand parameter show that, as expected, the total penalty of soft time windows violations and the costs associated with production, recovery, transportation, utilization of vehicles, and other costs are increased as the retailer's demand increases. The sensitivity analysis conducted by [16] and [82] reveals the same result that the cost function is directly dependent on the demand parameter. As seen in *Table 11* and *Fig. 8*, when the retailer's demand increases by 20% over the original values, the total costs of CLSC and total costs incurred by earliness/lateness penalties will increase by 46.21% and 35.91%, respectively. Similarly, if the retailer's demand decreases by 20% over the original values (-20%), a 32.99% and a 56.69% reduction in total costs and earliness/lateness penalties are perceived, respectively. In other words, since vehicle routing aims to reduce the number of used vehicles and the time and costs associated with transportation through route management, the probability of increasing earliness/lateness penalties seems reasonable following increased demand rates. The risk of an early/late delivery will have an upward trend, and earliness/lateness penalties will increase, as well as production, recovery, and transportation costs. It is worth noting that although the amount of savings from route management will be larger than costs related to a penalty of violating soft time windows, an incremental slope in the resultant costs is observed.

Further on, to investigate the effects of the rate of returned product parameters on the objective functions' values, a sensitivity analysis for the problem P4 and utilization of the MOPSO algorithm is conducted. As derived from the [5] paper, an increase in the rate of returned products will be followed by an increase in the total costs of CLSC. As depicted in *Table 12* and *Fig. 9*, when the rate of returned product increases or decreases by 20% over the original values, the total costs of CLSC will slightly increase by 10.48% and decrease by 7.98%, respectively. However, the behavior of the total earliness/lateness penalties against the changes in the rate of returned product parameter is not regular, and different results are achieved.

Table 12. Results of sensitivity analysis on rate of returned product.

Objective Functions	Demand's Change Interval				
	-20%	-10%	0%	10%	20%
Total cost	587,407	630,292	638,415	684,891	705,349
Total penalty	272	228	274	227	238

Fig. 9. Sensitivity analysis on the rate of returned product.

7 | Managerial Implications

This research aims to meet today's requirements of businesses by considering some real-world constraints and proposing a more practical CLSC model. As the proper management of products' flow in distribution networks plays a prominent role in reducing logistics costs, some supply chains may prefer to adopt the cross-docking strategy considering some factors like the demand rate, nature of product, distance to customers, and information flow. A cross-docking strategy significantly influences the quantity of transported products and the related costs. Thus, the model itself demonstrates an interesting concept in the CLSC literature.

On the one hand, the number and location of facilities significantly impact the efficiency of supply chains, while one thing to bear in mind is that most of these facilities have resource limitations where the available resources are not predetermined. In this condition, the De Novo programming approach could be applied to search for the optimum solutions when the constraints, like the opened facility is maximum capacity, are not predefined. The vehicle routing with simultaneous pickup and delivery proposed in this study allows organizations to reduce energy and fuel consumption while reducing transportation costs. Integrating vehicle routing and cross-docking strategy provides a broader view for managers who want to simultaneously optimize strategic and operational decisions. The developed meta-heuristic solution methods can help managers make the best decision by providing near-optimal results for real-sized problems at an appropriate time.

8 | Conclusion and Future Research Directions

This study aims to optimize and design an integrated forward/ RL network in a multi-product, multi-time period, and multi-echelon CLSC with hybrid facilities. In the problem discussed here, cross-dock is considered a hybrid facility, which has the role of cross-dock in the forward flow and collection center in the reverse flow. Moreover, vehicle routing with soft time windows is included in the model. Indeed, the main contribution of the present work is to address vehicle routing with a soft time window, cross-docking strategy in CLCS, and their integration into one model. Considering the problem's complexity and NP-hard nature, the MOPSO and NRGA are proposed to solve real-sized problems in rational computational time. As the performance of the meta-heuristic algorithms depends greatly on their parameters, the Taguchi method is employed to determine the optimum level of the algorithms' parameters. The efficiency and practicality of the developed model and the proposed solution methods are evaluated by solving a set of experimental problems of different sizes. In addition, the performance measures of multi-objective algorithms and statistical analysis are applied to assess computational results. Finally, the sensitivity analysis was conducted to evaluate the effects of changes in demand and rate of returned products as the input parameters on the values of the objective functions.

Based on the computational results, the consequent achievements are: 1) the proposed algorithms are suitable for finding as many Pareto optimal solutions as possible for the discussed optimization problem to show the trade-off between the two conflicting objectives, 2) the results of the proposed meta-heuristic algorithms are very close to those of Lingo software and the ε-constraint method in small-scale problems. In the case of the MID index, the results of the developed algorithms indicate less than 3% deviation from the optimal solution obtained by Lingo software, 3) five comparison measures, namely MID, SM, NPS, QM, and computational times are used to evaluate the performance of the proposed algorithms for different problems' sizes (small, medium and large sizes). According to the results, the MOPSO algorithm generally has better performance than the NRGA in solving the proposed problem, 4) the technique of one-way ANOVA and Kruskal–Wallis method were employed to assess the performance of the proposed algorithms through statistical analysis. According to the ANOVA results, the p-values 0.000 and 0.042, respectively, for MID and SM, show that MOPSO outperforms NRGA by considering these performance measures. In QM and NPS measures, the two algorithms have close performance, and there is no significant difference between the results. In addition, based on the result of the Kruskal-Wallis test, the computational time is the only measure that is much better for the NRGA than the MOPSO, and 5) to evaluate the behavior of the objective functions, the sensitivity analysis was conducted on demand, and rate of returned product parameters. According to the results, it can be concluded that the total costs of CLSC and total costs incurred by earliness/lateness penalties are directly affected by the demand fluctuations. Furthermore, the sensitivity analysis on the rate of returned product parameter indicates that, unlike the total costs of CLSC, which increases as the returned rate rises, the total costs related to the earliness/lateness penalties have no regular behavior against change ranges.

There are numerous research issues to further elaborate on in the present study. First, to overcome one of the limitations of the paper, uncertainty in some parameters, such as retailer demands or transportation time needed for shipping products, can be embedded in the proposed optimization model, and new uncertainty-based solution methods can be developed. Second, this study assumes that the recoverable products returned to manufacturers in the reverse flow have equal quality. Thus, the qualitative difference of returned products can be considered for future work to develop more practical models. Third, facility location, allocation, and vehicle routing are among the main decisions in the proposed optimization model. Therefore, a new combination of strategic, tactical, and operational decisions in the proposed model can be considered another future research venture. Fourth, in this study, the two objective functions are the total costs of CLSC and the total penalty of soft time windows violations. Hence, it is possible to add some objective functions to the model, such as carbon emission, community welfare, and social responsibility, as environmental or social objectives, thereby extending a new model based on sustainability concepts. Fifth, Due to the complexity of the considered problem, meta-heuristic algorithms were employed to solve the proposed model. Thus, another suggestion for future research is to use Lagrangian relaxation and determine the upper and lower bounds of an optimal solution to solve the problem more efficiently. Sixth, the complexity of the proposed model and the large number of parameters make accessing real-world data difficult. As a result, we have generated some experimental problems and designed the values of the input parameters at random to cope with the developed model. Thus, applying real-world data related to a case study can be considered another future work direction. Finally, the efficiency of the developed meta-heuristics may be improved by changing the solution representation.

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