THE OPTIMIZATION OF A MULTI-PERIOD MULTI-PRODUCT
CLOSED-LOOP SUPPLY CHAIN NETWORK WITH
CROSS-DOCKING DELIVERY STRATEGY

Fatemeh Kangi
Department of Industrial Engineering
Faculty of Industrial and Mechanical Engineering
Qazvin Branch, Islamic Azad University, Qazvin, Iran

Seyed Hamid Reza Pasandideh∗
Department of Industrial Engineering, Faculty of Engineering
Kharazmi University, Tehran, Iran

Esmaeil Mehdizadeh
Department of Industrial Engineering
Faculty of Industrial and Mechanical Engineering
Qazvin Branch, Islamic Azad University, Qazvin, Iran

Hamed Soleimani
Department of Industrial Engineering
Faculty of Industrial and Mechanical Engineering
Qazvin Branch, Islamic Azad University, Qazvin, Iran

School of Mathematics and Statistics, University of Melbourne
Melbourne, Parkville, VIC 3010, Australia

(Communicated by Gerhard-Wilhelm Weber)

Abstract. The main reason for the development of this research refers to the increased attention of businesses to the CLSC concept due to the social responsibilities, strict international legislations and economic motives. Hence, this study investigates the issue of optimizing a CLSC problem involving multiple manufacturers, a hybrid cross-dock/collection center, multiple retailers and a disposal center in deterministic, multi-product and multi-period contexts. The bi-objective MILP model developed here is to simultaneously minimize total costs and total processing time of CLSC. Both strategic and tactical decisions are considered in the model where retailer demands and capacity constraints are satisfied. Since the presented model is NP-hard, NSGAII and MOPSO are hired to find near-to-optimal results for practical problem sizes in polynomial time. Then, to increase the accuracy of solutions by tuning the algorithms’ parameters, the Taguchi method is applied. The practicality of the developed

2020 Mathematics Subject Classification. Primary: 58F15, 58F17; Secondary: 53C35.
Key words and phrases. Closed-loop supply chain, hybrid facilities, transportation cost discount, outsourcing, third-party logistics providers, multi-objective optimization, de novo programming.
∗ Corresponding author: Seyed Hamid Reza Pasandideh.
model and the efficiency of the proposed algorithms are demonstrated using a set of real-sized problems. Furthermore, sensitivity analysis is conducted to study the effects of variations in demand, on the objective function values. Finally, the results are examined by the statistical analysis and performance measures which indicates the better performance of MOPSO in comparison with NSGAII in general.

1. **Introduction.** Environmental concerns, governmental obligations and economic benefits from recycling/reuse of returned products are the decisive factors which persuade organizations to welcome the planning, establishment and management of reverse logistics (RL) networks. In the relevant literature, “closed loop supply chain” (CLSC) is the term for the combination of forward and reverse logistics. In fact, the CLSC has a holistic perspective on supply chain, derived from the forward and reverse logistics’ integration and encompasses the whole product life cycle. The CLSC networks and remanufacturing activities come into focus of a large number of corporations with strong brands such as Ford, GE Transportation, IBM and Xerox [28]. Over the past decades, a great deal of research has been carried out in the area of CLSC and many researchers have applied their findings in the industrial sector (e.g. plastic containers [52], steel industry [83], aluminum industry [16], single-use medical needle and syringe [69], glass industry [22, 32], automotive industry [74, 73, 28, 6], gold industry [93], electronic devices [92], lead acid battery [61], melting industry [36] and food industry [80]).

In addition to the necessity of designing RL networks in different industries, having an efficient supply chain is known as a permanent competitive advantage for businesses that can guarantee their survival in the global markets. The increase in the effectiveness of supply chain activities is one way of achieving this goal. A large part of such activities which may lead to cost saving in the supply chain are related to distribution and logistics operations. Cross-docking as the consolidation process of shipments with the same destination is one of the most appropriate strategies among distribution systems. Compared to direct shipment and conventional distribution centers, cross-docking strategy can meet different goals [35, 14]: reducing costs, satisfying customers via shorter delivery lead time, generating faster turnover of inventory, decreasing the risk of loss and damage, reducing the need for storage space and economies in transportation costs through consolidation of shipments with common destination and using full truck loads.

Despite the attention paid to the inclusion of strategic and tactical decisions in the CLSC problems, to the best of our knowledge, no efforts have been made to incorporate the transportation cost discounts on outsourcing decisions and cross-docking delivery strategy in one integrated CLSC optimization model and investigate these issues at the same time. Therefore, the main contribution of this paper lies in developing a more realistic and practical model by improving the CLSC optimization problem taking into account these subjects simultaneously. Consequently, this research study develops a mathematical model for the tactical planning and strategic design of a multi-product and multi-period CLSC network. In this model, the total costs and total processing time of CLSC are minimized with respect to retailer demands fulfillment and capacity constraints. Furthermore, the tactical decisions deal with production decisions and the strategic decisions concerned with selecting third party logistics (3PL) companies for outsourcing and determining the location of hybrid cross-dock/collection centers among others where the De Novo programming approach is utilized to determine the capacity of hybrid cross-dock/collection facility.
The proposed problem can be considered as the problem of choosing the 3PL companies for transporting products between levels of the CLSC network. In this paper, delivery time and transportation cost are the two evaluation factors which are considered for the 3PL company selection. Accordingly, the 3PL companies with the shortest delivery time and the lowest transportation cost will be chosen for outsourcing transportations. The optimization problem proposed in this study lies in the class of NP-hard problems since the problem has objectives that conflict with each other and quantity discount policy is incorporated into the problem. As a result, two multi-objective meta-heuristic algorithms are developed that can be appropriately used to solve the considered NP-hard problem. Then, to increase the accuracy of solutions, the parameters of the proposed solution methods are adjusted utilizing the Taguchi method. Finally, the validity of the developed model and the performance of the algorithms are evaluated applying some comparison criteria and statistical analysis.

Indeed, this paper is developed with the intention of addressing the subsequent questions:

- What is an appropriate method for determining the maximum capacity of a hybrid facility?
- How to integrate location, allocation, outsourcing and cross-docking delivery strategy to deal with a CLSC network design problem?
- How transportation cost discounts offered by 3PL companies may influence the flow of products from manufacturers to retailers?
- What is the proper approach to find near-to-optimal results for the presented multi-objective model?
- What are the effects of variations in demand on the objective function values?
- What are the appropriate techniques for evaluating the performance of the solution methods compared to each other?

The structure of the paper is as explained in the following. The Introduction Section followed by a literature review in Section 2. The characteristics of the considered CLSC problem and mathematical formulation are presented in Section 3. The explanation of the proposed solution methodologies and algorithms’ parameter tuning method are given in Section 4. In Section 5, the behavior of the proposed model and solution methodologies are evaluated through computational results obtained from solving some numerical instances. Furthermore, a number of comparison measures and statistical analysis are applied to examine the experimental results. Section 6 is dedicated to sensitivity analysis. Finally, concluding remarks and some directions for further researches are presented in Section 7.

2. Related literature. In recent years, rising environmental concerns, social responsibilities, strict international laws and financial profits of businesses have generated a great deal of interests among both practitioners and academics in applying the RL and CLSC issues in various fields such as sustainability [22, 86], environmental considerations [1, 11, 27], production planning [82, 13], inventory control [60, 10, 57, 38], vehicle routing [49, 46, 43], queuing system [53, 89, 63], pricing [56, 47, 44, 71], competition strategy [17, 73] and outsourcing [19, 41].

In this section, according to the characteristics of the discussed problem, a review of the most relevant literature on outsourcing, multi-objective optimization and cross-docking strategy in CLSC is provided. Then, referring to the research gaps, the main contributions of the paper are presented.
2.1. Outsourcing in CLSC. Many businesses prefer to outsource all or some of their RL activities to 3PLs. This happens due to various reasons such as uncertainty of return time and quality and quantity of returned products, limited internal resources and capabilities of supply chains’ facilities [19].

Research by [58] is one of the first studies in the field of RL service providers’ evaluation. In this study, the best 3PL for outsourcing the RL functions is determined by a decision-making model based on the analytical network process (ANP). Considering both qualitative and quantitative attributes, [26] presented a two-phase decision making tool based on fuzzy logic and artificial neural networks to determine the most appropriate third-party reverse logistics providers. [19] suggested a systematic method using ANP to check the relative importance of RL service necessities and choose a proper 3PL for a TFT-LCD manufacturer in Taiwan. Experimental results demonstrate that usual physical distribution service necessities like warehousing and shipment are important operations which companies consider when outsourcing RL processes to 3PLs. [41] defined the main factors and systematic approaches to assess and rank the most appropriate third-party reverse logistics providers (3PRLPs). Additionally, they proposed a conceptual framework based on multi criteria decision aid approach for 3PRLP selection. [2] proposed a framework for outsourcing decisions in RL applying graph theoretic approach. In this research, to select attributes and sub-attributes, a sustainable balanced scorecard which is the combination of stakeholder, internal business process, learning and growth, finance and sustainability perspectives is utilized. Considering the risk factors, [91] proposed a fuzzy complex proportional assessment of alternatives to assess and choose the sustainable 3PRLPs. In this paper, a fuzzy step-wise weight assessment ratio analysis (SWARA) method is applied for weighting the assessment criteria. [34] suggested two-period game models to study the third-party remanufacturing (3PR) strategy in a CLSC where the manufacturer can adopt two scenarios for 3PR including outsourcing and authorization. This study illustrates that how the manufacturer’s strategy is affected by the green consumption behavior of customers.

As indicated earlier, outsourcing decision is an extremely important and complicated issue for companies’ competitiveness in today’s global marketplace. Offering discounts by outside contractors (here, 3PL companies) to influence the ordering pattern of company will make the decision process more complex. The problem discussed in this paper develops the literature on outsourcing in CLSC considering all-unit quantity discounts on CLSC’s shipping costs.

2.2. Multi-objective optimization in CLSC. Over the years, single-objective optimization in CLSC area has attracted the attention of researchers. Nevertheless, multi-objective optimization has been an interesting subject in CLSC literature in recent years. The research studies conducted by [5, 67, 20, 54, 85] and [37] have benefited from applying classical multi-objective optimization methods to integrate the objective functions and tackle the model as a single-objective problem. [68] developed a multi-objective memetic solution method to deal with an integrated forward/reverse logistics network design problem. To find the set of non-dominated solutions, the algorithm uses a new dynamic search strategy by employing three different local searches. In 2014, [22] developed three novel hybrid meta-heuristic approaches based upon adapted imperialist competitive algorithms (AICA) and variable neighborhood search (VNS) to find the set of Pareto-optimal solutions for a general CLSC network. [7] proposed a hybrid meta-heuristic algorithm based on MOPSO and NSGAII to deal with a dynamic closed-loop location-
inventory problem under facility disruption risks. In another study, [18] illustrated the application of MOPSO algorithm with crowding distance-based non-dominated sorting approach in optimizing an integrated CLSC network design problem with cost and environmental aspects in the solar energy industry. Virus Colony Search (VCS) and Keshtel Algorithm (KA) developed by [31] to deal with a two-echelon stochastic multi-objective model for a CLSC in which the environmental considerations and downside risk are considered. [40] presented a multi-objective problem for optimizing the physical and financial flow in a CLSC under fuzzy uncertainty. In this research, the increase in the cash flow, social responsibility of CLSC and reliability of consumed raw materials are maximized. The multi-objective simulated annealing algorithm (MOSA), multi-objective gray wolf optimization (MOGWO) and multi-objective invasive weed optimization (MOIWO) algorithm are applied for solving the considered problem. [66] addressed sustainability and uncertainty issues through designing a bi-objective CLSC model for an Indian paper industry. The developed MILP model which considers demand uncertainty, aims to maximize the supply chain surplus and minimize the carbon content. [65] suggested a fuzzy robust approach to optimize financial, environmental and social effects of a sustainable CLSC. The developed model considers strategic and planning decisions simultaneously and is able to determine the best suppliers and the best transportation modes.

In most supply chains, the costs incurred in transportation operations and the time needed for transporting products are closely interconnected and paying more for shipping products by faster transportation vehicles is usual for companies. In this study, total transportation time of the CLSC involving the time required for shipping products from manufacturers to retailers through selected cross-dock is influenced by the fixed and variable costs involved in the transportation process. The transportation time can be declined if products are transported by faster vehicles. Therefore, there is a contrast between using slow vehicles to decrease transportation costs and transporting products by fast vehicles to decrease transportation time. Thus, since the objective functions presented in our developed model are in conflict with each other, NSGAII and MOPSO as two multi-objective meta-heuristic algorithms are developed to tackle the presented problem.

2.3. Cross-docking strategy in CLSC. Cross-docking is one of the most suitable distribution methods which can lead to costs reduction and customer satisfaction in supply chains. Despite the increased attention paid to the cross-docking strategy in forward logistics systems, there is an apparent lack of research on deployment of this strategy in RL.

The first attempt of applying cross-docking strategy in RL network belongs to the research conducted by [48]. They studied the problem of designing a multi-echelon RL network in which all the customers’ returned products are gathered in cross-docks and after inspection and separation are sent to the different recovery centers. The proposed model minimizes the fixed costs of establishing cross-docks and the costs associated with transportation. [94] demonstrated that how cross-docking strategy can be implemented in the RL network. Their suggested linear programming model optimizes the cost of return process for unsold products particularly in industries with seasonal demand patterns. The results of this research show the role of reverse cross-docking in costs reduction, time saving and information management improvement. [72] designed a sustainable CLSC along with using
cross-docking strategy. The proposed problem has focused on recovery and treatment processes of used products (i.e. recovering, remanufacturing, recycling and disposal) and is to maximize social benefits while total costs and environmental impacts are minimized. For optimizing the problem, a multi-objective cuckoo search (MOCS) algorithm is developed and its performance has been compared with two meta-heuristics of multi-objective imperialist competitive algorithm (MOICA) and MOPSO method.

The incorporation of the cross-docking delivery strategy into CLSC optimization model is the topic which links the presented research to the abovementioned studies. In problem discussed here, cross-dock is considered to be a hybrid facility which plays the role of cross-dock in the forward flow and the role of collection center in the reverse flow.

2.4. Research gaps. In order to provide a better perspective of the associated literature on the CLSC and to find the relevant research gaps, a brief review of some researches is summarized in Table 1.

Although, the adoption of outsourcing strategy has been subject of some researches in CLSC literature, the main limitation of these studies is that they have not paid much attention to incorporating the transportation cost discounts on outsourcing decisions. Furthermore, researches in the area of applying cross-docking delivery strategy in CLSC have considered the cross-dock as a distribution center in forward flow or as a collection center in reverse flow, while the capacity of cross-dock is considered fixed and predetermined value. Therefore, other contribution of the current study is related to considering cross-dock as a hybrid facility which plays the role of cross-dock in the forward flow and the role of collection center in the reverse flow where the capacity of hybrid cross-dock/collection facility is determined using De Novo programming approach. In addition, with reviewing the previous works, it can be acknowledged that there is no investigation that studies transportation cost discounts on outsourcing decisions and cross-docking strategy in CLSC (as influencing factors in today’s dynamic markets) in one integrated model.

Accordingly, the main contributions of the presented paper lie into following areas:

- Applying the cross-docking delivery strategy as the consolidation process of shipments with common destination;
- Using hybrid facility (cross-dock/collection center) with the aim of cost saving and pollution reduction;
- Utilizing De Novo programming approach to determine the capacity of hybrid cross-dock/collection facility;
- Selection of the 3PL companies for outsourcing all transportations of the CLSC (in both forward and reverse flow) to them;
- Incorporating the transportation cost discounts on outsourcing decisions;
- Minimizing two objectives of conflicting nature, the total costs and total processing time of the CLSC.

3. Problem description. This study is driven by a multi-period multi-product CLSC problem which includes multiple manufacturers, a hybrid cross-dock/collection center, multiple retailers and a disposal center as depicted in Figure 1. In the forward flow of the proposed problem, products are produced and transported from manufacturers to cross-dock. In cross-dock, shipments from different manufacturers are consolidated and classified into certain groups according to their
### Table 1. A brief review of related literatures

| Reference | Model Characteristics | Decision variables | Objective | Method |
|-----------|-----------------------|--------------------|-----------|--------|
| Flow     | Hybrid fac. | Period | Product | Out. | Disc. | Cross. | Example | No. | Des. | Method |
| [50]     | CLSC         | Yes     | Mu     | Mu    | Yes   | No     | No     | Test problem | Loc/Alloc | Si    | ↓ total costs | LINGO software, Metaheuristic |
| [59]     | CLSC         | No      | Mu     | Mu    | Yes   | No     | No     | Test problem | Loc/Alloc | Si    | ↓ total logistics costs | LINGO software, Metaheuristic |
| [24]     | CLSC         | No      | Si     | Mu    | Yes   | No     | No     | Test problem | Loc/Alloc | Mu   | ↓ total costs, ↓ total tardiness | Scatter search, Dual simplex, θ-constraint |
| [68]     | CLSC         | No      | Si     | Si    | Yes   | No     | No     | Test problem | Loc/Alloc | Mu   | ↓ total costs, ↑ responsiveness | Metaheuristics |
| [67]     | CLSC         | Yes     | Mu     | Mu    | No    | No     | No     | Test problem | Loc/Alloc/Inv | Mu   | ↓ total costs, ↑ service efficiency | Goal programming, Compromise programming |
| [5]      | CLSC         | No      | Si     | Mu    | No    | No     | No     | Test problem | Loc/Alloc | Mu   | ↓ total costs, ↑ environmental factors | Weighted sums, θ-constraint |
| [22]     | CLSC         | No      | Si     | Si    | No    | No     | No     | Test problem | Loc/Alloc | Mu   | ↓ total costs, ↑ environmental impacts, ↑ social benefits | GAMS software, Metaheuristics |
| [7]      | CLSC         | No      | Mu     | Mu    | No    | No     | No     | Test problem | Loc/Alloc/Inv | Mu   | ↓ total costs, ↓ total travel time | GAMS software, Metaheuristics, θ-constraint |
| [20]     | CLSC         | Yes     | Si     | Mu    | No    | No     | No     | Test problem | Loc/Alloc | Mu   | ↓ total profit, ↓ total spent energy, ↓ harmful emissions | LINGO software, Goal programming |
| [89]     | CLSC         | Yes     | Si     | Mu    | No    | No     | No     | Test problem | Loc/Alloc | Mu   | ↓ total costs, ↓ waiting time in services | Interval-stochastic, robust optimization, Metaheuristic, Lower bound procedure, GAMS software |
| [48]     | RL           | No      | Si     | Mu    | No    | No     | Yes    | Test problem | Loc/Alloc | Si    | ↓ total costs | GAMS software |
| [93]     | CLSC         | No      | Si     | Si    | No    | No     | No     | Gold industry | Loc/Alloc | Mu   | ↓ total costs, ↑ total incomes, ↓ CO2 emissions | LINGO software, Metaheuristic |
| Reference | Model Characteristics | Decision variables | Objective | Method |
|-----------|-----------------------|--------------------|-----------|--------|
| [54]      | CLSC                  | No                 | No        | LINGO software, LP-metrics |
|           |                       | SI                 | Mu        | ↓ total costs, ↓ environmental impacts |
|           |                       | Period             | Product   | |
|           |                       | Disc               | Cross.    | |
|           |                       | Example            | No. Des.  | |
|           |                       | Total costs        | ↓          | |
| [85]      | CLSC                  | No                 | No        | c-constraint |
|           |                       | SI                 | Mu        | ↓ total costs, ↓ CO2 emissions |
|           |                       | Period             | Product   | |
|           |                       | Cross.             | No        | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [92]      | CLSC                  | No                 | Mu        | stochastic-possibilistic programming, modified game theory, lower bound procedure, GAMS software, Hybrid metaheuristic |
|           |                       | SI                 | No        | ↓ total costs, ↓ environmental impacts, ↑ social impacts |
|           |                       | Period             | Product   | |
|           |                       | Cross.             | No        | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [18]      | CLSC                  | No                 | SI        | Branch & bound, CPLEX software, Metaheuristic |
|           |                       | SI                 | No        | ↓ total costs |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [94]      | RL                    | No                 | Si        | CPLEX software |
|           |                       | SI                 | No        | ↓ total costs |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [37]      | CLSC                  | No                 | Mu        | Karush-Kuhn-Tucker, conditions possibilistic method, c-constraint, CPLEX software |
|           |                       | SI                 | Yes       | ↓ total profit, ↓ CO2 emissions |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [75]      | CLSC                  | Yes                | Mu        | CPLEX software, LP-metrics |
|           |                       | No                 | No        | ↓ total costs, ↑ customer satisfaction |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [72]      | CLSC                  | No                 | SI        | GAMS software, Metaheuristics |
|           |                       | SI                 | No        | ↓ total costs, ↑ social benefits |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| [40]      | CLSC                  | Yes                | Mu        | c-constraint, GAMS software, Metaheuristics |
|           |                       | No                 | No        | ↑ increase in the cash flow, ↑ social responsibility, ↓ amount of unreliable raw materials |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↑          | |
| [61]      | CLSC                  | No                 | Mu        | Fully fuzzy stochastic programming |
|           |                       | SI                 | Yes       | ↓ total profit, ↑ environmental compliance |
|           |                       | Period             | Cross.    | |
|           |                       | Example            | No        | |
|           |                       | Total costs        | ↓          | |
| Reference | Model Characteristics | Decision variables | Objective | Method |
|-----------|-----------------------|--------------------|-----------|--------|
| [86]      | CLSC No Mu Si No Yes No CFL light bulb Alloc/Inv/Price Mu | ↓ total costs ↓ environmental impacts ↓ social impacts | Fuzzy TH approach [86] |
| [65]      | CLSC No Si Mu No No No Tanker industry Loc/Alloc/SS Mu | ↓ total costs ↓ environmental impacts ↑ social impacts | Multi-choice goal programming with utility function |
| [66]      | CLSC No Mu Si No No No Test problem Loc/Alloc Mu | ↓ supply chain surplus ↓ CO2 emissions | MATLAB software |
| This paper | CLSC Yes Mu Mu Yes Yes Yes Test problem Loc/Alloc/TPS Mu | ↓ total costs ↓ total processing times | \( \epsilon \)-constraint, LINGO software, Metaheuristics |

Notes:
fac. (facility); Out. (outsourcer); Disc. (discount); 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)
destinations and then delivered to retailers. In the reverse flow, returned products are shipped to the collection center. The collection center is responsible for collecting and inspecting returned products to detect and separate recoverable and scraped products. The recoverable or recyclable products are transported to manufacturers and scraped products which cannot be recovered due to economic or technological reasons are transferred to the disposal center. All transporting of the CLSC are outsourced to the 3PL companies, while some factors such as transportation time, cost and capacity make a distinction between one 3PL company and others. All-unit quantity discount for shipping products is offered by the 3PL companies and they are able to transfer all or part of retailers’ demands according to their transportation capacities.

The aim of this study is to simultaneously minimize the total costs and total processing time of the CLSC considering some real-world constraints. Precisely, the first objective function minimizes operation costs (i.e., the sum of production cost, recovery cost, establishing cost of hybrid cross-dock/collection center and transportation cost) in which transportation cost consist of two parts: (I) variable transportation cost which depends on the shipment quantities and (II) fixed transportation cost related to driver wages, depreciation and vehicle insurance. Furthermore, in second objective function, two types of time are minimized as the total processing time of the CLSC: (I) time spent on consolidation and quality inspection of products at hybrid cross-dock/collection center and (II) time needed for shipping products from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center.

Many real world industries which undergo rapid changes and the life cycle of their products is short like clothing or electronic devices, have a structure similar to our proposed model framework. The characteristics of these products encourage the manufacturers to apply cross-docking strategy aimed at reducing inventory compared to conventional distribution centers. Furthermore, in these industries, the end of life products can be managed through different decisions like recycling, remanufacturing, repairing or disposing. In both garment and electronic industries, products are produced and transported from manufacturers to cross-dock. The cross-dock plays the role of an internet distribution center and retailers are able
to order their desired products online. In cross-dock, shipments are consolidated and classified according to their destinations and then delivered to retailers. The manufacturers have provided an opportunity for their customers to return the defective products or the products that have not been successful in bringing pleasure to their customers. These returned products are sent to the collection center and repairable/recoverable or scraped products are detected. In the case of clothing, the repairable products are transported to manufacturers for modifying and returned to the chain once again. Furthermore, products with major defects which cannot be recovered will put up for auction and they will be sold at a very low price (disposal). For electronic devices, recycling (for having raw parts) and remanufacturing/repairing (for sale products as new ones to first customers) strategies are adopted by manufacturers in the reverse logistics network. Besides, the scraped products or some used parts which cannot be recovered due to economic or technological reasons are transferred to the disposal center.

3.1. Assumptions and notations.

3.1.1. Assumptions. To portray the aforementioned situation, the following assumptions in the mathematical model formulation are considered. The selection of these assumptions has been made considering both the real-world situations and the previous literature. Some assumptions like limitation on available capacity of supply chains’ facilities, employing heterogeneous fleet of vehicles for shipping products and using hybrid facilities help the developed model to be harmonized with many real-world CLSC networks. Furthermore, consistent with the relevant literature, some assumptions such as deterministic parameters [29, 46], the same function and quality of new and recovered products [42, 87, 23], demands fulfillment [72, 33] and nonexistence of flow between the facilities of the same stage [32, 76] are included in the present model.

- There is no flow between the facilities of the same stage and products directly moved from each manufacturer to cross-dock (transportation routing decisions are ignored).
- Each manufacturer produces a product’s family type and several manufacturers are available to produce a family of products.
- The amount of products produced by each manufacturer is limited by its production capacity.
- Cross-dock is considered to be a hybrid facility which plays the role of cross-dock in the forward flow and the role of collection center in the reverse flow.
- Limitation on available capacity of hybrid cross-dock/collection center is taken into account.
- Only one disposal center is available which its capacity is considered to be infinite.
- Transportations are carried out by means of heterogeneous fleet of vehicles.
- Retailer’s demand for different products has to be completely fulfilled.
- Recovered products are as good as new and are interchangeable with new products.
- All parameters are presumed to be deterministically known.

The indices, parameters and decision variables applied to formulate the problem mathematically are described as below:
3.2. Indices.
- $i$: Index of manufacturers, $\{i = 1, 2, \ldots, I\}$;
- $j$: Index of retailers, $\{j = 1, 2, \ldots, J\}$;
- $c$: Index of potential locations for hybrid cross-dock/collection center, $\{c = 1, 2, \ldots, C\}$;
- $k$: Index of 3PL companies, $\{k = 1, 2, \ldots, K\}$;
- $m$: Index of product’s family types, $\{m = 1, 2, \ldots, M\}$;
- $n$: Index of product types, $\{n = 1, 2, \ldots, N\}$;
- $p$: Index of price breaks, $\{p = 1, 2, \ldots, P\}$;
- $t$: Index of planning periods, $\{t = 1, 2, \ldots, T\}$;

3.2.1. Parameters.
- $DE_{jt}^{nm}$: Demand for product $n$ of family type $m$ at retailer $j$ in period $t$ (units);
- $MC_{it}^{nm}$: Production capacity for product $n$ of family type $m$ at manufacturer $i$ in period $t$ (units);
- $VC_k$: Transportation capacity of 3PL company $k$ (units);
- $U_{kp}$: The maximum quantity of products transported by 3PL company $k$ with price break $p$ (units);
- $FCC_{ickpt}$: Fixed cost for shipping products from manufacturer $i$ to cross-dock located at candidate place $c$ by 3PL company $k$ with price break $p$ in period $t$ ($\$/$) ;
- $FCR_{cjkpt}$: Fixed cost for shipping products from cross-dock located at candidate place $c$ to retailer $j$ by 3PL company $k$ with price break $p$ in period $t$ ($\$/$);
- $FCD_{ckt}$: Fixed cost for shipping products from collection center located at candidate place $c$ to disposal center by 3PL company $k$ in period $t$ ($\$/$);
- $TIC_{ickpt}$: Cost of transportation per product unit from manufacturer $i$ to cross-dock located at candidate place $c$ by 3PL company $k$ with price break $p$ in period $t$ ($\$/unit);
- $TCJ_{cjkpt}$: Cost of transportation per product unit from cross-dock located at candidate place $c$ to retailer $j$ by 3PL company $k$ with price break $p$ in period $t$ ($\$/unit);
- $TCD_{ckt}$: Cost of transportation per product unit from collection center located at candidate place $c$ to disposal center by 3PL company $k$ in period $t$ ($\$/unit);
- $PC_{it}^{nm}$: Production cost per unit of product $n$ of family type $m$ at manufacturer $i$ in period $t$ ($\$/unit);
- $EC_{ct}$: Establishing cost of hybrid cross-dock/collection center in candidate place $c$ in period $t$ which is dependent on the capacity of the facility ($\$/unit);
- $RC_{it}^{nm}$: Recovery cost per unit of product $n$ of family type $m$ at manufacturer $i$ in period $t$ ($\$/unit);
- $TA_{nm}$: Time spent on consolidation and classification of each unit of product $n$ of family type $m$ at cross-dock (hour/unit);
- $TI_{nm}$: Inspection time per unit of returned product $n$ of family type $m$ at collection center (hour/unit);
\[ TC_{ick} \quad \text{: Transportation time needed for shipping products from manufacturer } i \text{ to cross-dock located at candidate place } c \text{ by 3PL company } k \text{ (hour);} \]
\[ TM_{cjk} \quad \text{: Transportation time needed for shipping products from cross-dock located at candidate place } c \text{ to retailer } j \text{ by 3PL company } k \text{ (hour);} \]
\[ TD_{ck} \quad \text{: Transportation time required for transporting products from collection center located at candidate place } c \text{ to disposal center by 3PL company } k \text{ (hour);} \]
\[ \alpha_{nm}^i \quad \text{: The fraction of returned product } n \text{ of family type } m \text{ produced at manufacturer } i \text{ (percent);} \]
\[ \beta_{nm}^i \quad \text{: The fraction of returned product } n \text{ of family type } m \text{ produced at manufacturer } i \text{ which is recoverable (percent);} \]
\[ \gamma_{nm} \quad \text{: Weight/volume of each unit of product } n \text{ of family type } m \text{ (Kg or } \text{m}^3); \]
\[ M \quad \text{: Arbitrary large number;} \]

3.2.2. Decision variables.
\[ Q_{ij}^{nm} \quad \text{: Quantity of product } n \text{ of family type } m \text{ transported from manufacturer } i \text{ to retailer } j \text{ in period } t \text{ (units);} \]
\[ SC_c \quad \text{: Maximum capacity of hybrid cross-dock/collection center located at candidate place } c \text{ (units);} \]
\[ QIC_{ic}^{ckpt} \quad \text{: Quantity of products transported from manufacturer } i \text{ to cross-dock located at candidate place } c \text{ by 3PL company } k \text{ with price break } p \text{ in period } t \text{ (units);} \]
\[ QCJ_{c}^{ckpt} \quad \text{: Quantity of products transported from cross-dock located at candidate place } c \text{ to retailer } j \text{ by 3PL company } k \text{ with price break } p \text{ in period } t \text{ (units);} \]
\[ R_{it}^{nm} \quad \text{: Quantity of product } n \text{ of family type } m \text{ recovered at manufacturer } i \text{ in period } t \text{ (units);} \]
\[ RP_{j}^{nm} \quad \text{: Quantity of product } n \text{ of family type } m \text{ returned from retailer } j \text{ to manufacturer } i \text{ in period } t \text{ (units);} \]
\[ W_{nm}^t \quad \text{: Quantity of product } n \text{ of family type } m \text{ wasted in period } t \text{ (units);} \]
\[ D_{kt}^{nm} \quad \text{: Quantity of product } n \text{ of family type } m \text{ transported from collection center located at candidate place to disposal center by 3PL company } k \text{ in period } t \text{ (units);} \]
\[ X_{ickpt} \quad \text{: 1, if product is transported from manufacturer } i \text{ to cross-dock located at candidate place } c \text{ by 3PL company } k \text{ with price break } p \text{ in period } t, \text{ 0, otherwise;} \]
\[ XI_{ikt} \quad \text{: 1, if product is transported from manufacturer } i \text{ to cross-dock located at candidate place } c \text{ by 3PL company } k \text{ in period } t, \text{ 0, otherwise;} \]
\[ Y_{cjkpt} \quad \text{: 1, if product is transported from cross-dock located at candidate place } c \text{ to retailer } j \text{ by 3PL company } k \text{ with price break } p \text{ in period } t, \text{ 0, otherwise;} \]
\[ Y_{jkt} \quad \text{: 1, if product is transported from cross-dock located at candidate place to retailer } j \text{ by 3PL company } k \text{ in period } t, \text{ 0, otherwise;} \]
\[ V_{ckt} : 1, \text{ if product is transported from collection center located at candidate place } c \text{ to disposal center by 3PL company } k \text{ in period } t, \] 0, otherwise; 

\[ Z_c : 1, \text{ if a hybrid cross-dock/collection center is opened at candidate place } c, \] 0, otherwise; 

3.3. Objective functions.

3.3.1. First objective: minimizing the total costs.

The sum of Eqs. (1-1) to (1-9) refers to the total costs of CLSC network over a given planning horizon. Eq. (1-1) represents the opening cost of hybrid cross-dock/collection center. In this equation, \( SC_c \) and \( EC_{ct} \) stand for the maximum capacity and establishing cost of hybrid cross-dock/collection center, respectively. The maximum capacity is a decision variable and is determined by the model and the opening cost is dependent on the capacity of the facility. Eq. (1-2) indicates the production cost which comes from multiplying quantity of products transported from manufacturers to retailers (\( Q_{ijt}^{nm} \)) by production cost per unit of product at each manufacturer (\( PC_{it}^{nm} \)). Eq. (1-3) states the recovery cost. The Quantity of products recovered at each manufacturer (\( R_{it}^{nm} \)) as decision variable and recovery cost per unit of product at each manufacturer (\( RC_{it}^{nm} \)) as parameter lead to this equation. Eq. (1-4) denotes the transportation cost incurred for shipping products from manufacturers to cross-cokc. In this equation, \( QIC_{ickpt} \) and \( TIC_{ickpt} \) indicate the quantity of products transported from manufacturers to cross-dock and the related transportation cost per product unit. Eq. (1-5) is similar to Eq. (1-4) but computes the transportation cost for shipments of products from cross-dock to retailers. In this equation, \( QCJ_{cjkpt} \) and \( TCJ_{cjkpt} \) point out to the quantity of products transported from cross-dock to retailers and the related transportation cost per product unit. Similarly, Eq. (1-6) considers the transportation cost incurred for shipping scraped products from collection center to disposal center. This equation will result from multiplying quantity of scraped products (\( D_{kt}^{nm} \)) by cost of transportation per product unit from collection center to disposal center (\( TCD_{ckt} \)). Indeed, Eqs. (1-4) to Eq. (1-6) calculate the transportation costs which are dependent on the shipment quantities. In Eqs. (1-7) to (1-9), the fixed costs for shipping products from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center are calculated. In these equations, \( FCC_{ickpt} \), \( FCR_{cjkpt} \) and \( FCD_{ckt} \) are fixed cost parameters and \( X_{ickpt} \), \( Y_{cjkpt} \) and \( V_{ckt} \) are binary decision variables and their values is “1” if shipment of products between the considered network facilities is carried out. In other words, Eqs. (1-7) to Eq. (1-9) indicate the fixed transportation cost incurred in shipping products between the network facilities. Therefore, the first objective function can be formulated as follows:

\[
\min(TC) = \sum_{c \in C} \sum_{t \in T} SC_c \cdot EC_{ct} 
+ \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} Q_{ijt}^{nm} \cdot PC_{it}^{nm} 
+ \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} \sum_{t \in T} R_{it}^{nm} \cdot RC_{it}^{nm} 
\]
3.3.2. Second objective: minimizing the total processing time.

The sum of Eqs. (2-1) to (2-5) refers to the second objective function which aims to minimize the CLSC’s total processing time. Eq. (2-1) to (2-3) considers the transportation time required for shipping products from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center. In these equations, $TC_{ick}$, $TM_{cjk}$ and $TD_{ck}$ are transportation time parameters and $X_{ickpt}$, $Y_{cjkpt}$ and $V_{ckt}$ are binary decision variables and their values is “1” if shipment of products between the considered network facilities is carried out. Eq. (2-4) indicates the quality inspection time required for returned products at collection center. To calculate this equation, quantity of products returned from retailers to manufacturers ($RP_{nm}^{jit}$) and inspection time per unit of returned products at collection center ($TI_{nm}^{it}$) are multiplied with each other. Finally, Eq. (2-5) shows the time required for consolidation and classification of shipments and products at cross-dock. In this equation, $Q_{nm}^{ijt}$ is the quantity of products transported from manufacturers to retailers and $TA_{nm}^{it}$ indicates the consolidation and classification time. Thus, the second objective function can be presented as follows:

$$
\text{min}(TOT) = \sum_{i \in I} \sum_{c \in C} \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} X_{ickpt} \cdot TC_{ick} \quad (2-1)
$$

$$
+ \sum_{c \in C} \sum_{j \in J} \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} Y_{cjkpt} \cdot TM_{cjk} \quad (2-2)
$$

$$
+ \sum_{c \in C} \sum_{k \in K} \sum_{t \in T} V_{ckt} \cdot TD_{ck} \quad (2-3)
$$

$$
+ \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} RP_{nm}^{jit} \cdot TI_{nm}^{it} \quad (2-4)
$$

$$
+ \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} Q_{nm}^{ijt} \cdot TA_{nm}^{it} \quad (2-5)
$$

3.4. Constraints. All constraints of the proposed model are presented as follows:

$$
\sum_{i \in I} Q_{nm}^{ijt} \geq DE_{jit}^{nm} ; \quad \forall n, m, j, t \quad (3)
$$

$$
\sum_{j \in J} Q_{ijt}^{nm} \leq MC_{it}^{nm} + R_{it}^{nm} ; \quad \forall n, m, i, t \quad (4)
$$
\[ \begin{align*}
R_{nm}^{ij} & = \lfloor Q_{ijt-1, nm} \rfloor; & \forall n, m, i, j, t > 1 & \quad (5) \\
\beta_{nm}^t & = \lfloor \sum_{j \in J} R_{nm}^{ij} \cdot \beta_{ij}^{nm} \rfloor; & \forall n, m, i, t & \quad (6) \\
W_t^{nm} & = \sum_{i \in I} \sum_{j \in J} R_{nm}^{ij} - \sum_{i \in I} R_{nm}^t; & \forall n, m, t & \quad (7) \\
QC_{ickpt} & \geq \left( \sum_{n \in N} \sum_{m \in M} \sum_{j \in J} Q_{nm}^{ij} \cdot \gamma_{nm} \right) \\
& - (1 - X_{ickpt}) \cdot M; & \forall i, c, k, p, t & \quad (8) \\
QC_{cjkpt} & \geq \left( \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} Q_{nm}^{ij} \cdot \gamma_{nm} \right) \\
& - (1 - Y_{cjkpt}) \cdot M; & \forall j, c, k, p, t & \quad (9) \\
D_{kt}^{nm} & \geq W_t^{nm} - \left( 1 - \sum_{c \in C} V_{ckt} \right) \cdot M; & \forall n, m, k, t & \quad (10) \\
QC_{cjkpt} & \leq VC_k; & \forall j, c, k, p, t & \quad (11) \\
QC_{cjkpt} & \leq VC_k; & \forall j, c, k, p, t & \quad (12) \\
\sum_{n \in N} \sum_{m \in M} W_{t}^{nm} \cdot \gamma_{nm} & \leq \sum_{c \in C} V_{ckt} \cdot VC_k; & \forall k, t & \quad (13) \\
\sum_{c \in C} \sum_{p \in P} X_{ickpt} & \leq XI_{ikt}; & \forall i, k, t & \quad (14) \\
\sum_{c \in C} \sum_{p \in P} Y_{cjkpt} & \leq YJ_{jkt}; & \forall j, k, t & \quad (15) \\
\sum_{k \in K} XI_{ikt} & \leq 1; & \forall i, t & \quad (16) \\
\sum_{k \in K} YJ_{jkt} & \leq 1; & \forall j, t & \quad (17) \\
\sum_{c \in C} \sum_{k \in K} V_{ckt} & \leq 1; & \forall t & \quad (18) \\
X_{ickpt} & \leq Z_{c}; & \forall i, c, k, p, t & \quad (19) \\
Y_{cjkpt} & \leq Z_{c}; & \forall j, c, k, p, t & \quad (20) \\
V_{ckt} & \leq Z_{c}; & \forall c, k, t & \quad (21) \\
\sum_{c \in C} Z_{c} & = 1; & \quad (22) \\
\sum_{c \in C} \sum_{p \in P} X_{ickpt} \cdot U_{kp-1} & \leq \sum_{n \in N} \sum_{m \in M} \sum_{j \in J} Q_{nm}^{ij} \cdot \gamma_{nm} \\
& + ((1 - XI_{ikt}) \cdot M); & \forall i, k, t & \quad (23) \\
\sum_{n \in N} \sum_{m \in M} \sum_{j \in J} Q_{nm}^{ij} \cdot \gamma_{nm} & < \sum_{c \in C} \sum_{p \in P} X_{ickpt} \cdot U_{kp} \\
& + ((1 - XI_{ikt}) \cdot M); & \forall i, k, t & \quad (24) \\
\sum_{c \in C} \sum_{p \in P} Y_{cjkpt} \cdot U_{kp-1} & \leq \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} Q_{nm}^{ij} \cdot \gamma_{nm} \\
\end{align*} \]
 CLSC NETWORK WITH CROSS-DOCKING DELIVERY STRATEGY

\[ \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} Q_{nm}^{ijt} \gamma_{nm} < \sum_{c \in C} \sum_{p \in P} Y_{cjkpt} U_{kp} + ((1 - Y_{Jkt}) \cdot M); \forall j, k, t \]  

\[ \sum_{n \in N} \sum_{m \in M} \sum_{i \in I} Q_{nm}^{ijt} \gamma_{nm} < \sum_{c \in C} \sum_{p \in P} Y_{cjkpt} U_{kp} + ((1 - Y_{Jkt}) \cdot M); \forall j, k, t \]  

while

\[ U_{k0} = 0; \]

\[ \sum_{p \in P} X_{ickpt} \leq 1; \forall i, c, k, t \]  

\[ \sum_{p \in P} Y_{cjkpt} \leq 1; \forall j, c, k, t \]  

\[ \sum_{n \in N} \sum_{m \in M} \sum_{j \in J} Q_{nm}^{ijt} \gamma_{nm} \leq SC_c + M \cdot (1 - Z_c); \forall c, t \]  

\[ Q_{nm}^{ijt}, Q_{IC}^{ickpt}, QC_{c}, D_{kt}^{nm}, R_{nt}^{njt}, W_{it}^{nm}, SC_c \geq 0 \& \text{Integer}; \forall n, m, i, j, c, k, t \]  

\[ X_{ickpt}, X_{Iikt}, Y_{Jkt}, Y_{cjkpt}, V_{ckt}, Z_c \in \{0, 1\} ; \forall i, j, c, k, p, t \]

Constraint set (5) which refers to the quantity of returned products from retailers and constraint set (6) which stands for the recovered products at manufacturers are non-linear constraints. Constraint sets (32) and (33) are used to overcome the non-linearity of these constraints and to transform the derived non-linear programming model into a linear mixed-integer programming model.

\[ (Q_{ijt-1}^{nm} \cdot \alpha_i^{nm}) - 1 \leq R_{ijt}^{nm} \leq Q_{ijt-1}^{nm} \cdot \alpha_i^{nm}; \forall n, m, i, j, t > 1 \]  

\[ (\sum_{j \in J} R_{ijt}^{nm} \cdot \beta_{ijt}^{nm}) - 1 \leq R_{ijt}^{nm} \leq \sum_{j \in J} R_{ijt}^{nm} \cdot \beta_{ijt}^{nm}; \forall n, m, i, t \]

The first objective attempts to minimize the total costs of CLSC involving the cost associated with establishing hybrid cross dock/collection center, production cost, recovery cost and variable and fixed transportation costs for shipping products from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center. The second objective aims to get the minimum CLSC’s total processing time including the time needed for consolidation and classification of shipments and products at cross-dock, quality inspection time required for returned products at collection center and the time spent on shipping products from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center.

Constraint set (3) assures that the all retailers’ demands for all products are completely satisfied. Constraint set (4) indicates that the demands of retailers are satisfied through new and recovered products. In other words, this constraint set guarantees that the manufacturer’s production capacity and recovered products are sufficient to meet retailers’ demands. Constraint sets (5), (6) and (7) are to determine the quantity of returned products from retailers, recovered products at manufacturers and wasted products, respectively. Constraint sets (8) and (9) impose that the total quantity of products in cross-dock should be responsive to retailers’ demands. Constraint set (10) states that the total quantity of products transported from collection center to disposal center in a specific time period can
be more than the quantity of wasted products in that period (this means that the wasted products of several periods can be collected in collection center and transferred to the disposal center at once).

Constraint sets (11), (12) and (13) impose that the total quantity of products transported from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center cannot exceed the 3PL companies’ capacity for transporting products. Constraint set (14) states that a 3PL company, whenever selected, should forward products from a specific manufacturer only to one established cross-dock with only one discount level. Constraint set (15) is similar to constraint set (14) but applies for shipments of products from one established cross-dock to retailers. Constraint sets (16), (17) and (18) make sure that at most one 3PL company must be selected for transporting products between two facilities. Constraint sets (19), (20) and (21) ensure that the movement of the products from manufacturers to cross-dock, from cross-dock to retailers and from collection center to disposal center can be conducted only when the hybrid cross-dock/collection center is opened at location c. Constraint set (22) guarantees that only one hybrid cross-dock/collection center can be established. The quantity discount policy is shown through constraint sets (23) - (26): Constraint sets (23) and (24) indicate that how the quantity of products should be transported from manufacturers to cross-dock fall into one of the discount intervals. Constraint sets (25) and (26) are similar to the constraint sets (23) and (24) but used for the quantity of products should be transported from cross-dock to retailers. Constraint sets (27) and (28) impose that a 3PL company, whenever selected, should forward products from manufacturers to cross-dock and from cross-dock to retailers with only one discount level. Constraint set (29) assures that the capacity of hybrid cross-dock/collection center is sufficient. Finally, constraint set (30) imposes the non-negativity integer condition while constraint set (31) represents the binary restrictions.

4. Solution methodologies. On the one hand, CLSC design and planning is known to be NP-hard problem [51, 79]; on the other hand, [15] have proven that when quantity discount policy is incorporated into the problem, solving the model for large-sized test problems in reasonable computational time will be difficult. Thus, the problem presented in this study is NP-hard as a result of designing and planning a CLSC together with quantity discount policy. Subsequently, to find near-optimal solutions for the given model in sensible times, two multi-objective meta-heuristic methods are hired.

To demonstrate the validity of the proposed CLSC problem and to make an assessment of the developed meta-heuristics’ performance, we optimized the problem in small-sized examples using $\epsilon$-constraint method. The $\epsilon$-constraint approach as a suitable technique for dealing with multi-objective problems, optimizes one objective function and considers the other objectives as the constraints with allowable ranges. Then, by consecutive modification of the ranges, the other Pareto optimal solutions are generated [30]. The results obtained by the LINGO software for MID measure indicate that the proposed meta-heuristics generate near-optimal solutions with less than 3% of deviations from the optimal solutions.

4.1. The non-dominated sorting genetic algorithm II (NSGAII). NSGAII introduced in 2002 by [21] is a popular and widely used multi-objective solution method. Similar to the single objective genetic algorithm, NSGAII applies the
common operators of the GA (selection, crossover and mutation) to obtain a population from the initial one. However, unlike single objective GA, NSGAII has benefited from two concepts: (I) non-dominated sorting process and (II) crowding distance. According to the first concept, all members of the population are ranked and classified into several fronts of non-dominated solutions and using the second concept, the algorithm promote the diversification of the solutions among the ones with the same ranks aimed at finding the optimal front [62]. The pseudo code of the NSGA-II used to tackle the proposed CLSC problem is depicted in Figure 2.

| Begin |
|-------|
| **Input** | Pop size, Crossover rate, Mutation rate and Max-iteration |
| Generate an initial population of solutions (chromosomes) randomly |
| **For** iteration=1: Max-iteration do |
| Calculate the value of all objective functions for each solution in the initial population |
| Specify the rank for each solution using the non-dominated sorting process |
| Apply the crossover operator on the initial population based on the crossover probability |
| Apply the mutation operator on the initial population based on the mutation probability |
| Acquire the new offspring |
| Combine the initial population and the new offspring to create a new population |
| Calculate the value of all the objective functions for each solution in the new population |
| Specify the rank for each solution in the new population using the non-dominated sorting process |
| Estimate the density for each solution in the new population through swarm distance calculation |
| Create a new initial population based on the ranks obtained and swarm distances |
| **End For** |
| **Until** The stopping criterion is met |
| Identify the solutions in the new population with rank ≤ 1 as the final non-dominated Pareto set |
| **End** |

**Figure 2.** The pseudo code of NSGA-II [62]

4.1.1. **Solution representation.** Designing an appropriate format to represent a solution is one of the most important steps, when using meta-heuristic algorithms to optimization problems. The reason for such an importance is that features of a problem and information about solutions are reflected by a solution representation.

In this paper, the solution representation is composed of five parts, namely LCN, DMN, I2C, C2J and C2W which are related to determination of the location and maximum capacity of hybrid cross-dock/collection center, assignment of retailers’ demands to the manufacturers and allocation of the products transportsations (from each manufacturer to cross-dock, from cross-dock to each retailer and from collection center to disposal center) to the 3PL companies, respectively. All parts of the representation scheme are composed of strings with real values in the range of zero and one.

(I) The first part is a vector with length of the number of potential locations. The maximum value in the vector will determine the location for establishing the hybrid cross-dock/collection center among others.

(II) The second part is a five-dimensional matrix \((I \times J \times N \times M \times T)\) which specifies the manufacturer which is responsible for producing retailer’s demand for each product of each family type in each period.

(III) The third part is a three-dimensional matrix \((I \times K \times T)\) which determines the
3PL for shipping products from each manufacturer to cross-dock in each period. (IV) The fourth part is a three-dimensional matrix \( \times K \times T \) which determines the 3PL for shipping products from cross-dock to each retailer in each period. Considering these four parts we are able to show that how the flow of products from manufacturer to retailer is formed. The associated pseudo code is depicted in Figure 3.

\[
\text{Figure 3. The pseudo code related to product's flow from manufacturer to retailer}
\]

Thus, due to the determination of the flow of products from manufacturers to retailers through cross-dock and the quantity of products which are transported by third-party logistics provider, we will be able to specify the amount of parameters \( SC_c \), \( X_{ickpt} \) and \( Y_{cjkpt} \) in each period. In addition, regarding the quantity of products received from each manufacturer, the amount of parameters \( RP_{nm}^{ij}, R_{nm}^{it} \) and \( W_{itt}^{nm} \) for all indices in period \( t \) can be determined by constraint sets (5), (6) and (7), respectively. Then, in the fifth part of the solution representation which is a two-dimensional matrix \( K \times T \), the third-party logistics provider with the highest value in the column for time period is selected for transporting products from collection center to disposal center.

4.1.2. Parent selection mechanism. Parent selection is the process of selecting better individuals to get copied in the next generations. Crowded tournament selection operator which is used in this paper is to generate the mating pool according to the crowding distance and the rank. In fact, in this operator, a group of individuals participate in a tournament and the data on crowding distance and rank for each individual is collected. The winner is evaluated by the fitness levels (a combination of crowding distance and rank) [12].
4.1.3. **Crossover operator.** Crossover and mutation are the key operators for creating new solutions (individuals) by combination or modification of the current good solutions. The crossover operator is related to changing information between selected parents hoping for generating better child who has characteristics of its parents [3]. In this paper, the crossover operator works based on a guide matrix. The guide matrix has binary members and is considered for each part of the solution representation in accordance with its dimension. Thus, for every member in each part of the solution representation there is a corresponding member in the guide matrix. To generate new offspring, if the value associated with the guide matrix equals to “1”, the values of those corresponding members in the chromosomes are swapped between the two parents. Otherwise, that member remains unchanged in both parents. Figure 4 illustrate that how the proposed crossover operator is adapted.

![Figure 4. A sample of crossover operator](image)

4.1.4. **Mutation operator.** Mutation operator helps for a wider exploration of the feasible solutions in order to provide population diversity whenever the population tends to become homogeneous as a result of frequent use of the parent selection and crossover operator. Furthermore, this operator prevents the solution method from trapping in local optimum. In this paper, in the mutation operator which is considered to be employed for five parts of the solution representation, a single chromosome is randomly chosen from the population. Then, the values of its some randomly selected genes are re-created randomly. A graphical representation of the proposed mutation operator is depicted in Figure 5.

![Figure 5. A sample of mutation operator](image)

4.1.5. **Termination condition.** The process of search will be continued until a stoppage condition has been met. In this study, the evolution process will be stopped whenever the solution method gets to a predetermined number of repetitions.
4.2. The multi-objective particle swarm optimization algorithm (MOPSO). The particle swarm optimization (PSO) is an optimization search algorithm proposed by [25], simulating the social behavior of birds and fish. The PSO algorithm usually starts with a population of randomly generated solutions (N-particles) where random position and velocity are the two characteristics of each solution. The particles move around a virtual D-dimensional search space by tracking the existing optimum particles. The particle movement is affected by the three main factors [81]: the velocity of the particle in the latest iteration, the personal best position (Pbest) which is the best solution in the particle’s history and the global best position (Gbest) which is the whole swarm’s best known solution. At each repetition, the position and velocity of each particle toward its Pbest and Gbest positions are updated using Eqs. (34) and (35), respectively. Then, the position of particle in the solution space is mapped, its fitness value is evaluated based on the objective function and the Pbest and Gbest positions are altered if required. This process will continue until the termination criterion is satisfied.

\[
\begin{align*}
v^t_{ij}^{t+1} &= w \times v^t_{ij} + C_1 \times r_1 \times (Pbest^t_{ij} - x^t_{ij}) + C_2 \times r_2 \times (Gbest^t_{ij} - x^t_{ij}) \\
v^t_{ij}^{t+1} &= x^t_{ij} + v^t_{ij}^{t+1}
\end{align*}
\]

where \(v_{ij}^t\) is called the velocity of the \(i\)th particle in \(j\)th dimension at \(t\)th repetition, \(x_{ij}^t\) is the current position of the \(i\)th particle in \(j\)th dimension at \(t\)th repetition, \(w\) is the inertia weight coefficient, \(C_1\) and \(C_2\) are the balance factors between the effect of individual and social knowledge on particle’s motion towards the goal and \(r_1\) and \(r_2\) are two random values with uniform distribution U(0,1).

The movement toward the optimum point in MOPSO algorithm is different from single-objective PSO because in MOPSO algorithm, there is more than one objective and the algorithm needs to consider all the objectives. Thus, in MOPSO algorithm, an external memory called “repository set” is considered as the collection of non-dominated solutions. The members of repository set provide an approximation of real Pareto frontier of the optimization problem [9]. The initial population solutions are copied considering dominant sorting and crowding distance criteria in repository set and are kept there. As the repository set usually has a limitation on the number of solutions, while updating the members of the repository set, three cases may occur: (I) if the number of dominant members of Rank 1 is less than the least capacity of repository set, the remained numbers will be provided from Rank 2. The dominant members (Rank 1 and Rank 2) are remained in repository set and the rest non-dominant members are eliminated; (II) if the number of dominant members of Rank 1 is more than the least capacity and less than the most capacity of repository set, the current dominant members are stayed in repository set and the other non-dominant members are eliminated; (III) if the number of dominant members Rank 1 is more than the most capacity of repository, 2N-particle superior number are remained in repository set according to crowding distance criteria and the rest ones are deleted.

At the end of this stage, if the stopping criterion is not fulfilled, then the personal and global best position of the particles are updated in the repository set to be used in next repetition. According to the domination relation between the current best position of the particle and its new position, the personal best position will be updated at each repetition [4]. The pseudo code of the proposed MOPSO is demonstrated in Figure 6.
In this study, objective functions’ assessment, solution representation and termination condition for MOPSO algorithm are considered as those of NSGAII dealt with in subsection 4.1.

![Figure 6. The pseudo code of MOPSO [55]](image)

### 4.3. Algorithms parameter tuning

Since the performance of a meta-heuristic method and the precision of its solutions depends considerably on algorithm’s parameters, an important issue is how to choose the parameters. Among various methods in the design of experiments (DOE), Taguchi method is the most frequently used method which evaluates many parameters with a few experiments through a number of designs. To determine the best level of each parameter, Taguchi method applies the signal-to-noise (S/N) ratio as a variation criterion as following [84]:

\[
S/No\text{ratio} = -10 \log_{10}\left(\frac{\sum_{i=1}^{n} y_i^2}{n}\right)
\]

where \(y_i\) is the solution point in \(i\)th experiment (\(i=1,\ldots,n\)) and \(n\) is the number of experiments.

According to the number of parameters to be tuned and their levels (see tables 2 and 3), orthogonal array L27 is chosen for the two meta-heuristic algorithms. Then, five problems with different sizes are generated and each solution method is run two times for each test problem under Taguchi plan and considering MID index. Next, the results are used in Minitab 16.2.0 to specify the appropriate levels applying the average of the S/N ratio for each solution method. The average S/N ratio achieved
at different levels of NSGAII and MOPSO parameters are illustrated in Figures 7 and 8, respectively. Since the maximum value of the S/N ratio is more favorable [90], in both Figures 7 and 8, the parameter level with the maximum value of S/N is chosen as the best level.

Figure 7. Average S/N ratio levels for NSGAII’s parameters

According to the results obtained by Taguchi approach, the best parameter values of NSGAII are 100, 200, 0.85 and 0.05 for pop size, iteration, crossover rate and mutation rate, respectively. Furthermore, the parameter values of MOPSO, pop size, iteration, C1, C2 and inertia weight were respectively set to 100, 200, 1.5, 1.5, and 0.75. The optimum level of the tuned parameters is illustrated in Tables 2 and 3.

Table 2. Parameters and their levels for NSGAII

| Parameters       | Symbols | Levels          | Value Tuned |
|------------------|---------|-----------------|-------------|
| Pop Size         | (A)     | 100 150 200     | 100         |
| 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        |

5. Computational results and discussions. This section is dedicated for presentation and comparison of the computational results obtained from the developed solution methods. MATLAB 7.10 is used for coding the algorithms. Considering that there are no benchmark instances for the presented model and using OR-LIBRARY site is not useful in algorithms’ efficiency evaluation due to the change
in the nature of the issue, a set of instances with various scales and different parameters’ values are designed. The parameters’ values in each problem (see Table 4), are generated at random according to the presumptions illustrated in Table 5.

The use of random-based operators in meta-heuristic algorithms causes the results obtained for each test problem to be different in various runs [8]. Thus, to eliminate the uncertainty of the computational results, problems need to be solved several times and the average or median of the results is reported. Since there was no significant difference between the average of 5, 7 and ten runs in our developed algorithms and with the aim of time saving, in this paper, each test problem is run five times under different random parameters and the ultimate result will be the average of these runs. Furthermore, to justify the efficiency of the proposed algorithms, their results are compared to those obtained by Lingo software in small-sized instances.

5.1. Comparison measures. During the optimization process of a multi-objective problem, keeping good diversity and converging to a good Pareto optimal front will specify the performance of a meta-heuristic solution method [70]. Thus, we have
Table 4. Size and level of problems

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

Table 5. Parameters’ range in test problems

| Parameter                                | Random generation function                                      |
|------------------------------------------|-----------------------------------------------------------------|
| Demand (DE)                              | U [50, 150]                                                     |
| Production capacity (MC)                  | U [200*I,J, 200*I,J+275*I,J]                                    |
| Transportation capacity (VC)              | U [200*N*I,J, 200*N*I,J+275*N*I,J]                              |
| Upper bound (U)                           | Transportation capacity/P+1                                     |
| Transportation fixed cost I (FCC)         | U [15, 20]                                                     |
| Transportation fixed cost II (FCR)        | U [8, 15]                                                      |
| Transportation fixed cost III (FCD)       | U [5, 10]                                                      |
| Transportation cost I (TIC)              | U [10, 15]                                                     |
| Transportation cost II (TCJ)              | U [4, 8]                                                       |
| Transportation cost III (TCD)             | U [3, 5]                                                      |
| 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]                                                 |
| Inspection time (TI)                      | U [0.03, 0.06]                                                 |
| Transportation time I (TC)                | U [2, 20]                                                     |
| Transportation time II (TM)               | U [1.5, 12]                                                    |
| Transportation time III (TD)              | U [3, 5]                                                      |
| 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]                                                     |

adopted five measures to assess the performance of the proposed algorithms.
• Mean ideal distance (MID) [45]
The average of distances between Pareto solutions and an ideal point is evaluated
by this criterion through the following relation:

\[ MID = \frac{\sum_{i=1}^{n} c_i}{n} \]  

(37)

where \( n \) stands for the number of non-dominating solutions and \( c_i \) is calculated as follows:

\[ c_i = \sqrt{(f_{1i} - f_1^*)^2 + (f_{2i} - f_2^*)^2 + \ldots + (f_{mi} - f_m^*)^2} \]  

(38)

where \( f_1^* \) is the ideal point and \( f_{mi} \) is the \( i \)-th non-dominated solution’s value for the \( m \)-th objective function. The lower value of \( MID \), the better performance of the algorithm.

- Spacing measure (SM) [78]
  The relative distance between successive solutions is shown by this measure as follows:

\[ SM = \left( \frac{1}{|Q|} \sum_{i=1}^{|Q|} (d_i - \bar{d})^2 \right)^{\frac{1}{2}} \]  

(39)

where \( |Q| \) is the size of Pareto archive and \( d_i \) and \( \bar{d} \) can be calculated by following relations:

\[ d_i = \min_{k \in Q \land k \neq i} \sum_{m=1}^M |f_{mi} - f_{mk}| \]  

(40)

\[ \bar{d} = \frac{\sum_{i=1}^{|Q|} d_i}{|Q|} \]  

(41)

Actually, this measure presents the amount of variation of the \( d_i \) values. The value of SM would be small when the solutions are arranged beside each other. Thus, the algorithm performs much well as this index decreases.

- Number of Pareto solutions (NPS) [77]
  This measure counts the total number of non-dominated solutions in the Pareto set obtained from the algorithm. Algorithm with more NPS has better performance and is more favorable.

- Quality metric (QM) [64]
  The value of this measure is determined by generating a combination Pareto set among all non-dominated solutions acquired by the solution methods and computing the percentage of non-dominated solution related to each meta-heuristic. The more the value of this measure, the better the performance of the algorithm.

Moreover, computational times are evaluated and reported in second to establish if our MOPSO algorithm was really faster than the NSGAII.

5.2. Computational results. The computational results of the NSGA-II and MOPSO for different problems’ scale (small, medium and large) and considering five comparison measures (MID, SM, NPS, QM and computational time) are given in Table 6 and Figure 9. According to Figure 9, it can be seen that MOPSO has a better performance with respect to the MID measure and the performance gap between the two algorithms becomes more in medium scale problems. In terms of QM measure, the difference between the results obtained by the two algorithms is significantly decreased as the problem’s size increases. The performance of the MOPSO algorithm in small-sized problems is notable due to the total number of non-dominated solutions in the Pareto set. Moreover, the computational time of NSGAII is almost independent of the size of test problems, but, by contrast, this measure for MOPSO is increased when the size of problems is risen. To find out
if there is a noticeable distinction between the performances of the solution methods, the results are examined by the technique of one-way Analysis of Variance (ANOVA). To do so, it is necessary to test the normality of data which is the main hypothesis for the validity of ANOVA. It has been observed that aside from the results of computational time, other results follow the normal distribution. As the normality of data recorded for computational time was questioned, we successfully applied Kruskal-Wallis test as a nonparametric method to compare the performance of the algorithms in terms of computational time. The null hypothesis of the applied methods investigates the equality of the medians of the performance measures achieved by the two algorithms. The results of statistical analysis which are the output of Minitab 16.2.0 are summarized in Tables 7-10 and Figure 10. According to the ANOVA tables, the p-values 0.006, 0.041 and 0.000 respectively for MID, NPS and QM indicate that the means are not equal when alpha is considered to be 0.05 and MOPSO obviously outperforms NSGAII by taking these performance metrics into account. But the SM is the only index which is much better for the NSGA-II than the MOPSO. Furthermore, the result of Kruskal-Wallis test indicates the supremacy of the MOPSO via NSGAII in terms of computational time as shown in Figure 11.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{individual_95_cis_for_mean_based_on_pooled_stdev}
\caption{Individual 95\% CIs for mean based on Pooled StDev}
\end{figure}
Table 6. The obtained metrics for algorithms’ performance (MID, SM, NPS, QM and Time)

| Problem size | T. P. | NSGA-II | MOPSO | NSGA-II | MOPSO | NSGA-II | MOPSO | NSGA-II | MOPSO | NSGA-II | MOPSO | NSGA-II | MOPSO | NSGA-II | MOPSO |
|--------------|-------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|
| Small        | P1.   | 0.2965  | 0.7985 | 0.30247 | 0.7924 | 2       | 13     | 0.11743 | 0.8825 | 152.2674 | 83.6138 | 93.31762 | 170.5  | 93.31762 |
|              | P2.   | 0.7985  | 0.7985 | 0.80303 | 1.3092 | 11      | 5      | 0.21714 | 0.8365 | 170.5483 | 112.2679 |
|              | P3.   | 0.6678  | 0.7985 | 0.34031 | 1.3161 | 4       | 12     | 0.03538 | 0.9646 | 169.0048 | 89.31582 |
|              | P4.   | 0.7380  | 0.8242 | 0.04645 | 0.7774 | 3       | 13     | 0.18888 | 0.8111 | 170.6363 | 105.0191 |
|              | P5.   | 0.8355  | 0.9214 | 0.45726 | 8.7383 | 9       | 11     | 0.14164 | 0.8583 | 170.8992 | 117.5417 |
|              | P6.   | 0.8890  | 0.8458 | 0.92847 | 1.4979 | 9       | 19     | 0.025   | 0.975  | 170.4384 | 115.9775 |
|              | P7.   | 0.6611  | 0.8644 | 1.26429 | 1.7417 | 8       | 12     | 0.03760 | 0.9624 | 170.6712 | 132.081  |
|              | P8.   | 0.6354  | 0.6519 | 0.63885 | 0.4046 | 4       | 7      | 0       | 1      | 170.698  | 131.0991 |
|              | P9.   | 0.8213  | 0.6899 | 2.4401  | 0.5992 | 9       | 3      | 0.01818 | 0.9818 | 170.9277 | 133.0108 |
| Medium       | P10.  | 1.2217  | 0.6922 | 0.76749 | 0.7216 | 7       | 10     | 0.25    | 0.75   | 174.4272 | 164.5119 |
|              | P11.  | 1.0500  | 0.7352 | 0.45799 | 1.1503 | 4       | 4      | 0.15320 | 0.8467 | 173.1716 | 174.1405 |
|              | P12.  | 0.9179  | 0.6964 | 0.56273 | 0.5975 | 6       | 10     | 0.38333 | 0.6166 | 178.755  | 175.1082 |
|              | P13.  | 0.8986  | 0.8084 | 0.13531 | 0.7930 | 2       | 7      | 0.05714 | 0.9428 | 173.6318 | 173.4457 |
|              | P14.  | 0.9193  | 0.7470 | 0.75717 | 0.5468 | 7       | 7      | 0.28666 | 0.7133 | 175.8487 | 164.4145 |
|              | P15.  | 1.0065  | 0.6942 | 0.76486 | 0.4498 | 3       | 4      | 0.24    | 0.76   | 172.0987 | 173.5972 |
| Large        | P16.  | 0.9107  | 0.6542 | 0.41413 | 1.0785 | 7       | 10     | 0.51414 | 0.4858 | 171.5135 | 174.0156 |
|              | P17.  | 0.9056  | 0.5901 | 0.54131 | 1.2302 | 6       | 4      | 0.64047 | 0.3595 | 183.5318 | 182.9749 |
|              | P18.  | 0.7044  | 0.8123 | 0.98102 | 0.6413 | 4       | 8      | 0.375   | 0.625  | 196.9311 | 178.7448 |
|              | P19.  | 0.8133  | 0.5921 | 0.70779 | 0.3938 | 5       | 9      | 0.40090 | 0.5990 | 189.7017 | 195.596  |
|              | P20.  | 0.8936  | 0.6095 | 0.74845 | 0.3266 | 7       | 5      | 0.60333 | 0.3966 | 196.8208 | 173.8915 |
| Large        | P21.  | 0.8663  | 0.6634 | 0.43799 | 0.3902 | 7       | 3      | 0.61555 | 0.3844 | 180.2806 | 180.9208 |
|              | P22.  | 0.8617  | 0.7219 | 0.63042 | 0.6304 | 7       | 3      | 0.31666 | 0.6833 | 184.1588 | 183.5843 |
| Large        | P23.  | 0.7576  | 0.7515 | 1.17926 | 0.9181 | 7       | 9      | 0.23690 | 0.7630 | 180.4263 | 193.2142 |
|              | P24.  | 0.9310  | 0.6332 | 0.85165 | 0.9508 | 8       | 5      | 0.59047 | 0.4095 | 192.3841 | 180.048  |
|              | P25.  | 0.7122  | 0.7540 | 0.77547 | 0.9940 | 7       | 4      | 0.34801 | 0.6561 | 177.788  | 186.2371 |
|              | P26.  | 0.9133  | 0.7173 | 0.48094 | 0.9104 | 5       | 5      | 0.59285 | 0.4071 | 211.5774 | 188.7306 |
Table 7. ANOVA results for MID criterion

| Source | DF | SS  | MS    | F-Test | P-Value |
|--------|----|-----|-------|--------|---------|
| Factor | 1  | 0.1517 | 0.1517 | 8.09   | 0.006   |
| Error  | 58 | 1.0869 | 0.0187 |        |         |
| Total  | 59 | 1.2386 |        |        |         |

Table 8. ANOVA results for SM criterion

| Source | DF | SS  | MS    | F-Test | P-Value |
|--------|----|-----|-------|--------|---------|
| Factor | 1  | 0.603 | 0.603 | 4.59   | 0.036   |
| Error  | 58 | 7.620 | 0.131 |        |         |
| Total  | 59 | 8.224 |       |        |         |

Table 9. ANOVA results for NPS criterion

| Source | DF | SS  | MS    | F-Test | P-Value |
|--------|----|-----|-------|--------|---------|
| Factor | 1  | 56.1 | 56.1  | 4.35   | 0.041   |
| Error  | 58 | 747.9 | 12.9  |        |         |
| Total  | 59 | 803.9 |       |        |         |

Table 10. ANOVA results for QM criterion

| Source | DF | SS  | MS    | F-Test | P-Value |
|--------|----|-----|-------|--------|---------|
| Factor | 1  | 3.0071 | 3.0071 | 75.25  | 0.000   |
| Error  | 58 | 2.3179 | 0.0400 |        |         |
| Total  | 59 | 5.3250 |       |        |         |

6. **Sensitivity analysis.** Since the demand parameter has a significant effect on the structure of supply chains and the changes of this parameter is more than others in real situations [39], in this paper, the sensitivity analysis is performed on retailers’ demand. To assess the impact of changes in this parameter on the objective function values, the analyses are carried out for the problem P4 using MOPSO algorithm. Moreover, the change interval of this parameter is considered to be -20% to +20%. The results of the sensitivity analysis, based on the changes in retailers’ demand, are illustrated in Table 11 and Figure 12.

The obtained results indicate the normal behavior of the proposed model. Accordingly, the values of the objective functions would increase as the value of retailers’ demand increases. This means that the objective functions are directly
Figure 10. Individual 95% CIs for mean based on Pooled StDev

![Graph showing individual 95% CIs for mean based on Pooled StDev.](image)

Table 11. Results of sensitivity analysis

| Objective functions | Demand’s change interval |
|---------------------|--------------------------|
|                     | -20%         | -10%       | 0%        | 10%         | 20%         |
| Total cost          | 431,871      | 553,901    | 806,133   | 849,666     | 948,245     |
| Total processing time | 186         | 221        | 240       | 276         | 298         |

Figure 11. Kruskal-Wallis test on computational time

![Kruskal-Wallis Test on Time](image)
dependent on the demand parameter, however, the behavior of the total cost reveals a greater dependence on demand compared to the total processing time. As illustrated in Table 11 and Figure 12, when the demand of all retailers is increased by 20% of their original values, a 17.63% and a 24.3% rise in total costs and total processing time is observed, respectively. Similarly, decreasing retailer’s demands to 20% of their original values (-20%), leads to a 46.43% and a 22.63% reduction in total costs and total processing time.

7. Concluding remarks and future research directions. In this paper, a bi-objective mixed-integer linear programming model was proposed to deal with a multi-product, multi-time period and multi-echelon CLSC optimization problem. The proposed problem considers quantity discount on transportation costs, cross-docking delivery strategy, integration of strategic and tactical decisions and De Novo programming concept. The aim of the developed optimization model is to determine the quantity of transported, returned, recovered and wasted products, allocate the transportation of products to the 3PL companies and determine the location and maximum capacity of hybrid cross-dock/collection center. The model is to satisfy the retailer demands and capacity constraints such that the total costs and total processing time of CLSC are minimized. High computational complexity of the proposed problem necessitates the use of multi-objective Pareto-based meta-heuristic algorithms, the NSGAII and MOPSO to achieve near-to-optimal solutions for realistically sized problems in reasonable computational time. To achieve the optimum level of parameters of the developed algorithms, the Taguchi method is used. To make sure about the efficiency of the proposed algorithms, the results obtained by NSGA-II and MOPSO are compared to the global optimum of Lingo software for small-sized problems. Since the results showed a slight difference between the global optimum and those obtained by the developed algorithms, in next step, the practicality of the proposed model and the performance of the developed solution methodologies are tested through solving a set of randomly generated real-sized problem instances. In addition, sensitivity analysis is conducted on the demand
parameter and the obtained results are presented. Finally, the results are analyzed by the statistical analysis and performance measures.

According to the computational results, the subsequent achievements are: (I) The developed meta-heuristic algorithms are able to find as many Pareto-optimal solutions as possible for the considered multi-objective optimization problem to illustrate the trade-off between the two objectives of conflicting nature. (II) The results of the proposed meta-heuristic algorithms and those obtained by Lingo software and $\varepsilon$-constraint method are very close to each other in small-sized problems. The results obtained by the LINGO software for MID measure indicate that the proposed meta-heuristics generate near-optimal solutions with less than 3% of deviations from the optimal solutions. (III) To assess the performance of the proposed algorithms, five comparison measures, namely MID, SM, NPS, QM and computational times are evaluated for different problems’ scale (small, medium and large scales). The results indicate the better performance of MOPSO in comparison with NSGAII in general. (IV) To carry out a thorough examination of the performances of the solution methods, a statistical analysis by the technique of one-way ANOVA and nonparametric method is applied. Based on the ANOVA results, the p-values 0.006, 0.041 and 0.000 respectively for MID, NPS and QM prove that the means are not equal and MOPSO outperforms NSGAII by taking these performance measures into consideration. But the SM is the only metric which is much better for the NSGA-II than the MOPSO. Moreover, the result of Kruskal-Wallis test illustrates the supremacy of the MOPSO via NSGAII in terms of computational time. (V) To make an assessment of the model behavior, a sensitivity analysis is performed on retailers’ demand. According to the results obtained, it can be concluded that the total costs and total processing time of CLSC network depend directly on demand fluctuations.

The theoretical, practical and managerial implications of this research paper are as follows:
• The emergence of circular economy persuaded companies to focus on RL and CLSC as a basis for creating economic value and environmental considerations. Thus, this paper considers the today’s requirements of businesses by introducing a more realistic and practical model.
• In general, manufacturers prefer to manage the forward flows among different levels of supply chain and tend to delegate tasks related to product distribution to the 3PL companies. The outsourcing strategy enables manufacturers to concentrate on their particular area of expertise (here, production and recovery to fulfill the retailers’ demands) and improve their logistics operations while reducing the related costs.
• Providing products at the right time, at the right place and at the right quantities is the main task of physical distribution. Obviously, logistics cost reduction in supply chains is affected by managing the physical flow of products in distribution networks. Thus, according to some factors like the nature of product, demand rate, distance to customers and information flow, some supply chains prefer to implement the cross-docking strategy as the consolidation process of shipments with the same destination (but from several origins).
• In real-world, the efficiency of the supply chain is strongly influenced by the number and location of its facilities. Furthermore, production, distribution and transportation facilities are faced with resource limitations where the available resources have not been determined in advance. De Novo programming method searches for
the optimum solutions in accordance with the “variable” constraints and could be applied in model formulation to find out favorable solutions when the maximum capacity of the opened facility is not predefined.

• The optimization model proposed in this paper considers some real-world constraints and could be helpful, in case the supply chain is interested in reorganizing its current transportation and distribution strategy, by applying an outsourcing and cross-docking policy. The choice of outsourcing transportations and applying cross-docking strategy significantly influences the quantity of products transported between facilities and consequently, the associated costs. Thus, the model itself illustrates a fascinating concept to the CLSC literature.

• The discount concept proposed in this study will help the decision makers to study the effect of this factor on outsourcing strategies. The inclusion of transportation cost discounts on outsourcing decisions and cross-docking delivery strategy provides a realistic and holistic view for managers who seeks to optimize both strategic and tactical decisions simultaneously.

• The proposed meta-heuristic algorithms which can handle real-sized problems in appropriate time and near-to-optimal results, help managers by providing a quick solution approach for making the best decision.

There are a number of potential subjects for future research. First, a practical limitation of the present study is that the developed model is a deterministic model and may be less successful in real world applications. Therefore, for future research, uncertainty of some parameters such as time, demand of retailers or the amount of returned products can be involved in the optimization model and consequently new algorithms can be developed to deal with fuzziness and uncertainty. Second, the two objective functions have been considered in this model are total costs and total processing time of CLSC network. Thus, another recommendation for future work is to add some objectives like CO2 emissions or social responsibility and community welfare as environmental or social objectives to the model and develop a model based on sustainability aspects. Third, in this paper, it is assumed that the recoverable or recyclable products which are transported to manufacturers in the reverse logistics of the network have the same quality. To develop a more realistic and practical model, it can be considered that the returned products have different grades. As a result, recovery cost differs for products with different quality. Fourth, facility location, allocation and third-party selection are the main decisions in the proposed optimization model. Thus, an effort can also be taken to include a new combination of strategic, tactical and operational decisions like scheduling or routing in the formulation. Lastly, the efficiency of the developed solution methodologies may become better by modifying the representation scheme of solution.

REFERENCES

[1] R. Accorsi, R. Manzini, C. Pini and S. Penazzi, On the design of closed-loop networks for product life cycle management: Economic, environmental and geography considerations, *Journal of Transport Geography*, 48 (2015), 121–134.

[2] S. Agrawal, R. K. Singh and Q. Murtaza, Outsourcing decisions in reverse logistics: Sustainable balanced scorecard and graph theoretic approach, *Resources, Conservation and Recycling*, 108 (2016), 41–53.

[3] F. Altiparmak, M. Gen, L. Lin and T. Paksoy, A genetic algorithm approach for multi-objective optimization of supply chain networks, *Computers & Industrial Engineering*, 51 (2006), 196–215.
[4] J. E. Alvarez-Benitez, R. M. Everson and J. E. Fieldsend, A MOPSO algorithm based exclusively on pareto dominance concepts, International Conference on Evolutionary Multi-Criterion Optimization, 3410 (2005), 459–473.

[5] S. H. Amin and G. Zhang, A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return, Applied Mathematical Modelling, 37 (2013), 4165–4176.

[6] A. Aminipour, Z. Bahrroun and M. Hariga, Cyclic manufacturing and remanufacturing in a closed-loop supply chain, Sustainable Production and Consumption, 25 (2021), 43–59.

[7] J. Asl-Najafi, B. Zahiri, A. Bozorgi-Amiri and A. Taheri-Moghaddam, A dynamic closed-loop location-inventory problem under disruption risk, Computers & Industrial Engineering, 90 (2015), 414–428.

[8] E. Babaee Tirkolaee, A. Goli, A. Faridnia, M. Soltani and G.-W. Weber, Multi-objective optimization for the reliable pollution-routing problem with cross-dock selection using Pareto-based algorithms, Journal of Cleaner Production, 276 (2020), 122927.

[9] S. Barak, M. Yousefi, H. Maghsoudlou and S. Jahangiri, Energy and GHG emissions management of agricultural systems under multi objective particle swarm optimization algorithm: A case study, Stochastic Environmental Research and Risk Assessment, 30 (2016), 1167–1187.

[10] E. Bazan, M. Y. Jaber and S. Zanoni, A review of mathematical inventory models for reverse logistics and the future of its modeling: An environmental perspective, Applied Mathematical Modelling, 40 (2016), 4151–4178.

[11] E. Bazan, M. Y. Jaber and S. Zanoni, Carbon emissions and energy effects on a two-level manufacturer-retailer closed-loop supply chain model with remanufacturing subject to different coordination mechanisms, International Journal of Production Economics, 183 (2017), 394–408.

[12] T. Blickle, Handbook of Evolutionary Computation, Chapter Tournament Selection, IOP Publishing Ltd, 1997.

[13] A. Bouras and L. Tadj, Production planning in a three-stock reverse-logistics system with deteriorating items under a continuous review policy, Journal of Industrial & Management Optimization, 11 (2015), 1041–1058.

[14] N. Boysen and M. Fliedner, Crossdock scheduling: Classification, literature review and research agenda, Omega, 38 (2010), 413–422.

[15] G. J. Burke, J. Carrillo and A. J. Vakharia, Heuristics for sourcing from multiple suppliers with alternative quantity discounts, European Journal of Operation Research, 186 (2008), 317–329.

[16] A. Chaabane, A. Ramudhin and M. Paquet, Design of sustainable supply chains under the emission trading scheme, International Journal of Production Economics, 135 (2012), 37–49.

[17] J.-M. Chen and C.-I. Chang, The co-opetitive strategy of a closed-loop supply chain with remanufacturing, Transportation Research Part E: Logistics and Transportation Review, 48 (2012), 387–400.

[18] Y.-W. Chen, L.-C. Wang, A. Wang and T.-L. Chen, A particle swarm approach for optimizing a multi-stage closed loop supply chain for the solar cell industry, Robotics and Computer-Integrated Manufacturing, 43 (2017), 111–123.

[19] Y.-H. Cheng and F. Lee, Outsourcing reverse logistics of high-tech manufacturing firms by using a systematic decision-making approach: TFT-LCD sector in Taiwan, Industrial Marketing Management, 39 (2010), 1111–1119.

[20] K. Das and N. R. Poinsasetti, Addressing environmental concerns in closed loop supply chain design and planning, International Journal of Production Economics, 163 (2015), 34–47.

[21] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation, 6 (2002), 182–197.

[22] K. Devika, A. Jafarian and V. Nourbakhsh, Designing a sustainable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridization techniques, European Journal of Operational Research, 235 (2014), 594–615.

[23] J. Dong, L. Jiang, W. Lu and Q. Guo, Closed-loop supply chain models with product remanufacturing under random demand, Optimization, 70 (2021), 27–53.

[24] F. Du and G. W. Evans, A bi-objective reverse logistics network analysis for post-sale service, Computers & Operations Research, 35 (2008), 2617–2634.

[25] R. Eberhart and J. Kennedy, A new optimizer using particle swarm theory, in Proceedings of the Sixth International Symposium on Micro Machine and Human Science, IEEE, (1995), 39–43.
[26] T. Efendigil, S. Ö nút and E. Kongar, A holistic approach for selecting a third-party reverse logistics provider in the presence of vagueness, Computers & Industrial Engineering, 54 (2008), 269–287.

[27] B. Fuhimnia, J. Sarkis, F. Dehghanian, N. Banihashemi and S. Rahman, The impact of carbon pricing on a closed-loop supply chain: An Australian case study, Journal of Cleaner Production, 59 (2013), 210–225.

[28] H. Fallah, H. Eskandari and M. S. Pishvaee, Competitive closed-loop supply chain network design under uncertainty, Journal of Manufacturing Systems, 37 (2018), 649–661.

[29] M. Fareeduddin, A. Hassan, M. N. Syed and S. Selim, The impact of carbon policies on closed-loop supply chain network design, Procedia CIRP, 26 (2015), 335–340.

[30] A. M. Fathollahi-Fard, F. Ghollan-Jouybari, M. M. Paydar and M. Hajiaghaei-Keshteli, A bi-objective stochastic closed-loop supply chain network design problem considering downside risk, Industrial Engineering & Management Systems, 16 (2017), 342–362.

[31] A. M. Fathollahi-Fard and M. Hajiaghaei-Keshteli, A stochastic multi-objective model for a closed-loop supply chain with environmental considerations, Applied Soft Computing, 69 (2018), 232–249.

[32] A. M. FathollahiFard and M. Hajaghaei-Keshteli, A tri-level location-allocation model for forward/reverse supply chain, Applied Soft Computing, 62 (2018b), 328–346.

[33] A. M. Fathollahi-Fard, M. Hajiaghaei-Keshteli and S. Mirjalili, Multi-objective stochastic closed-loop supply chain network design with social considerations, Applied Soft Computing, 71 (2018), 505–525.

[34] Z. Feng, T. Xiao and D. J. Robb, Environmentally responsible closed-loop supply chain models with outsourcing and authorization options, Journal of Cleaner Production, 278 (2021), 123791.

[35] M. R. Galbreth, J. A. Hill and S. Handley, An investigation of the value of cross-docking for supply chain management, Journal of Business Logistic, 29 (2008), 225–239.

[36] H. Gholizadeh and H. Fazlollahtabar, Robust optimization and modified genetic algorithm for a closed loop green supply chain under uncertainty: Case study in melting industry, Computers & Industrial Engineering, 147 (2020), 106653.

[37] M. Ghomi-Avili, S. G. J. Naeini, R. Tavakkoli-Moghaddam and A. Jabbarzadeh, A fuzzy pricing model for a green competitive closed-loop supply chain network design in the presence of disruptions, Journal of Cleaner Production, 188 (2018), 425–442.

[38] A. Goli and S. M. R. Davoodi, Coordination policy for production and delivery scheduling in the closed loop supply chain, Production Engineering, 12 (2018), 621–631.

[39] A. Goli, E. B. Tirkolaee and G.-W. Weber, A perishable product sustainable supply chain network design problem with lead time and customer satisfaction using a hybrid whale-genetic algorithm, Logistics Operations and Management for Recycling and Reuse, (2020), 99–124.

[40] A. Goli, H. K. Zare, R. Tavakkoli-Moghaddam and A. Sadegheih, Multiobjective fuzzy mathematical model for a financially constrained closed-loop supply chain with labor employment, Computational Intelligence, 36 (2020), 4–34.

[41] P. Guarnieri, V. A. Sobreiro, M. S. Nagano and A. L. M. Serrano, The challenge of selecting and evaluating third-party reverse logistics providers in a multicriteria perspective: A Brazilian case, Journal of Cleaner Production, 96 (2015), 209–219.

[42] X. Hong, L. Xu, P. Du and W. Wang, Joint advertising, pricing and collection decisions in a closed-loop supply chain, International Journal of Production Economics, 167 (2015), 12–22.

[43] Z.-H. Hu, J.-B. Sheu, L. Zhao and C.-C. Lu, A dynamic closed-loop vehicle routing problem with uncertainty and incompatible goods, Transportation Research Part C: Emerging Technologies, 55 (2015), 273–297.

[44] H. Huang, Y. He and D. Li, Pricing and inventory decisions in the food supply chain with production disruption and controllable deterioration, Journal of Cleaner Production, 180 (2018), 280–296.

[45] N. Karimi, M. Zandieh and H. R. Karamooz, Bi-objective group scheduling in hybrid flexible flowshop: A multi-phase approach, Expert Systems with Applications, 37 (2010), 4024–4032.

[46] S. Kassem and M. Chen, Solving reverse logistics vehicle routing problems with time windows, The International Journal of Advanced Manufacturing Technology, 68 (2013), 57–68.

[47] O. Kaya and B. Ürek, A mixed integer nonlinear programming model and heuristic solutions for location, inventory and pricing decisions in a closed loop supply chain, Computers & Operations Research, 65 (2016), 93–103.
A. Kheirkhah and S. Rezaei, Using cross-docking operations in a reverse logistics network design: A new approach, Production Engineering, 10 (2016), 175–184.

H. Kim, J. Yang and K.-D. Lee, Vehicle routing in reverse logistics for recycling end-of-life consumer electronic goods in South Korea, Transportation Research Part D: Transport and Environment, 14 (2009), 291–299.

H. J. Ko and G. W. Evans, A genetic algorithm-based heuristic for the dynamic integrated forward/reverse logistics network for 3PLs, Computers & Operations Research, 34 (2007), 346–366.

J. Krrup and P. M. Pruzaan, The simple plant location problem: Survey and synthesis, European Journal of Operational Research, 12 (1983), 36–81.

L. Kroon and G. Vrijens, Returnable containers: An example of reverse logistics, International Journal of Physical Distribution & Logistics Management, 25 (1995), 56–68.

K. Lieckens and N. Vandaele, Reverse logistics network design with stochastic lead times, Computers & Operations Research, 34 (2007), 395–416.

R. Ma, L. Yao, M. Jin, P. Ren and Z.Lv, Robust environmental closed-loop supply chain design under uncertainty, Chaos, Solitons & Fractals, 89 (2016), 195–202.

H. Maghsoudlou, M. R. Kahag, S. T. A. Niaki and H. Pourvaziri, Bi-objective optimization of a three-echelon multi-server supply-chain problem in congested systems: Modeling and solution, Computers & Industrial Engineering, 99 (2016), 41–62.

M. Mahmoudzadeh, J. S. Sadjadi and S. Mansour, Robust optimal dynamic production/pricing policies in a closed-loop system, Applied Mathematical Modelling, 37 (2013), 8141–8161.

B. K. Mawandiya, J. K. Jha and J. Thakkar, Production-inventory model for two-echelon closed-loop supply chain with finite manufacturing and remanufacturing rates, International Journal of Systems Science: Operations & Logistics, 4 (2017), 199–218.

L. Meade and J. Sarkis, A conceptual model for selecting and evaluating third-party reverse logistics providers, Supply Chain Management: An International Journal, 7 (2002), 283–295.

H. Min and H.-J. Ko, The dynamic design of a reverse logistics network from the perspective of third-party logistics service providers, International Journal of Production Economics, 113 (2008), 176–192.

S. Mitra, Inventory management in a two-echelon closed-loop supply chain with correlated demands and returns, Computers & Industrial Engineering, 62 (2012), 870–879.

B. Mohamadpour Tosarkani and S. Hassanzadeh Amin, An environmental optimization model to configure a hybrid forward and reverse supply chain network under uncertainty, Computers & Chemical Engineering, 121 (2019), 540–555.

A. Mohtashami, M. Tavana, F. J. Santos-Arteaga and A. Fallahian-Najafabadi, A novel multi-objective meta-heuristic model for solving cross-docking scheduling problems, Applied Soft Computing, 31 (2015), 30–47.

Z. Mohtashami, A. Aghsami and F. Jolai, A green closed loop supply chain design using queuing system for reducing environmental impact and energy consumption, Journal of Cleaner Production, 242 (2019), 118452.

H. Moradi, M. Zandieh and I. Mahdavi, Non-dominated ranked genetic algorithm for a multi-objective mixed-model assembly line sequencing problem, International Journal of Production Research, 49 (2011), 3479–3499.

S. Nayeri, M. M. Paydar, E. Asadi-Gangraj and S. Emami, Multi-objective fuzzy robust optimization approach to sustainable closed-loop supply chain network design, Computers & Industrial Engineering, 148 (2020), 106716.

K. Pant, V. S. Yadav and A. Singh, Design of multi-tier multi-time horizon closed-loop supply chain network with sustainability under uncertain environment for Indian paper industry, International Journal of Sustainable Engineering, 14 (2020), 107–122.

S. Pazhani, N. Ramkumar, T. T. Narendran and K. Ganesh, A bi-objective network design model for multi-period, multi-product closed-loop supply chain, Journal of Industrial and Production Engineering, 30 (2013), 264–280.

M. S. Pishvaee, R. Z. Farahani and W. Dullaert, A memetic algorithm for bi-objective integrated forward/reverse logistics network design, Computers & Operations Research, 37 (2010), 1100–1112.

M. S. Pishvaee and J. Razmi, Environmental supply chain network design using multi-objective fuzzy mathematical programming, Applied Mathematical Modelling, 36 (2012), 3433–3446.
[70] S. H. A. Rahmati, M. Zandieh and M. Yazdani, Developing two multi-objective evolutionary algorithms for the multi-objective flexible job shop scheduling problem, The International Journal of Advanced Manufacturing Technology, 64 (2013), 915–932.

[71] Y. Ranjbar, H. Sahebi, J. Ashayeri and A. Teymouri, A competitive dual recycling channel in a three-level closed loop supply chain under different power structures: Pricing and collecting decisions, Journal of Cleaner Production, 272 (2020), 122623.

[72] S. Rezaei and A. Kheirkhah, A comprehensive approach in designing a sustainable closed-loop supply chain network using cross-docking operations, Computational and Mathematical Organization Theory, 24 (2018), 51–98.

[73] S. Rezapour, R. Z. Farahani, B. Fahimnia, K. Govindan and Y. Mansouri, Competitive closed-loop supply chain network design with price-dependent demands, Journal of Cleaner Production, 93 (2015), 251–272.

[74] Y. M. B. Saavedra, A. P. B. Barquet, H. Rozenfeld, F. A. Forcellini and A. R. Ometto, Remanufacturing in Brazil: Case studies on the automotive sector, Journal of Cleaner Production, 53 (2013), 267–276.

[75] R. Sadeghi Rad and N. Nahavandi, A novel multi-objective optimization model for integrated problem of green closed loop supply chain network design and quantity discount, Journal of Cleaner Production, 196 (2018), 1549–1565.

[76] N. Sahebjamnia, A. M. Fathollahi-Fard and M. Hajighaei-Kesh teli, Sustainable tire closed-loop supply chain network design: Hybrid metaheuristic algorithms for large-scale networks, Journal of Cleaner Production, 196 (2018), 273–296.

[77] M. Saidi Mehrabad, A. Aazami and A. Goli, A location-allocation model in the multi-level supply chain with multi-objective evolutionary approach, Journal of Industrial and Systems Engineering, 10 (2017), 140–160.

[78] J. R. Schott, Fault Tolerant Design Using Single and Multicriteria Genetic Algorithm Optimization, Master’s thesis, Massachusetts Institute of Technology, Cambridge, 1995.

[79] A. Schrijver, Combinatorial Optimization: Polyhedra and Efficiency, Springer, Berlin, 2003.

[80] F. Sgarbossa and I. Russo, A proactive model in sustainable food supply chain: Insight from a case study, International Journal of Production Economics, 183 (2017), 596–606.

[81] D. Y. Sha and C.-Y. Hsu, A new particle swarm optimization for the open shop scheduling problem, Computers & Operations Research, 35 (2008), 3243–3261.

[82] J. Shi, G. Zhang and J. Sha, Optimal production planning for a multi-product closed loop system with uncertain demand and return, Computers & Operations Research, 38 (2011), 641–650.

[83] Th. Spengler, H. Püchert, T. Penkuhn and O. Rentz, Environmental integrated production and recycling management, European Journal of Operational Research, 97 (1997), 308–326.

[84] G. Taguchi, Introduction to Quality Engineering: Designing Quality Into Products and Processes, Asian Productivity Organization, Tokyo, 1986.

[85] M. Talaei, B. F. Moghaddam, M. S. Pishvaea, A. Bozorgi-Amiri and S. Gholamnejad, A robust fuzzy optimization model for carbon-efficient closed-loop supply chain network design problem: A numerical illustration in electronics industry, Journal of Cleaner Production, 113 (2016), 662–673.

[86] A. A. Taleizadeh, F. Haghighi and S. T. A. Niaki, Modeling and solving a sustainable closed loop supply chain problem with pricing decisions and discounts on returned products, Journal of Cleaner Production, 207 (2019), 163–181.

[87] Z. G. Tao, Z. Y. Guang, S. Hao, H. J. Song and D. G. Xin, Multi-period closed-loop supply chain network equilibrium with carbon emission constraints, Resources, Conservation and Recycling, 104 (2015), 354–365.

[88] S. A. Torabi and E. Hassini, An interactive possibilistic programming approach for multiple objective supply chain master planning, Fuzzy Sets and Systems, 159 (2008), 193–214.

[89] B. Vahdani and M. Mohammadi, A bi-objective interval-stochastic robust optimization model for designing closed loop supply chain network with multi-priority queuing system, International Journal of Production Economics, 170 (2015), 67–87.

[90] V. P. Vinay and R. Sridharan, Taguchi method for parameter design in ACO algorithm for distribution-allocation in a two-stage supply chain, The International Journal of Advanced Manufacturing Technology, 64 (2013), 1333–1343.

[91] N. Zarbakhshnia, H. Soleimani and H. Ghaderi, Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria, Applied Soft Computing, 65 (2018), 307–319.
[92] M. Zhalechian, R. Tavakkoli-Moghaddam, B. Zahiri and M. Mohammadi, Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty, Transportation Research Part E: Logistics and Transportation Review, 89 (2016), 182–214.

[93] M. Zohal and H. Soleimani, Developing an ant colony approach for green closed-loop supply chain network design: A case study in gold industry, Journal of Cleaner Production, 133 (2016), 314–337.

[94] J. P. S. Zuluaga, M. Thiell and R. C. Perales, Reverse cross-docking, Omega, 66 (2017), 48–57.

Received December 2020; revised March 2021.

E-mail address: f.kangi@yahoo.com
E-mail address: shr.pasandideh@khu.ac.ir
E-mail address: emehdi@qiau.ac.ir
E-mail address: hdsoleimani@yahoo.com