An integrated dynamic model to locate a competitive closed-loop supply chain facility under conditions of uncertainty: A case study of the auto parts industry

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Abstract

With the expansion of competitive markets, supply chain management has become one of the critical issues facing businesses. One of the advantages of sustainable competition for companies is to make supply chain activities more efficient and effective. This paper aims at an integrated closed-loop supply chain (CLSC) problem which is multi-objective, multi-product, multi-period, and multi-level with limited capacities and uncertain conditions of demand and return products. The proposed supply chain network consists of five levels in the forward flow. There are five centers in the backward flow as well. The purpose of this network is to determine the optimal number and location of facilities required in each period and the optimal amount of the transfer flow of products or raw materials through different transportation modes between facilities. In this proposed model, three objective functions are taken into consideration. The first one minimizes all the costs. The second objective function maximizes the quality of products. The third objective function seeks to minimize the sum of deviations from the ideal score of the principal component of each supplier. The data of this research are taken from Pishro Diesel Company. To solve the proposed problem, several methods and algorithms have been used, including unscaled goal programming, boundary objectives, three single-objective meta-heuristic algorithms (PSO, RDA, and TGA), and multi-objective meta-heuristic algorithm (MOGA-II). As the results show, considering products and returned parts in products, a simultaneous practice of forward and reverse supply chains leads to better product quality, less damage to the environment, and lower costs for customers.

Keywords: Competitive CLSC network, Facility location, Supplier evaluation, Uncertainty, Product quality, Meta-heuristic algorithms.

1- Introduction

Nowadays, measuring the rate of competition in supply chains is vital in most organizations worldwide [63, 74]. However, it has been shown that many companies do not evaluate the overall performance of their supply chains, and the evaluation of competition in their supply chains is even

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more neglected [27]. With the expansion of the competitive environment, supply chain management has become one of the primary issues facing businesses. It bears upon all the activities to produce products, improve quality, reduce costs, and provide customer services. Over time, organizations have felt a need to shift toward being customer-centered and giving better responses. This shift needs to occur due to such factors as competitiveness of markets, increased focus on technology and customer, shortened life cycle of products, rapid introduction of new products to the market as well as customers' need of high quality, quick response and reliable products and services [26, 69].

With the increasing uncertainty in supply, demand, markets and technology, many companies have used organizational structures with increased flexibility and speed of response to create a fundamental approach to achieving a competitive advantage. Evaluating the best supplier according to the competitive conditions in the market has forced organizations to improve their supply chains in terms of such criteria as price/cost, quality and supply speed. Along with the progress in the economic environment, concerns about environmental and social factors have led companies to pay special attention to reverse supply chains to put used goods back to use and prevent the damage of consumed products to the environment. In addition to environmental benefits, it is crucial in terms of economic and financial opportunities to be competitive in different sections of a closed-loop supply chain (CLSC). The notion of using supply chains has emerged as an attitude for organizations and companies in recent years. In this approach, a component or a loop is supposed to provide a product or a service to the customer. The approach has to do with making strategic, tactical and operational decisions so that supply chains can compete together more efficiently and effectively.

Supply chain management covers the entire supply network, from the initial supply of raw materials to the final products. Supply chain management focuses on how companies use technology and expertise in supply processes to maximize their competitive advantage [12, 70]. A supply chain configuration includes managing materials and information from suppliers to final manufacturers and then to distributors and consumers.

The development of competition and the globalization of product markets have caused organizations to make significant efforts to supply, produce and distribute their goods to meet the various needs of customers in the shortest possible time and at the least cost. In recent years, due to the intensified competition, the concept of competitive advantage has come into special focus of economy and industry. Competitive advantage is the ability of an organization to create a defensible position against competitors. Li et al. (2006) [40] believe that competitive advantage is a clear competency that distinguishes an organization from its competitors and gives it an advantage in the market. They consider this situation as the result of critical management decisions and the consideration of price, quality, reliability and delivery speed as priorities. The time a product takes to reach the consumer is a factor of competitive advantage for an organization. The issue of supply chain competitiveness in this paper is explored in connection with suppliers who compete to meet ideal production standards and minimize the standard deviation from the main criteria. According to many experts, competition has shifted from companies to their supply chains. An efficient and agile supply chain is a significant and decisive competitive advantage that can be of benefit at both quality and quality levels. As a product flows from one member of a supply chain to another, its quality may be affected by rival companies. Also, according to some paradigms newly proposed in business, competitive advantage is simultaneously based on three factors including competitive quality, competitive delivery and competitive price [37, 71]. Since competitive quality is a matter of quality management and competitive delivery is dealt with in the field of supply chain management, and it seems necessary to integrate quality management and supply chain management. In a CLCS, where products are made in a forward supply chain and regenerated products are processed in a reverse supply chain, the importance of quality is obvious, and maximum quality is essential alongside other goals.

In this paper, an integrated multi-layered multi-product closed-loop dynamic competitive supply chain network is proposed with limited capacities and uncertainty in demand and return products. The network is, indeed, a mixed-integer linear programming (MILP) model. Given the importance of supplier selection in a competitive supply chain, it is considered an objective and placed next to several other ones, such as minimizing the costs of construction and transportation costs and maximizing the quality. Maximizing quality is in complete conflict with reducing costs. This is because producing higher-quality goods naturally leads to higher costs. Also, to minimize the deviation of points, the main component of the supplier comes into conflict with the ideal criteria; the quality of most products reflects the ideals and criteria pursued to supply those products. So, attempts are made to minimize the deviation of the principal component scores from the ideal criteria. Given that there is a cost of purchasing the product from the supplier in the objective function, cost minimization gains importance in supplier selection. The more costs decrease, the more the deviation of the supplier's principal component increases from the ideal criteria. Because the criteria are correlated and the cost affects the other criteria, the model in this study is a multi-objective one.

This type of supplier selection is applied in real world conditions when, in addition to cost reduction, other criteria are important for managers too. In today's industrial world, some factors like the quality of the product and the delivery time are more important than the cost. Also, the correlation among these criteria may lead to wrong decisions. To avoid any error, it is better to eliminate that correlation.

Based on the above-explained issues, this study tries to bridge the gap in the literature by answering the following questions:

- How to minimize supply chain costs, maximize product quality, and evaluate and select suppliers by providing a dynamic and integrated mathematical model of forward/reverse competitive supply chain?
- According to the criteria for selecting suppliers in a competitive environment, which of the suppliers surpasses the other competitors in purchasing primitive parts?
- When and where should we provide facilities to minimize transportation costs between centers and layers?
- To maximize the quality of the products according to the returned parts, how much of each part should be used to manufacture the product?
- How much material flow is exchanged by different transport types between the centers in the network?

The network studied in this paper is an integrated model of a closed-loop dynamic supply chain to support industries which perform reproduction and reconstruction operations, burial of non-renewable materials and recycling of end-of-life products. By and large, the proposed network is a promising one for industries such as automotive, electronics, digital equipment, and all those that seek to gain a competitive advantage.

The present research is innovative in terms of configuration, the number of levels, some goals, and solution methods as follows:

- Designing a dynamic and integrated reverse competitive supply chain network which is multi-objective, multi-period and multi-product as well as using certain transportation modes to minimize the costs and maximize the quality;

- Evaluation and selection of suppliers according to the criteria of price/cost, quality, and delivery time in competitive conditions;
- Considering the uncertainty of demand in both a forward supply chain and the return products in a reverse supply chain simultaneously;
- Locating centers for manufacture, distribution, collection, inspection, disposal, and recycling simultaneously in an integrated mathematical model in a competitive environment;
- Considering different capacities for combined facilities;
- Making the model dynamic in terms of supplier selection in each period and inventory according to previous periods;
- Comparing and evaluating the proposed model according to PSO, TGA, and RDA, as three new single-objective meta-heuristic algorithms, and MOGA-II, as a new multi-objective meta-heuristic algorithm, to achieve the best solution;
- Optimizing the three main objectives of the proposed closed-loop competitive supply chain (i.e., minimizing costs, maximizing product quality, and minimizing supplier components to select the best supplier) simultaneously;
- Establishing optimal flows of products or raw materials by different transportation modes among all the facilities interconnected within the closed-loop competitive supply chain network.

The rest of the manuscript is organized in several parts. In the second part, the literature on supply chain design models and their variety is reviewed. In the third part, the problem is explained. The proposed mathematical model for a CLCS in multi-objective, multi-product, multi-level and sustainable conditions is presented in the fourth part. In the fifth part, the solution methods are introduced. In this paper, the unscaled goal programming method, boundary objectives, three new single-objective meta-heuristic algorithms, and a new multi-objective meta-heuristic algorithm are used to solve the model. In the sixth part, numerical examples are taken from the selected company as a case study, the model is solved by GAMS and MATLAB, and then the computational results are presented to show the performance of different model modes and the proposed solution methods. Parameter tuning for the proposed meta-heuristic algorithms and the analysis of the proposed solution methods are conducted in this section. Finally, in the seventh part, the conclusion of the study is presented along with some suggestions for future research.

2- Literature Review

This section is dedicated to the review of some studies in the field of competitive CLCS networks. Each study is carefully described, and the critical decisions made in it are extracted. The review of the studies on supply chains is presented in four general sections.

A) *Supply chain network designs*

A supply chain network design is based on the efficiency of strategic factors and customer needs. One of the most critical decisions in a supply chain regards the location of facilities and the allocation of flows among the selected facilities. This decision is made at a strategic level. In the case of discrete facility location, a limited number of locations can be used as candidates for a new facility. The simplest way to deal with this issue in network design is to deploy facilities in such a way as to minimize the total distances or the costs of meeting customer demands [22, 72]. In the literature, this task is generally known as facility location, regardless of capacity. Also, each customer is assigned to a certain facility so as to minimize the total costs [50]. This has emerged as an important development in locating facilities without considering the capacity. Drezner and Wesolowsky (2003) [25] presented a single-layer location model for a certain period. This network design model involved two problems. Ambrosino and Scutella (2005) [5] presented a dynamic model for a multilayer network that took the product flow into account. The proposed model included such factors as central distribution centers, local distribution centers, and customers or demand points. Govindan et al. (2015) [31] comprehensively reviewed the studies on reverse chains and closed loops. In the field of closed-loop supply chain management, Schenkel et al. (2015) [54] examined some useful factors to create value for shareholders in a closed-loop supply chain. Zikopoulos and Tagaras, (2015) [67] analyzed the quality of the returned products in a closed-loop supply chain under uncertainty. They analyzed the solution method's cost and accuracy for profitability with a straightforward numerical method. Abdolazimi et al. (2020) [2] also designed a forward supply chain to group items in stock based on ABC analysis. Their supply chain was a three-layer one including suppliers, a central warehouse and various local warehouses.

Another critical development in network design models has been the consideration of uncertain parameters. It regards the assumption of uncertainty in some parameters, such as the demand and supply of goods for future customers [41]. In a study by Snyder et al. (2007) [59], a supply chain network model was presented with uncertain parameters to optimize the network's location and inventory. Indeed, the model sought to determine distribution centers to provide services to retailers and thus to minimize costs. The uncertain demand was considered as a probabilistic function. Another attempt in this field was made by Qi and Shen (2007) [47]. They devised a nonlinear model and studied the effect of strategic decisions (e.g., on facility location) on tactical decisions (e.g., on inventory and transportation) in the network. In this model, the demand of each customer was uncertain and followed a specific probability function. In situations where no estimate is available regarding probability distribution functions or parameter behavior and there is no complete certainty about the accuracy of the collected data, a robust optimization approach may be of benefit. Goyal, (2010) [14] used such a robust model to solve possible two-stage problems. Similarly, Chen et al. (2007) [17] came up with a model of this kind where the demand parameter was considered uncertain and fuzzy. Also, Jin et al. (2009) [38] considered fuzzy uncertainty for the rate of returned products and their quality level for reuse. In a similar case, Abdolazimi et al. (2020) [3] considered uncertainty for the demand parameter. Their proposed model was implemented in the tire industry, and two robust optimization approaches, including scenario-based and Soyster modes, were used to deal with uncertainty. Shavazipour et al. (2020) [55] performed strategic planning for a sugar-bioethanol supply chain under uncertainty using a multi-objective optimization method based on a two-stage scenario. In another study, Abdel-Basset et al. (2020) [1] conducted a set of measurements to finance a sustainable supply chain in the gas industry under conditions of uncertainty. Hosseini-Motlagh et al. (2020) [34], did a case study in the real world to address the issues of uncertainty in the design of robust and sustainable power supply networks. Because uncertainty always exists in the prediction of electricity demand, a complete foresight is not possible. Therefore, the researchers proposed a new way of dealing with electricity demand uncertainty based on a robust optimization approach and a possibilistic theory in fuzzy logic.

I) *Investigation of network design models based on decision levels*

In supply chain management, there are the three levels of strategic, tactical and operational decision making. At the strategic level, the decisions to consider are those with long-term effects on facilities. At this level, decisions are made on the number, location and capacity of facilities as well as the material flow in logistics networks. Given the nature of decisions at the strategic level, they also significantly impact tactical-level decisions. Therefore, due to the interrelationship of the decisions at these levels, a simultaneous review of those decisions can greatly reduce costs and, thus, make decisions more effective [47, 73]. In this section, the papers in the network design literature are examined based on the relationship between the decision levels in them. In the following, three fundamental and famous models in this field, namely the location-allocation-inventory model in network design, location-allocation-routing model in network design, and location-allocation-inventory-routing model in network design, are examined. Many researches work on network design have offered models that simultaneously optimize the location-allocation and inventory issues. One of them is by Ameli et al. (2009) [6], who presented a network design model to simultaneously optimize inventory, location, and allocation decisions. In this model, customer demand and the delivery time of distribution centers are uncertain and have a normal distribution. As a whole, location-allocation-routing models solve the problem of determining the optimal number, capacity, and location of service facilities for more than one supplier or customer, the amount of flow between different layers of the network as well as the optimal set of timing and routes for vehicles [58, 75]. Due to the importance of these issues, Lashine et al. (2006) [39] discussed simultaneous decision-making on location-allocation and routing issues. The purpose of that study was to present a model of minimizing the total costs of transportation and routes as well as the fixed and variable costs of allocating warehouses to factories and retailers. Besides, Amiri (2006) [7] presented a location-allocation-routing model for the design of a distribution network. This linear model sought to determine the number, location and capacity of the warehouses and factories in the distribution network. Due to the importance of simultaneous decisions at strategic and tactical levels, many studies have presented models that consider these decisions simultaneously. Thanh et al. (2008) [62] worked out a linear model to design and plan a production and distribution system. This was a multi-period, multi-product and multi-layer model with a particular demand. Among the characteristics of this model, one may refer to the structure of the parts in the model and the division of materials into the three categories of final products, semi-finished materials and raw materials.

II) *Investigation of solution methods in network design*

Due to the NP-hard nature of most network design models, the method of solving these models is of great importance. In this section, several such methods are examined. The main ones are the exact method, heuristic algorithms, and meta-heuristic algorithms. Cornuejols (2007) [20] used the branching and cutting method as a hybrid optimization one to solve integer programming problems. It, indeed, involved a combination of branching and bound as well as cutting plan procedures. Obreque et al. (2010) [45] proposed an algorithm for hierarchical network design problems to minimize the cost in a multi-level space in the network. To solve this model, a three-step algorithm based on the branch and cut method was applied. The responses of the algorithm were compared with the results reported in the literature, and significant improvements were achieved in the solution. Also, Abdolazimi et al. (2020) [3] used the method of exact solution through ε-constraint and LP-metric procedures, and then compared them presenting two robust planning approaches.

Many heuristic algorithms have been proposed to solve network design models. Dai et al. (2020) [21] coped with the cost of loss due to the corruption of perishable products. It was assumed that demand would depend on price and stocks. The models proposed in that study were nonlinear mixed-integer programming and NP-hard. To solve these models, a heuristic hybrid algorithm was developed as a combination of the cuckoo algorithm and the improved Clarke-Wright savings algorithm. Gunpinar and Centeno (2016) [32] modeled a vehicle navigation problem to manage a blood center in a blood collection system. They used an integer programming approach to detect the number of blood collection vehicles and reduce the distances traveled by them. The model was developed under uncertainty, and the heuristic branch and price algorithms were used to solve it. Zheng et al. (2020)

[65] performed production planning for a sustainable supply chain, taking into account factors such as CO_2 emission constraints, random demand, service level, and inventory capacity. They developed a mixed-integer programming model and devised a heuristic Lagrange Relaxation algorithm for the cost-effective planning of large-scale production. The location-inventory routing problem is in the NP-hard category. Solving a large-scale problem requires a heuristic method that can be applied to the system's actual state. Saragih et al. (2019) [51] developed a heuristic approach to a location-inventory routing problem in a three-level supply chain system in which inventory decisions were made in three inputs. The entities involved in the system were single suppliers, multiple warehouses, and several retailers. The heuristic algorithm consisted of two construction phases and an improvement phase. In the improvement phase, there were three steps developed to improve the iterative solution. The phases included position, inventory, and routing.

Depending on their structure, meta-heuristic algorithms can achieve general or optimal solutions. Using them is very efficient in problems with very large dimensions. In the future, these algorithms as well as other meta-heuristic algorithms make it possible to solve more realistic problems that require more data [42, 76]. Ameli et al. (2009) [6] used a two-step taboo search method to solve their model. In the first stage, a standard taboo search method was devised. In the second stage, the answers obtained in the first stage were improved through four movements. Haghjoo et al. (2020) [33] offered a dynamic, robust location-allocation model to design a blood supply chain network under the risks of facility disruption and uncertainty in a disaster situation. Two self-adaptive imperialist competitive algorithms were introduced along with invasive weed optimization to solve the model on a large scale. Shoja et al. (2019) [56] provided a mixed-integer linear programming (MILP) model for a multi-product four-stage flexible supply chain network design (SCND) problem in a reliable transport environment. Since the problem was NP-hard, meta-heuristic algorithms had to be used to solve it. For this purpose, ten classical and adaptive meta-heuristic algorithms were developed. Finally, Abdolazimi et al. (2020) [2] proposed a supply chain to control inventory based on ABC analysis. They used exact LP-metric and ε-constraint methods for their small-scale model as well as two meta-heuristic algorithms including MOPSO and NSGA-II for their large-scale model. The results showed the efficiency of the proposed methods and algorithms.

B) *Supplier selection*

Supplier selection is another important issue that should be considered by manufacturers in a CLSC. Its significance lies in its impact on the core activities required to manage CLSCs [46]. Supplier selection is defined as the method of identifying suitable suppliers who can provide services or products of appropriate quality to buyers at a reasonable and accurate price, at the right time, and in the right numbers [52]. Choosing the right supplier can be considered as an essential factor for a company to compete in today's global market [28]. Being essential is mainly due to its direct effect on the total purchase cost, i.e., costs of components, parts, and raw materials [53]. Therefore, purchasing is a fundamental task [23]. Choosing the right supplier not only reduces operating costs but also increases market competition. In addition, identifying the best supplier increases customer satisfaction [60]. Selecting the right suppliers is based on different criteria such as price, quality, customer service, and delivery time. Since cooperation with the right supplier has become a key factor for the sustainable continuation of business, the supplier's evaluation and selection serves as a vital component of supply chain management [9]. Azadi et al. (2015) [10] evaluated suppliers by data envelopment analysis (DEA) and measured Russell to select the best supplier. They showed the supplier's important role in a sustainable supply chain concerning data output. The choice of a supplier for decision-makers is considered as a factor to deal with environmental, economic and social factors. Hishamuddin et al., (2015) [35] investigated transportation disruptions and supplier selection in a supply chain network with three layers including suppliers, manufacturers, and retailers. The purpose of this study was to investigate the effects of disruption on the total network recovery costs. Once different scenarios were used in combination with disruptions, the transportation disruption proved to have more destructive effects on the supplier. According to Rajesh and Ravi (2015) [48], supplier selection is a challenging issue and an inevitable source of external risks in a supply chain. Bashiri and Sherafati (2012) [11] discussed a closed-loop supply chain network with fuzzy parameters and selected the best supplier. Supplier evaluation in the present study is derived from the supplier evaluation in [11]. This is because the evaluation and selection of suppliers in that study is closer to reality and seems competitive. Finally, Abdolazimi et al. (2020) [3] selected internal and external suppliers based on the delivery time as a separate objective function in their proposed model. Since supplier selection is based on different criteria, multi-objective programming techniques can be of benefit. In other words, the decision-making process in supplier selection problems is multi-objective.

C) *Supply chain quality management*

Robinson and Malhotra, (2005) [49] defined supply chain quality management as the formal coordination and integration of business processes of all organizations involved in a supply chain to measure, analyze and continuously improve the quality of products, services, and processes, leads to creation of value added and achievement of the satisfaction of the middle and final customers. In this regard, Nagurney et al. (2015) [44] examined a competitive supply chain network in the field of competition on quality and price in transport providers in both static and dynamic modes. Evaluation of shipping types was considered according to quality and price. Finally, by providing the qualitative properties of an equilibrium price and quality model and evaluating it by an exact algorithm, they showed the importance of product quality over profitability. Bhattacharya and Kaur (2015) [15] considered a multi-layer, single-period closed-loop supply chain whose reverse supply chain layer included the reproduction, recycling, and remanufacturing of returned products. The main discussion was the variability of price and quality in each layer of this supply chain. Seifbarghy et al. (2015) [57] presented a forward supply chain with manufacturer and retailer as two layers. It delivered the final products to a competitive market that was price-sensitive. The model was optimized in both centralized and decentralized conditions. Finally, the price value and the quality degree were determined, and customers were divided into price-oriented and quality-oriented. The percentage of the potential quality-oriented customers was higher than that of the price-oriented ones, indicating that quality is more important than price in a competitive market. Zhao et al. (2021) [64] developed a comprehensive model to investigate the impact of integrating agro-food supply chains that consisted of internal suppliers and customers on agricultural product quality and financial performance. The findings showed that internal integration and supplier integration are important factors to improve the product quality in a food supply chain. Besides, the product quality fully mediated the relationship between internal integration and financial performance and the relationship between supplier integration and financial performance. This study also showed that ensuring product quality and food safety achieves better financial performance for agro-food processing businesses. In their study, Zhou and Li (2020) [66] used the data collected from 138 small and medium-sized enterprises (SMEs) in China to examine the impact of supply chain and quality management practices on firm business performance. The business performance included market share performance and innovation performance. The results showed that a) supply chain information sharing has a significant positive effect on quality management practices and supplier-specific investment, and b) quality management practices and the specific investment of the supplier have a positive impact on market share performance and innovation performance. Many recent researchers have hypothesized that items which do not match in quality can be sold in the secondary market at a lower price. They ignore secondary customers' demand and, instead, assume that low-quality items can be sold. The following main insights were obtained in the research by Beranek and Buscher (2020) [13] who introduced price and quality-dependent demand for primary and secondary markets: a) a limited secondary market leads to more realistic results compared to an unlimited case; secondary demand can be ignored only in certain circumstances; b) decisions on quality are mainly influenced by both primary and secondary market parameters as well as quality cost parameters; finally, c) in some cases, the lack of service to the secondary market and the focus of the sales process on the main customers are not beneficial.

D) *Research gap*

Designing a supply chain is a strategic decision to determine the locations, facilities, inventories, and the amount of flow in a network. Designating the location of production and distribution centers and the other designed centers in a supply chain is necessary to meet the objectives, mainly to minimize costs and maximize profits, customer satisfaction and quality. In addition, choosing the best suppliers can significantly reduce the purchasing costs and increase the organization's competitiveness. In most industries, the cost of raw materials and product components accounts for a large part of the production cost. Hence, determining the most appropriate supplier is considered as a strategic task in a supply chain [24].

3- Problem Description

In this section, the specifications and assumptions of the proposed model are fully explained. The supply chain network discussed in this research is multi-layer, multi-product and multi-period with the possibility of product return. The network layers are suppliers, production centers (factories), warehousing producers, distribution and collection centers, inspection and reconstruction centers, recycling centers, disposal centers, and customers. For a better understanding, an overview of the supply chain is given in **Figure 1**.

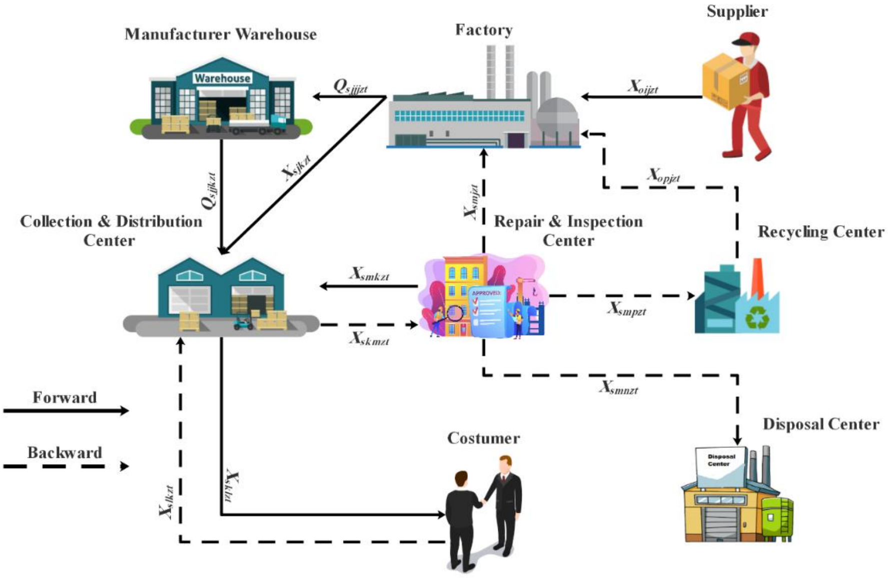

Figure 1. The proposed supply chain

In general, in an integrated logistics network, hybrid facilities are advantageous over separate distribution and collection centers. In a reverse mode, returned products are shipped by customers to inspection centers through combined distribution-collection centers. The management of all the reverse flows is centralized in the inspection center. The concentration of flow management in one center improves the control of product recovery processes. In inspection centers, returned products are classified as recyclable and non-recyclable, and recyclable products are considered as recoverable. Recoverable products are sent to manufacturers, produced again as raw or upgraded parts, and turned into valuable goods. These products are repaired in the same inspection center by repair experts and sent to distribution centers as goods for sale. Some returned products sent to recycling centers enter the production cycle as raw materials for manufacturers. Non-recoverable, non-marketable, and non-repairable or reproducible products are, however, shipped from inspection centers to disposal centers.

The network studied in this research is a logistics network with limited capacities as well as uncertainty in demand and returned products. Also, the presented model is a mixed-integer linear programming (MILP) one. Given the importance of supplier selection in the supply chain, it is an objective function placed alongside several other ones such as minimizing supply chain costs and maximizing quality. According to some criteria such as price/cost, quality and delivery time, supplier evaluation in competitive conditions is considered as a factor in the category of suppliers.

3.1. *Main Assumptions*

- The capacity of the facilities (including supplier, production center, distribution center, repair, and recycling center) is limited;
- The location of customer areas and the location of suppliers and manufacturers are fixed and predetermined;
- The potential locations for establishing distribution, collection, repair and recycling centers are known and discrete;
- The model is multi-product and multi-period;
- In each layer of the network, it is possible to provide the required resources from several or all of the previous layer centers;
- There is a possibility that a customer will get a damaged product;
- In case of delay in payment, the customer is not lost, and the late payment cost is considered in the competitive part of the supplier selection;
- There are different capacity levels for distribution centers in each potential location;
- Demand and returned products are considered uncertain;
- All the products sent to the recycling centers can be recycled and sent to the factory.

4- Mathematical Model

In this section, according to the gaps in the design of supply chain networks for competitive CLCS, as reported in the literature, a model with three objective functions and the afore-mentioned layers is proposed to design a supply chain network.

4.1. ***Sets***

i Suppliers
j Manufacturers
jj Manufacturers' warehouse
k Candidate locations for distribution and collection centers
l Customers
m Candidate locations for inspection and reconstruction centers
p Candidate places for recycling centers

n Candidate places for disposal centers
s Products
o Parts (raw materials)
t Periods
z Transportation modes

4.2. ***Parameters***

F_{kt} Fixed cost of opening distribution and collection centers at location k in period t
F_{mt} Fixed cost of opening inspection and reconstruction centers at location m in period t
F_{pt} Fixed cost of opening recycling centers at location p in period t
F_{nt} Fixed cost of opening disposal centers at location n in period t
C_{oijzt} Transportation costs for each part o from supplier i to production/rehabilitation center j with transportation mode z in period t
C_{sjkzt} Transportation costs for each product s from the production/rehabilitation center j to distribution center k with transportation mode z in period t
C_{sklzt} Transportation costs for each product s from distribution center k to customer l with transportation mode z in period t
C_{slkzt} Transportation costs for each product s from customer l to distribution center k with transportation mode z in period t
C_{skmzt} Transportation costs for each product s from distribution center k to inspection center m with transportation mode z in period t
C_{smnzt} Transportation costs for each product s from inspection center m to disposal center n with transportation mode z in period t
C_{smpzt} Transportation costs for each product s from inspection center m to recycling center p with transportation mode z in period t
C_{smjzt} Transportation costs for each product s from inspection center m to production center/rehabilitation center j with transportation mode z in period t
C_{smkzt} Transportation costs for each product s from inspection center m to distribution center k with transportation mode z in period t
C_{spjzt} Transportation costs for each product s from recycling center p to production center/rehabilitation center j with transportation mode z in period t
G_{oit} Purchasing cost for each part o from supplier i in period t
G_{sjjt} Purchasing cost for each product s from manufacturer's warehouse jj in period t
Ca_{oit} The maximum amount for each part o by supplier i in period t
Ca_{sjt} The capacity of production center j for each product s in period t
Ca_{jjt} The capacity of manufacturer’s warehouse jj in period t
Cr_{jt} The capacity of production/rehabilitation center j for reproducing products in period t
Ca_{kt} The capacity of distribution center k in period t
Cr_{kt} The capacity of distribution center k for repaired products in period t
Ca_{mt} The capacity of inspection and reconstruction center m in period t
Ca_{pt} The capacity of recycling center p in period t
Ca_{nt} The capacity of disposal center n in period t
Cp_{jt} The capacity of production/rehabilitation center j for recycled parts in period t
Cs_{kt} The capacity of collection center k for returned products in period t
Q_{otpj} Quality of part o from recycling center p to production/rehabilitation center j in period t
Q'_{otij} Quality of part o from supplier i to production/rehabilitation center j in period t
d_{slt} The demand of product s from customer l in period t

r_{slt}	The return rate of product *s* from customer *l* in period *t*
β_{smjt}	The return rate of product *s* from inspection center *m* to production/rehabilitation center *j* in period *t*
β_{smpt}	The return rate of product *s* from inspection center *m* to recycling center *p* in period *t*
β_{smnt}	The return rate of product *s* from inspection center *m* to disposal center *n* in period *t*
β_{smkt}	The return rate of product *s* from the inspection center *m* to distribution center *k* in period *t*
η_t	The return rate of part *o* from recycling center *p* to production/rehabilitation center *j* in period *t*
δ_{os}	Number of part *o* to produce a final product *s*

4.3. ***Decision variables***

X_{oijzt}	Quantity of part *o* from supplier *i* to production/rehabilitation center *j* by transportation mode *z* in period *t*
X_{sjkzt}	Quantity of product *s* from production/rehabilitation center *j* to distribution center *k* by transportation mode *z* in period *t*
Q_{sjjjzt}	Quantity of product *s* from production/rehabilitation center *j* to manufacturer's warehouse *jj* by transportation mode *z* in period *t*
X_{sklzt}	Quantity of product *s* from distribution center *k* to customer *l* by transportation mode *z* in period *t*
Q_{sjjkzt}	Quantity of returned product *s* from manufacturer's warehouse *jj* to distribution center *k* by transportation mode *z* in period *t*
X_{slkzt}	Quantity of returned product *s* from customer *l* to collection center *k* by transportation mode *z* in period *t*
X_{skmzt}	Quantity of returned product *s* from collection center *k* to inspection center *m* by transportation mode *z* in period *t*
X_{smpzt}	Quantity of returned product *s* from inspection center *m* to recycling center *p* by transportation mode *z* in period *t*
X_{smnzt}	Quantity of returned product *s* from inspection center *m* to disposal center *n* by transportation mode *z* in period *t*
X_{smjzt}	Quantity of returned product *s* from inspection center *m* to production/rehabilitation center *j* by transportation mode *z* in period *t*
X_{smkzt}	Quantity of returned product *s* from inspection center *m* to distribution center *k* by transportation mode *z* in period *t*
X_{opjzt}	Quantity of returned part *o* from recycling center *p* to production/rehabilitation center *j* by transportation mode *z* in period *t*
U_{sjjt}	Amount of inventory in manufacturer's warehouse *jj* in period *t*
Y_m	If inspection and reconstruction center *m* is opened, 1; otherwise, 0
Y_k	If distribution and collection center *k* is opened, 1; otherwise, 0
Y_p	If recycling center *p* is opened, 1; otherwise, 0
Y_n	If disposal center *n* is opened, 1; otherwise, 0
Y_i	If supplier *i* is one of the main centers of the supply chain, 1; otherwise, 0

According to the symbols and descriptions above, the MILP model of designing an integrated forward and reverse competitive supply chain network is presented as follows:

$$\begin{aligned}\text{Min } Z_1 = & \sum_t \sum_m f_{mt} Y_{mt} + \sum_t \sum_n f_{nt} Y_n + \sum_t \sum_p f_{pt} Y_p + \sum_t \sum_k f_{kt} Y_k \\ & \sum_t \sum_o \sum_i G_{oit} Y_i + \sum_t \sum_s \sum_{jj} G_{sjjt} U_{jjt} \\ & \sum_t \sum_z \sum_o \sum_j \sum_i C_{oijzt} X_{oijzt} + \sum_t \sum_z \sum_s \sum_k \sum_j C_{sjkzt} X_{sjkzt} + \sum_t \sum_z \sum_s \sum_l \sum_k C_{sklzt} X_{sklzt} \\ & + \sum_t \sum_z \sum_s \sum_k \sum_l C_{slkzt} X_{slkzt} + \sum_t \sum_z \sum_s \sum_m \sum_k C_{skmzt} X_{skmzt} + \sum_t \sum_z \sum_s \sum_n \sum_m C_{smnzt} X_{smnz} \\ & + \sum_t \sum_z \sum_s \sum_p \sum_m C_{smpzt} X_{smpzt} + \sum_t \sum_z \sum_s \sum_j \sum_m C_{smjzt} X_{smjzt} + \sum_t \sum_z \sum_s \sum_k \sum_m C_{smkzt} X_{smkzt} \\ & + \sum_t \sum_z \sum_o \sum_j \sum_p C_{opjzt} X_{opjzt}\end{aligned} \tag{1}$$

$$\text{Max } Z_2 = \sum_t \sum_z \sum_o \sum_j \sum_p \sum_i (Q_{ot} X_{opjzt} + Q'_{ot} X_{oijzt}) \tag{2}$$

$$\text{Min } Z_3 = \sum_i PCDSS_i Y_i \tag{3}$$

4.4. *Capacity constraints*

$$\sum_z \sum_s \sum_m X_{smjzt} \le \sum_s Ca_{sjt} \qquad \forall t, j \tag{4}$$

$$\sum_o \sum_i \sum_z X_{oijzt} \le \sum_o \sum_i Ca_{oit} \qquad \forall t, j \tag{5}$$

$$\sum_o \sum_p \sum_z X_{opjzt} \le Cr_{jt} \qquad \forall t, j \tag{6}$$

$$\sum_z \sum_s \sum_m X_{smnzt} \le Ca_{nt} \qquad \forall t, n \tag{7}$$

$$\sum_z \sum_s \sum_m X_{smpzt} \le Ca_{pt} \qquad \forall t, p \tag{8}$$

$$\sum_z \sum_s \sum_l X_{slkzt} + \sum_z \sum_s \sum_{jj} Q_{sjjkzt} \le Cs_{kt} \qquad \forall t, k \tag{9}$$

$$\sum_z \sum_s \sum_k X_{skmzt} \le Ca_{mt} \qquad \forall t, m \tag{10}$$

$$\sum_z \sum_s \sum_k X_{sjkzt} \le \sum_k Ca_{kt} \qquad \forall t, j \tag{11}$$

$$\sum_z \sum_s \sum_k X_{smkzt} \le \sum_k Cr_{kt} \qquad \forall t, m \tag{12}$$

$$\sum_z \sum_s \sum_j Q_{sjjjzt} \le Ca_{jjt} \qquad \forall t, jj \tag{13}$$

4.5. *Constraints on the return of products*

$$\sum_z \sum_p X_{smpzt} = \sum_p \beta_{smpt} \sum_z \sum_k X_{skmzt} \qquad \forall m, t, s \tag{14}$$

$$\sum_z \sum_n X_{smnzt} = \sum_n \beta_{smnt} \sum_z \sum_k X_{skmzt} \qquad \forall m, t, s \tag{15}$$

$$\sum_z \sum_j X_{smjzt} = \sum_j \beta_{smjt} \sum_z \sum_k X_{skmzt} \qquad \forall m, t, s \tag{16}$$

$$\sum_z \sum_k X_{smkzt} = \sum_k \beta_{smkt} \sum_z \sum_k X_{skmzt} \qquad \forall m, t, s \tag{17}$$

$$\sum_m \sum_p \beta_{smpt} + \sum_m \sum_n \beta_{smnt} + \sum_m \sum_j \beta_{smjt} + \sum_m \sum_k \beta_{smkt} = 1 \qquad \forall t, s \tag{18}$$

4.6. *Demand constraints of product and returned product*

$$P(\sum_{z}\sum_{k}X_{sklzt} \le d_{slt}) \ge 1-\alpha \qquad \forall s,l,t \tag{19}$$

$$P(\sum_{z}\sum_{k}X_{slkzt} \le r_{slt}) \ge 1-\alpha \qquad \forall s,l,t \tag{20}$$

4.7. *Constraints of equilibrium among centers*

$$\sum_{z}\sum_{o}\sum_{p}X_{opjzt} + \sum_{s}\sum_{m}\sum_{z}X_{smjzt} + \sum_{o}\sum_{i}\sum_{z}X_{oijzt} = \sum_{s}\sum_{jj}\sum_{z}Q_{sjjjzt} + \sum_{s}\sum_{k}\sum_{z}X_{sjkzt} \qquad \forall j,t \tag{21}$$

$$\sum_{z}\sum_{j}X_{sjkzt} + \sum_{jj}\sum_{z}Q_{sjjkzt} + \sum_{m}\sum_{z}X_{smkzt} + \sum_{l}\sum_{z}X_{slkzt} = \sum_{m}\sum_{z}X_{skmzt} + \sum_{l}\sum_{z}X_{sklzt} \qquad \forall s,k,t \tag{22}$$

$$\sum_{z}\sum_{k}X_{skmzt} = \sum_{z}\sum_{k}X_{smkzt} + \sum_{z}\sum_{p}X_{smpzt} + \sum_{z}\sum_{n}X_{smnzt} + \sum_{z}\sum_{j}X_{smjzt} \qquad \forall s,m,t \tag{23}$$

$$\sum_{z}\sum_{j}Q_{sjjjzt} = \sum_{z}\sum_{k}X_{sjjkzt} \qquad \forall s,jj,t \tag{24}$$

$$\sum_{z}\sum_{m}\sum_{s}X_{smpzt} = \sum_{z}\sum_{o}\sum_{j}X_{opjzt} \qquad \forall p,t \tag{25}$$

4.8. *Constraints of center construction*

$$\sum_{m}Y_{m} \le M \tag{26}$$

$$\sum_{k}Y_{k} \le K \tag{27}$$

$$\sum_{p}Y_{p} \le P \tag{28}$$

$$\sum_{n}Y_{n} \le N \tag{29}$$

$$\sum_{i}Y_{i} \le I \tag{30}$$

$$X_{slkzt},\ X_{skmzt},\ X_{smpzt},\ X_{smnzt},\ X_{smkzt},\ X_{opjzt},\ X_{sjkzt},\ X_{sklzt},\ Q_{sjjjzt},\ Q_{sjjkzt},\ U_{sjjt} \ge 0 \tag{31}$$

$$Y_{i},\ Y_{n},\ Y_{p},\ Y_{k},\ Y_{m} \in \{0,1\} \tag{32}$$

Objective function (1) seeks to minimize the fixed costs of opening inspection and reconstruction centers, disposal centers, recycling centers as well as distribution and collection centers. It also deals with the purchasing cost per unit of product from supplier, holding cost of each product in the manufacturer's warehouse, transportation cost of parts from supplier to manufacturer, transportation cost of products from manufacturer to distributor, transportation cost of products from the manufacturer's warehouse to distributor, transportation cost of products from distribution centers to customers, transportation cost of the products returned from customer to distribution centers, transportation cost of the products returned from distribution centers to inspection and reconstruction centers, transportation cost of the products returned from inspection and reconstruction centers to disposal centers, transportation cost of the products returned from inspection and reconstruction centers to recycling centers, transportation cost of the products returned from inspection and reconstruction centers to production/rehabilitation centers, transportation cost of the products returned from inspection and reconstruction centers to distribution centers, and transportation cost of the parts returned from recycling centers to production/rehabilitation centers.

Objective function (2) maximizes the quality of products according to the parts produced by recycling and the parts delivered from the supplier to the manufacturer. This objective function also includes the quality of the parts returned from recycling and the quality of the supplier's parts.

Finally, objective function (3), according to the final score of the main component of each supplier, seeks to select the best supplier. Here is the procedure of calculating the final score of the main component of the suppliers. Assume that decision making is done to select suppliers based on such criteria as price appropriateness, price stability, quality of raw materials, delivery time, capability, flexibility and reliability. These criteria are correlated with one another. Through the analysis of the principal components while reducing the criteria dimensions, new criteria are identified independently. Analyzing the principal components is done for the supplier and ultimately decided on in the form of the third objective function. There will be a matrix of different criteria and supply chain components. The score of each supplier component in each criterion will be accompanied by a certain degree of membership.

Furthermore, the primary input data for calculating the principal component relationship are the variance-covariance matrix. Therefore, it is necessary to extract the matrix from fuzzy data. For this purpose, the fuzzy-covariance matrix is calculated with Equations (33) to (35) proposed as follows:

$$N = \sum_i \mu_A(i) \tag{33}$$

$$x_u = \frac{1}{N} \sum_i x_{ui} \mu_A(i) \tag{34}$$

$$S_{uv} = \sum_i (x_{ui} - x_u)(x_{vi} - x_u)\mu_A(i) \tag{35}$$

Where i is the supplier index, and u and v are the indices of the criteria. Also, $\mu_A(i)$, x_{ui}, S_{uv}, and $\widetilde{x_u}$ are the degree of each supplier membership, the score of supplier i on criteria u, variance, and fuzzy mean respectively.

After the creation of a fuzzy variance-covariance matrix, the eigenvalue, the eigenvector, and the linear combinations of the principal components are developed. Then, the eigenvalue is multiplied by each supplier's initial values, and the score of each principal component (PC_i) is calculated and used. Since the coefficients obtained for the principal component relationship can be different, the direction of the extracted components is uncertain, so it is necessary to determine the direction correctly. For this reason, the process reported by Bashiri and Sherafati (2012) [11] is used to identify the extracted components. Equations (36) to (38) calculate PCS^*, T, and $PCDSS$ respectively.

$$PCS^* = Eigen\ Value \times Max\,(Criteria\ Score) \tag{36}$$

$$T_u = \left| PCS_u - PCS^* \right| \tag{37}$$

$$PCDSS = \sum_u Var_u \times T_u \tag{38}$$

Max (criteria score) is the maximum value in each criterion multiplied by specific values to determine the principal component score of the best PCS^* status. Next, for each supplier, the deviation of the principal component score is calculated with PCS^* and is considered as the deviation for the desired component (T_i). Equation (38) calculates the final rhythm deviation of all the components for each supplier.

Constraint (4) ensures that the product shipped from the inspection and reconstruction center to the production/rehabilitation center is less than or equal to the manufacturer's capacity for renewable products. Constraint (5) ensures that the product shipped from the suppliers to the production/rehabilitation center is less than or equal to the supplier's capacity. Constraint (6) provides that the product transported from the recycling center to the production/rehabilitation center is less than or equal to the capacity intended by the reproducer. Constraint (7) ensures that the product transported from the inspection and reconstruction center to the disposal center is smaller than or equal to its capacity. Constraint (8) guarantees that the product shipped from the inspection and reconstruction center to the recycling center is smaller than or equal to its capacity. Constraint (9) ensures that the product shipped from the customer and the product shipped from the manufacturer's warehouse to the distribution and collection center are less than or equal to the capacity provided by the distribution centers for the returned products. Constraint (10) ensures that the product shipped from distribution and collection centers to the inspection and reconstruction center is less than or equal to its capacity. Constraint (11) ensures that the product shipped from the production/rehabilitation center to the distribution and collection center is less than or equal to the distribution centers' capacity. Constraint (12) ensures that the product shipped from the inspection and reconstruction center to the distribution center is less than or equal to the distributor's capacity for the repaired products. Constraint (13) ensures that the product transported from the production/rehabilitation center to the warehouse is less than or equal to the manufacturer's warehouse capacity. Constraint (14) ensures that the amount of the product shipped to the recycling center is equal to the return rate of the recycled products. Constraint (15) ensures that the amount of the product shipped to the disposal center is equal to the return rate of the returned product disposal. Constraint (16) ensures that the product shipped to the production/rehabilitation center is equal to the return rate of the returned products. Constraint (17) ensures that the amount of the product shipped to the distribution center is equal to the return rate related to the distribution of repairing the returned products. Constraint (18) ensures that the sum of the returned rates is exactly 1. Constraints (19) and (20) show the amount of the customer demand and the returned products respectively. They are random factors. Constraint (21) shows the balance between the input and the output of the production/rehabilitation center. Constraint (22) shows the balance between the amount of the product input to the distribution center and its output. Constraint (23) shows that the amount of the product returned to distribution centers is equal to the amount of the product sent to inspection and reconstruction centers. Constraint (24) shows the balance between the amount of the input to the manufacturer's warehouse and its output. Constraint (25) shows the balance between the amount of the input to the recycling center and its output. Constraint (26) indicates the upper limit of the number of inspection and reconstruction centers. Constraint (27) indicates the upper limit of the number of distribution and collection centers. Constraint (28) indicates the upper limit of recycling centers. Constraint (29) indicates the upper limit of disposal centers. Constraint (30) indicates the upper limit of the number of suppliers. Finally, constraints (31) and (32) show the non-negative and binary variables of the proposed model.

5- Solution Methods and Algorithms

In this section, our proposed solution methods have been presented. There are three kinds of solutions in this paper: exact, single meta-heuristic, and multi meta-heuristic.

5.1. *Unscaled goal programming method*

Goal programming is a well-known way of generating Pareto optimal solutions to multi-objective optimization problems. This method was first proposed by Charnes et al. (1955) [16] and is currently used by many researchers to solve various problems such as renewable energy production [68], portfolio management [8, 79] and supply chain management [61, 77]. This method seeks to find a solution to minimize the differences between objective functions and their optimal values by using Equation (39):

$$\text{Min} \sum_{g=1}^{p} a_g h_g (d_g^+, d_g^-)$$

Subject to: (39)

$$f_g - d_g^+ + d_g^- = f_g^* \qquad \forall g$$

$$d_g^+, d_g^- \geq 0$$

Where p is the number of the conflicting objective functions whose preference over each other is shown using the a_g parameter. Also, d_g^- and d_g^+ represent the negative and positive deviations of the objective function g from the optimal value, respectively. The value of $h_g(d_g^-, d_g^+)$ is calculated as Equation (40):

$$h_g (d_g^+, d_g^-) = \begin{cases} d_g^+ & \text{for Min Problem} \\ d_g^- & \text{for Max Problem} \\ d_g^+ + d_g^- & \text{O.W} \end{cases} \qquad (40)$$

In most multi-objective mathematical models, the objective functions have different scales, and the difference between their values is enormous. This may cause the objective function of the goal programming method to minimize the difference between the functions that are larger in scale. Given that in the mathematical model presented in this section, the scales of the values of the first and the second objective functions are very different from each other. To solve this problem, an unscaled version of the goal programming method is proposed (Equation 41):

$$\text{Min} \sum_{g=1}^{p} a_g h_g (d_g^+, d_g^-)$$

Subject to: (41)

$$\frac{f_g}{f_g^*} - d_g^+ + d_g^- = 1 \qquad \forall g$$

$$d_g^+, d_g^- \geq 0$$

5.2. *Boundary objectives method*

The framework used for this approach is shown in Equation (42). In this method, one of the objective functions is optimized while the other objective functions are considered as constraints and lower and upper bounds are assigned. In this case, the first objective function of the problem remains as the primary objective function, and the other two are transferred to the constraints.

$$\text{Min} f_i(x)$$

Subject to: (42)

$$LB_g \leq f_g(x) \leq UB_g \qquad g = 1, \dots, p \quad g \neq i$$

$$x \in S$$

In this way, the three-objective model is transformed into a single-objective model (including the first objective function, which is to minimize costs). The solution methods already provided are used for this model.

5.3. *Tree Growth Algorithm (TGA)*

Tree Growth Algorithm is one of the meta-heuristic algorithms recently reported by Cheraghalipour et al. (2017, 2018) [18, 19] and inspired by the competition of trees for light and nutrients. In this algorithm, the elements are divided into four groups. In one of these groups called the best tree group, some better trees will grow more, given the favorable conditions for growth. Because they are satisfied with the amount of light received, they compete for food. The growth of trees is slow, so good trees are generally taller, smoother and, most importantly, older. Due to their age, the growth rate of these trees is lower than before, and most of their competition is over food at the roots. In another group called the light competition group, some trees move at different angles to reach the light from their nearest trees. In the third group called the replacement and removing group, some weak trees that have grown little or are cut down by foresters are replaced by new seedlings. In the last group called the reproductive group, the best trees begin to multiply and form new seedlings due to optimal growth. Since they occur near the mother tree, they inherit some factors in that place (such as soil, insects and water). The detailed description of the algorithm is as follows:

Step 1. Generate the initial population of trees randomly around the upper and lower bounds and calculate the value of their objective function.
Step 2. Find the best tree. Considering a minimization-optimization problem, the best tree is the minimum objective function and vice versa. In the j_{th} iteration, T_{GB}^{J} is the best element.
Step 3. Find the best tree. Considering a minimization-optimization problem, the best tree is the minimum objective function and vice versa. In the j_{th} iteration, it is the best element. Note the following Equation:

$$T_i^{j+1} = \frac{T_i^{j}}{\theta} + rT_i^{j} \tag{43}$$

Where θ is the decline rate of tree strength due to old age, high growth and the reduction of the surrounding nutrients, and $r = U\,(0,1)$. When a tree is satisfied with light, it instructs its roots to move to absorb food. It grows by $rT_i{}^{j}$.
Step 4. Move the *N2* solution to the distance between the nearby solutions at different α angles. To do this, first find the distance between the selected tree and the other trees with Equation (44) and choose two of the shortest distances to move towards.

$$d_i = \Big(\sum_{i=1}^{N1+N2} (T_{N2}^{j} - T_i^{j})^2\Big)^{\frac{1}{2}} \quad \text{and} \quad d_i = \begin{cases} d_i & if \quad T_{N2}^{j} \neq T_i^{j} \\ \infty & if \quad T_{N2}^{j} = T_i^{j} \end{cases} \tag{44}$$

Then, choose two of the solutions with the lowest d_i as x_1 and x_2 (**Figure SI-1** and Equation 45).

$$y = \lambda x_1 + (1-\lambda) x_2 \tag{45}$$

Finally, move the tree between these two adjacent trees at the angle $\alpha_i = U(0,1)$ (**Figure SI-2** and Equation 46).

$$T_{N2}^{j} = T_{N2}^{j} + \alpha_i y \tag{46}$$

Step 5. Eliminate *N3* solutions from the worse ones and generate random solutions instead.
Step 6. Create a new population through *N1* + *N2* + *N3* = *N*.
Step 7. *N4* new solution is generated randomly. Each new solution is randomly masked with one of the best solutions (from the population *N1*) and then added to the latest population (i.e., new population = new population + *N4*).
Step 8. After the new population is sorted according to the objective function, *N* better solutions are selected from this new population and considered as the initial population for the next iteration (based on the roulette wheel, tournament, and selection of the best).
Step 9. Repeat step 2 if the stop conditions are not met.

The flowchart of the proposed algorithm is shown in **Figure SI-3**.

5.4. *Red Deer Algorithm (RDA)*

Like other meta-heuristic algorithms, the RDA starts with an initial random population equivalent to RDs (red deer). Some of the best RDs are selected from the population and are called male RDs. The rest are called hinds. First of all, the male RDs must roar. Based on the power of the roaring phase, they are divided into commanders and deer. After that, the commanders and the heads of each harem fight to get the harem. Besides, the harems are formed by the commanders. The number of the hinds in the harems is directly related to the commanders' ability in the process of roaring and war. As a result, the commanders are paired with several hinds in the harem. Note that the other males (e.g., deer) mate with the nearest hinds, regardless of harem restrictions. In general, RDA stages are designed in such a way as to provide satisfactory exploitation and exploration. The user can set steps related to the parameters used and the mathematical formulas. Accordingly, the male RD roar is the local search counterpart in the solution to improving the exploitation characteristics. Fights between the commanders and the deer are considered as local search. In this process, however, only better-observed solutions are accepted. This stage is mainly based on the exploitation characteristics.

In the next stage, the harems are formed and assigned to the commanders according to their power. This stage helps the algorithm do the exploration. Accordingly, the harem commander mates up with a number of hinds in his harem and another harem. These stages have also improved the exploitation characteristics. All the deer should be paired with the nearest hind; they pair up with the hinds at a minimum distance regardless of the harem restrictions in the breeding season. This phase also focuses simultaneously on exploration and exploitation issues.

Another primary stage of RDA is the mating process that leads to the production of RD offspring. This stage is equivalent to building new solutions in the solution space. Finally, the next generation of algorithms allows weak solutions to evolve by classifying them as algorithms.

Figure SI-4 shows a flowchart to give more details about the RDA structure. The blue boxes and the red ones indicate the intensification and diversification phases respectively. According to the algorithm's evolutionary concept, the green boxes show a part of the algorithm to escape the local optimum. As a result, it seems that the tool for setting the exploration and exploitation phases is available for the user to manipulate these steps according to the characteristics of the intended problem. There are more details given by Fathollahi-Fard et al. (2020) [30], and the main stages of the algorithm are summarized in that study as follows:

Initialize the Red Deer population.
Calculate the fitness and sort them and form the hinds (N_{hind}) and the male RDs (N_{male}).
X^* = the best solution
T_1 = clock
While t < maximum time of simulation,
for each male RD:

$$\text{male}_{new} = \begin{cases} \text{male}_{old} + a_1 \times ((UB - LB) \times a_2) + LB), & if \;\; a_3 \geq 0.5 \\ \text{male}_{old} - a_1 \times ((UB - LB) \times a_2) + LB), & if \;\; a_3 \prec 0.5 \end{cases}$$

Update the position if it is better than the prior ones.
end for
Sort the males and form the stags and the commanders:

$$N_{Com} = round\,(\gamma . N_{male})$$

$$N_{stag} = N_{male} - N_{Com}$$

for each male commander

Fight between the male commanders and the stags:

$$\text{New 1} = \frac{(\text{Com} + \text{Stag})}{2} + b_1 \times ((UB - LB) \times b_2) + LB)$$

$$\text{New 2} = \frac{(\text{Com} + \text{Stag})}{2} - b_1 \times ((UB - LB) \times b_2) + LB)$$

Update the position of the male commanders and the stags.

end for

Form harems:

$$V_n = v_n - max_i \{v_i\}$$

$$P_n = \left| \frac{V_n}{\sum_{i=1}^{N_{Com}} V_i} \right|$$

$$N \times \text{harem}_n = round\{P_n \times N_{hind}\}$$

for each male commander,

$$N \times \text{harem}_n^{mate} = round\{\alpha \times N \times \text{harem}_n\}$$

Mate a male commander with the selected hinds of his harem randomly:

$$\text{offs} = \frac{(\text{Com} + \text{Hind})}{2} + (UB - LB) \times c$$

Select a harem randomly and name it *k*.

$$N \times \text{harem}_k^{mate} = round\{\beta \times N \times \text{harem}_k\}$$

Mate a male commander with some of the selected hinds of the harem:

$$\text{offs} = \frac{(\text{Com} + \text{Hind})}{2} + (UB - LB) \times c$$

end for

for each stag

Calculate the distance between the stag and all the hinds and select the nearest hind:

$$d_i = \left(\sum_j (\text{stag}_j - \text{hind}_j^i)^2\right)^{\frac{1}{2}}$$

end for

Select the next generation with the roulette wheel selection.

Update X^* if there is a better solution.

T_2 = clock;

$T = T_2 - T_1$;

end while

Return X^*

5.5. *Particle Swarm Optimization (PSO) Algorithm*

The particle swarm optimization algorithm is one of the essential algorithms in collective intelligence (swarm intelligence). It was introduced by Kennedy and Eberhart (1995) [36] and inspired by the social behavior of such animals as fish and birds in small and large groups. In some ways, this algorithm is similar to evolutionary computation techniques, such as genetic algorithms (GA). Unlike GA, PSO does not have evolutionary functions such as crossover and mutation. One of the critical actions to successfully implement PSO is to find a solution to the problem within the PSO particles that properly affect its performance and feasibility [4, 78].

According to Kennedy and Eberhart (1995) [36], the PSO of each particle represents a possible answer that moves randomly in the solution problem. Its knowledge and neighbors influence the displacement of each particle in the search space. Therefore, the position of other swarm particles affects how a particle is searched. The result of modeling this social behavior is a search process in which particles move to appropriate areas. The particles learn from one another in the group and, based on their knowledge, move towards their best neighbors. The PSO works on the basis that, at any given moment, each particle adjusts its location in the search space according to the best location it has ever been as well as the best location in the entire neighborhood. Suppose there is a *d*-dimensional space and the i_{th} particle of a population can be represented by a velocity vector and a position vector. Changing the position of each particle is possible by switching the previous position structure and velocity. Each particle has the potential to include the best value ever achieved (*pbest*), the best answer ever obtained (in the group) from the value of *pbest* (*gbest*), and the position of x_i. This information comes from the comparison of the efforts of each particle to find the best solution. Each particle tries to change its position to reach the best answer. The velocity of each particle varies according to Equation (47):

$$v_{ij}(t+1) = \omega\, v_{ij}(t) + c_1 r_1 (pbest_{ij}(t) - x_{ij}(t)) + c_2 r_2 (gbest_j(t) - x_{ij}(t)) \tag{47}$$

Where $v_{ij}\,(t)$ is the j_{th} dimension of each particle in the t_{th} iteration, ω is the inertia weight, c_1 and c_2 are the weighting factors, r_1 and r_2 are the random numbers between 0 and 1, $x_{ij}\,(t)$ is the position of the *ith* dimension of each particle in the t_{th} iteration, $pbest_{ij}$ is equal to the *pbest* dimension *j* of each particle, and $gbest_j$ is the *gbest* of each particle in the group. Also, the new position of each particle is determined by the sum of the previous position and the new velocity, using Equations (48) and (49):

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{48}$$

$$v_{ij} = sign(v_{ij}) \min(|v_{ij}|, v_{\max}) \tag{49}$$

The steps of the PSO algorithm are as follows:

Step 1. Initialize the particle swarm (n) and the other parameters.
Step 2. Give an initial random value to the position and velocity of every particle.
Step 3. When the stop criterion is not met, do:

a) $t=t+1$;
b) Estimating the value of the merit for each particle;
c) $gbest(t) = \arg\ \min_{t=1}^{n}(f\ (gbest(t-1)), f\ (x_1(t)), f\ (x_2(t)), \dots, f\ (x_n(t)))$;
d) For $i=1$-n;
    i) $pbest_i(t) = \arg\ \min_{t=1}^{n}(f\ (pbest_i(t-1)), f\ (x_i(t)))$;
    ii) For j = 1 in terms of dimension: Update the j_{th} dimension of x_i and v_i according to Equations (47) to (49);
    iii) *j* dimension;
e) *i* dimension;

Step 4. End.

5.6. *Multi-Objective Genetic Algorithm-II (MOGA-II)*

MOGA-II is a multi-objective genetic algorithm used to search for optimizations. It is an efficient algorithm that uses smart multi-search elitism [43]. The elitism operator can maintain some excellent solutions without creating premature convergence at local-optimal frontiers. The elitism is applied in MOGA-II according to the following steps:

Step 1. MOGA-II starts with an initial population P of size N and the elite set $E = \emptyset$.
Step 2. $P' = P \cup E$ is calculated for each generation.
Step 3. If the cardinality of P' is greater than P, P is randomly subtracted from the exceeding points.
Step 4. The evolution from P to P' is calculated using all the MOGA operators.
Step 5. Fitness is calculated for population P'.
Step 6. All the non-dominated designs of P' are copied to E.
Step 7. E is updated by the removal of duplicated or dominated designs.
Step 8. If the size of elite set E is larger than that of generation N, it will change due to the accidental removal of excess points.
Step 9. Finally, there is a return to step 2, and P' is considered as a new P.

For simplicity, MOGA-II requires only a small number of user-defined parameters. Several other parameters are internally settled to create the power and performance of the optimizer. This algorithm performs all the evaluations, which are numerically equal to the points in the DOE (design of experiments) table multiplied by generations. Readers can check out the study by Mohammed et al., (2017) [43] for more details.

6- Case Study

In this section, computational results are presented to show the performance of different model modes and the proposed solution methods. The section is subdivided into three parts. In the first part, the proposed model is presented as a definite one and in a multi-objective manner. It is then written in the unscaled goal programming and solved and analyzed with the GAMS software. In the second part, due to the inefficiency of the GAMS software to solve large-scale problems, the boundary objectives method turns the presented model into a single-objective function. Then, it is solved and compared with three new single-objective meta-heuristic algorithms. Finally, in the third part, the proposed model is solved with a new multi-objective meta-heuristic algorithm. The best algorithm is examined based on several specific criteria and the performance results of the other algorithms. It is to be noted that the GAMS software has been used to solve the model by the unscaled goal programming method. All the proposed meta-heuristic algorithms have been solved by the MATLAB R2015b software on a personal computer with a CPU Intel Core i7 and a 16-GB RAM. Also, all the parameters have been tuned by the Minitab 19 software.

6.1. *Analysis of the unscaled goal programming method*

In this section, in order to review the results and comparatively study the unscaled goal programming method, three sample problems are presented in different dimensions on the basis of the data obtained from Pishro Diesel Compani, as the case study in this paper (**Table SI-1**). The various parameters of the problem are created by the MATLAB software, according to the data of the case study and with even distribution (**Table SI-2)**.

Pishro Diesel Asia Company (Pishro Yadak) started its activity in 1978 to produce auto parts, molds and car cabins. Registered in 1984, the company operates in the city of Najafabad Isfahan Province.

Its workforce currently includes more than 400 people, including engineers, technicians, experts, and skilled workers. From 1979 to 1990, the company manufactured 450 minibus chassis, 1000 assembly counters and a complete car cabin assembly line per year. It also produced minibus body parts with a capacity of 400,000 pieces per year.

According to the unscaled goal programming method, the values f_1^*, f_2^* and f_3^* are obtained from the payoff table using the individual optimization method. The model is solved separately for each sample problem in the afore-mentioned dimensions under uncertainty. This is done with the GAMS software and through the unscaled goal programming optimization method. The values of objectives Z_1, Z_2 and Z_3 as well as CPU time are obtained as reported in **Tables 1** and **2**. **Table 1** provides the results for the first to the third objective functions and the CPU time in sample problem 1. **Table 2** specifically shows the mean values of the objective functions and the CPU time for all the dimensions of the three sample problems.

Table 1. Computational results in sample problem 1

Unscaled Goal Programming Method	Values
Z_1	2064681.933
Z_2	609.529
Z_3	0.57
The best value of Z_1	2064681.46
The best value of Z_2	3604.43
The best value of Z_3	0.53
CPU Time	10.16

Table 2. Mean objective functions and CPU Time for all the dimensions of the problem

	Z_1	Z_2	Z_3	CPU Time
Sample Problem 1	2109557.73	728.01	0.44	10.26
Sample Problem 2	5944218.31	3188.06	0.56	726.73
Sample Problem 3	13206763.33	11764.64	0.53	2892.08

According to the results obtained from **Table 2**, the total cost of the supply chain system increases in consistence with the dimensions of the problem. The mean CPU time also increases exponentially with the increase of the problem's dimensions.

6.2. *Analysis of the proposed model using meta-heuristic algorithms*

According to the results and referring to **Table 2**, as the size and the complexity of a problem increases, GAMS fails to provide answers for sizes larger than the mentioned samples in a reasonable time. Therefore, in this section, single-objective and multi-objective meta-heuristic algorithms are proposed to solve the proposed model. In the first case, the objective functions of the proposed model under uncertain situations are transformed into a single-objective model by the boundary objectives method. In many cases, there may be differences among decision-makers in terms of tendencies and desires. Since the model proposed in this study has three objectives and the inclination level for each goal is different for managers, it has been transformed into a single-objective model by the boundary objectives method. Then, the model is solved by the proposed single-objective meta-heuristic algorithms. The mean of the objective functions obtained from each method is examined as a comparison criterion. Then, in the second case, the proposed model is solved by the multi-objective meta-heuristic algorithm, and the results are analyzed.

6.3. *Single-objective meta-heuristic algorithms*

Here four single objective meta-heuristic algorithms are introduced in detail.

6.3.1. *Parameter tuning*

Evaluation makes sense when done in a fair environment. For a fair comparison of the proposed methods, it is necessary to adjust the input parameters of the algorithms for each model to solve [29]. If those parameters are not set well, comparison and problem-solving with them will be useless. In this study, the Taguchi method is used to adjust the parameters of the problem. **Table SI-3** shows the final results of the parameters tuning of single-objective meta-heuristic algorithms by the Taguchi method. According to the table, the corresponding values are presented at low, medium and high levels for each algorithm. Finally, the ideal value is selected.

6.3.2. *Analysis of single-objective meta-heuristic algorithms*

For the analysis of one-objective algorithms, three sample problems are selected according to **Table SI-1**. The nominal data of the proposed algorithms are generated with an even distribution according to **Table SI-2** and then solved. After setting the parameters for each algorithm, the three sample problems are investigated. For each sample problem, five nominal data were generated and repeated five times based on **Table SI-2**. Finally, the minimum value of each iteration is selected as the best value of the algorithm and the decision method. **Table 3** presents the results of solving the proposed algorithms using the boundary objectives method.

Table 3. The results of solving meta-heuristic algorithms

Algorithm	Size	Problem	Z_1	Z_2	Z_3	CPU Time
RDA	1	1	2435555.05	3521.50	0.20	61.32
		2	2027972.60	3391.19	0.59	60.91
		3	2457668.57	3850.14	0.45	61.72
		4	2435969.61	4707.69	0.67	61.37
		5	2355333.64	5063.03	0.31	62.13
		Average	2342499.89	**4304.71**	**0.44**	**61.49**
TGA		1	2439584.27	3626.84	0.20	123.95
		2	2030451.01	3394.29	0.59	122.34
		3	2460222.79	3483.92	0.45	119.99
		4	2439497.77	4695.63	0.67	119.50
		5	2360326.10	5073.73	0.31	118.87
		Average	**2341385.29**	4124.21	**0.44**	120.93
PSO		1	2439584.27	3626.84	0.52	169.98
		2	2030451.01	3394.29	0.59	167.32
		3	2460222.79	3483.92	0.45	166.60
		4	2439497.77	4695.63	0.67	165.21
		5	2360326.10	5073.73	0.31	167.15
		Average	2346016.38	4126.88	0.50	167.25
RDA	2	1	6870449.74	39499.48	0.39	115.02
		2	7141194.56	34965.20	0.22	117.62
		3	6866834.44	28842.18	0.66	116.40
		4	6789694.22	30720.06	0.50	117.06
		5	6982043.77	34584.41	0.40	120.54
		Average	6930043.34	33712.26	0.43	117.32
TGA		1	6861279.19	39442.01	0.39	293.47
		2	7133485.78	34946.26	0.22	202.54

		3	6869237.28	28838.46	0.66	201.62
		4	6796226.39	30786.47	0.27	201.92
		5	6971776.48	34556.03	0.40	201.41
		Average	**6926401.02**	33709.84	**0.38**	**209.39**
PSO		1	6940286.77	39513.42	0.39	324.84
		2	7185143.68	34945.49	0.22	322.94
		3	6904334.70	28865.63	0.66	317.70
		4	6828341.50	30743.86	0.50	321.90
		5	6989420.46	34573.04	0.40	324.66
		Average	6969505.42	**33728.28**	0.43	322.40
RDA	3	1	16591267.14	104842.51	0.67	220.65
		2	17072093.15	105843.25	0.68	223.62
		3	16210098.32	100364.98	0.59	221.28
		4	16619952.26	119894.44	0.46	220.18
		5	17125980.03	109365.15	0.82	255.98
		Average	16723878.18	108062.10	0.62	228.34
TGA		1	16213548.56	105842.25	0.67	330.60
		2	16619952.09	105763.51	0.68	345.22
		3	16219823.32	106376.48	0.59	348.93
		4	16528952.26	118448.24	0.46	365.28
		5	17489380.03	110368.32	0.82	358.14
		Average	**16614331.25**	**109359.76**	0.64	349.63
PSO		1	16491982.43	105763.51	0.67	570.47
		2	17173083.54	106376.48	0.59	566.54
		3	16236598.56	102354.98	0.59	560.62
		4	16619952.09	120894.44	0.46	562.92
		5	17054980.56	109365.15	0.82	565.41
		Average	16715319.44	108950.91	**0.62**	565.192

6.3.3. *Filtering method (an ideal displacement solution)*

This method is designed to compare the proposed single-objective optimization methods and select the best approach. In this method, the indicators selected to compare the methods are written in the rows of a table. Next, the best value of each row is determined as a representative. After the table is normalized, the lowest total absolute value of each method is selected as the best index. Equation (50) is used for normalization as follows:

$$(F_g^* - F_g)/F_g^* \tag{50}$$

Where F_g^* is the best value of each row.

To compare the algorithms, four indicators including the CPU time and three objective functions are taken into account. Thus, the average results of the three problems make up the final indicator. **Table 4** shows the results of the filtering method.

Table 4. The results of the filtering method

	PSO	**TGA**	**RDA**
Z_1	0.0057	0	0.0044
Z_2	0.0026	0	0.0076
Z_3	0.0616	0	0.0342
CPU Time	1.5908	0	0
Normalization	1.6608	0.6700	0.0462

Getting back to **Table 3**, for small size problems, the TGA algorithm shows better results than RDA and PSO. However, its CPU time in small size problems is about twice as much as that of the RDA algorithm. For medium and large-size problems, TGA provides better answers than the other algorithms do. Besides, based on the CPU time presented in three sizes, RDA shows the best value. According to **Table 4**, using the filtering method and the corresponding criteria and indicators, RDA is the best algorithm to solve the model. However, due to the importance of the model objectives, the TGA results are of better quality and closer to the goals of the managers of the Pishro Diesel Company and its research and development department.

6.4. *Multi-objective meta-heuristic algorithm*

Here the MOGA-II algorithm is presented in detail.

6.4.1. *Parameter tuning*

Following the procedure stated in the parameter setting of single-objective meta-heuristic algorithms, the proposed multi-objective meta-heuristic algorithm was processed. **Table SI-4** shows the final results of the parameters adjustment of the multi-objective meta-heuristic algorithm by the Taguchi method.

6.4.2. *Analysis of the multi-objective meta-heuristic algorithm*

To analyze the multi-objective algorithm, three sample problems are selected according to **Table SI-1**. The nominal data of the proposed algorithm are generated through even distribution as in **Table SI-2** and solved by the proposed algorithm. The Pareto solutions of the algorithm are shown in **Table 5**.

Table 5. Pareto solutions

Problem size 1			**Problem size 2**			**Problem size 3**		
Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3
2576218.32	3549.10	0.20	7026514.50	39799.05	0.29	16839757.46	105257.11	0.55
2579097.59	3516.71	0.20	6894197.18	39456.34	0.39	17107883.65	104802.71	1.16
2399510.27	3617.87	0.52	6874904.81	39492.88	0.39	16838452.60	105106.13	0.83
2401316.60	3608.89	0.52	7153708.10	39718.73	0.29	17683806.42	104696.14	0.90
2490172.02	3594.77	0.52	6876589.43	39486.27	0.39	17452700.90	104831	0.81
2576230.42	3549.01	0.20	7112134.15	39681.46	0.33	17025261.38	104873.89	1.04
2404743.90	3595.10	0.52	7030764.27	39762.54	0.29	16864284.58	105070	0.81
2576525.70	3537.77	0.20	6950872.36	39741.64	0.35	17323404.12	104936.48	0.63
2576231.78	3548.47	0.20	6983697.42	39696.90	0.33	16994390.37	105156.91	0.72
2577750.69	3532.96	0.20	6951727.14	39741.42	0.35	17270660.09	105237.59	0.55
2577929.42	3524.30	0.20	7088067.57	39692.76	0.33	17125795.01	104726.71	0.90
2400245.66	3609.70	0.52	6938221.16	39767.68	0.35	16945510.07	104956.65	0.86
2402548.20	3597.63	0.52	7051639.82	39692.77	0.33	17583836.99	104922.34	0.63
2577936.54	3522.64	0.20	6980658.83	39700.90	0.33	17046135.73	104956.92	0.63
2401408.53	3607.46	0.52	6990133.44	39695.40	0.33	17253863.95	104953.06	0.63
24001552.94	3602.35	0.52	6953089.24	39726.46	0.35	17119770.38	104880.06	0.93
2577577.92	3535.12	0.20	7027980.78	39771.08	0.29	17622166.16	104898.67	0.63
2402084.12	2602.11	0.52	6941408.37	39743.82	0.35	16995428.19	105123.49	0.72
2401238.14	3609.19	0.52	7037497.35	39730.74	0.29	17242155.15	104877.79	0.75
-	-	-	6877823.85	39481.85	0.39	17077809.94	104881.32	0.93
-	-	-	6878234.23	39458.83	0.39	17213188.61	104861.52	0.81
-	-	-	6879166.31	39458.49	0.39	17151376.98	105254.35	0.55
-	-	-	7032702.67	39732.85	0.29	17240178.60	104850.47	0.81
-	-	-	6875549.69	39488.45	0.39	-	-	-

According to **Table 5**, there are 19, 24 and 23 Pareto solutions obtained to problem sizes 1, 2 and 3 respectively. To solve small problems, the use of the GAMS or the MOGA-II algorithm does not make much difference because both have an outstanding ability to produce quality solutions in less than thirty seconds. As the problem size increases, however, the MOGA-II algorithm is a much better option than the GAMS software. Due to the complexity of medium and large problems and their high number of decision variables, the solution by the GAMS software loses its efficiency to solve those problems. According to the MOGA-II algorithm results in **Table 5**, in small-size cases, the best solutions for all the three objectives are given in one Pareto, which indicates the coordination and integration of the entire supply chain network. As the size increases, discrepancies emerge between the objectives. With the increase of quality in the second objective, the first objective, namely the minimization of costs, grows. Since quality is a criterion in selecting and evaluating suppliers, it has had less effect on the third objective. In a large-size problem, the results show that the first objective function is to buy raw materials at a lower cost than what suppliers tend to charge, which naturally affects the quality of products. Due to the enlargement of the supply chain network, the problem has less impact than the medium-size problem, providing decision-makers with better insight and scope of action.

7- Conclusion

The increasing growth in the world of competition and the globalization of product markets have pushed organizations to make significant efforts to meet customers' diverse needs in the shortest time and at the least cost. In recent years, this issue has been recognized as an influential element in economy and industry. In this regard, competitive advantage is the ability of an organization to take a defensible position against competitors. This research has aimed at an integrated competitive supply chain network which is a multi-layer, multi-product and multi-period dynamic closed-loop system with limited capacities and uncertain demand and return products. The model proposed in this case is a multi-objective mixed-integer nonlinear programming model (MINLP). The first objective is to minimize costs. The second objective function is to maximize the quality of the products made in forward supply chains and the regenerative products in reverse supply chains. Finally, after the value of each supplier is calculated in the form of the final score of a principal component and based on the desired criteria (e.g., price/cost, quality and delivery time), the third objective function minimizes the sum of deviations from the ideal score of the principal component for each supplier. In this way, the most desirable components are selected for the total chain.

After the model and its characteristics are introduced, the unscaled goal programming method is used and the model is solved by the GAMS software. Based on the results, with an increase in the problem size, the CPU time rises sharply. Therefore, the exact method only responds to small-size models; as the model size increases, the exact method loses its efficiency. In other words, it is not possible to use exact methods to solve real-world cases because it takes a lot of time. To solve the model within an appropriate time, therefore, meta-heuristic algorithms have been used in this study. For this purpose, PSO, TGA and RDA are introduced as three new meta-heuristic algorithms. Given the uncertain conditions, the model is transformed into a single-objective one by the boundary objectives method and then solved by the proposed meta-heuristic algorithms. Before the model is solved, the parameters of each algorithm are adjusted. When implementing a meta-heuristic algorithm, an important decision is to set the parameters and find an optimal combination of them. In this research, the meta-heuristic algorithms are put to practice only after appropriate values are discovered for the parameters of each algorithm. Based on the results, for small-size problems, the PSO algorithm sometimes has better performance, but, at times, the TGA algorithm provides better results. Hence, in the case of small-size problems, the RDA algorithm does not perform as well as the other two algorithms and is not recommended. In terms of CPU time, the RDA algorithm has proved to achieve acceptable results much faster. Therefore, RDA is generally recommended for small-size models. As for medium-sized models, the TGA algorithm performs better. It is to be noted that the medium-sized data used to solve the model in this research belong to the case study auto company. Using TGA algorithms to solve models in the real world have significantly reduced the company's logistics costs. In the case of large-sized models, the TGA algorithm performs well in terms of time and cost. Considering all the results gained through solving the model with boundary objectives, it can be generally stated that the TGA algorithm performs better in terms of both CPU time and costs.

After the model is solved as a single objective, the new MOGA-II method is used to solve the proposed model as a multi-objective one. First, the required parameters are adjusted by the experimental design approach. To solve small problems, the use of the GAMS or the MOGA-II algorithm does not make much difference because both have an excellent ability to produce suitable solutions in less than 30 seconds. As the size of the problem increases, however, the MOGA-II algorithm is much better than GAMS. Due to the complexity of medium and large problems and the high number of decision variables in them, the GAMS software loses its efficiency to solve them. According to the MOGA-II algorithm results, in small-size problems, the best solutions are provided for all the three objectives in one Pareto, which illustrates the coordination and integration of supply chain networks with small-size problems. As the size increases, conflicting objectives emerge. As the quality increases in the second objective function, the first objective, which is to minimize the costs, grows too. Since quality is a criterion in selecting and evaluating suppliers, it naturally has less effect on the third objective. In a large problem, the first objective function is to buy raw materials at a lower cost than what suppliers tend to charge, which naturally affects the quality of products. Due to the enlargement of the supply chain network, the problem turns out to be of less effect than a medium-size problem, giving insights for better and freer decision making.

Finally, a few recommendations for future research in the field are as follows:

- Incorporation of the concepts of reliability and probability of facility failure into closed-loop models, which will lead to uncertain models for closed-loop networks verifiable in terms of reliability;
- Combination of a robust theory and a queuing theory so as to make a queuing system model in situations where the parameters of a queuing system are presented as discrete or continuous scenarios to achieve stronger solutions;
- Recently, the expansion of relief chain designs as well as global planning to optimize relief operations has become of particular importance. Therefore, with slight changes in the problem hypotheses of this study and possibly through re-modeling, new problems in relief chains can arise. To do this, the proposed supply chain facilities can be changed to relief supply chain facilities, such as mobile relief service facilities, hospitals, suppliers related to the relief supply chain, etc. Therefore, changes are also made in the mathematical model due to changes in the relevant facilities. For example, new sets, parameters, and decision variables are added to the model, followed by objective functions and constraints changes. Regarding the objective functions, many ideas can be considered, such as service time, service quality, people's satisfaction with the amount of service, and the like. Hence, a new model can be designed by considering these objective functions and the cost objective function related to a relief supply chain network. After solving the model with different solution methods, the optimal values of each of the selected objective functions can be achieved;

- Due to the computational complexity of network design models, other algorithms than those used in this study can be selected to solve the intended models and then to compare the results with those of this study;
- The fuzzy approach is proper to deal with uncertainty.

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