International Journal of Applied Operational Research
Vol. 6, No. 2, pp. 57-74, Spring 2016

Journal homepage: ijorlu.liau.ac.ir

An Efficient Imperialistic Competitive Algorithm for Closed-loop Supply Chains Considering Pricing for Product and Fleet of Heterogeneous Vehicles

M. Mohammadnejad*, I. Nakhai Kamalabadi, R, Sadeghian, F. Ahmadizar

Received: 25 September 2015 ; **Accepted:** 22 February 2016

Abstract This study investigates multi-period pricing closed-loop supply chains (CLSCs) with two echelons of producers and customers. Products delivered to customers might be defective which would be picked up and gathered in the collection center and fixed if it is possible and returned to the chain. Otherwise, they will be sold as waste materials. This problem determines the price and distribution of the product, supply of the material, and also determines vehicles with simultaneous pick-up and delivery in order to maximize the profit. A fleet of heterogeneous vehicles was routed to deliver the products from producers to customers and to pick up defective products from the customers and shipped them to the collection-repair center. The objective function was the maximization of the profit. Total cost consisted costs of defective products, ordering cost, the cost of holding in producers and collection-repair center, transportation costs, and the cost of assigning the place for the collection-repair center. This problem has been known as Np-hard; therefore, two meta-heuristic algorithms namely genetic algorithm (GA) and imperialist competitive algorithm (ICA) have been applied to solve the randomly generated test problems. Computational results revealed that GA was statistically better than ICA based on RPD metric reaching solutions with high quality.

Keyword: Closed-loop supply chain, Heterogeneous vehicles routing, Inventory, Pricing, Genetic algorithm (GA), Imperialist competitive algorithm (ICA).

1 Introduction

The supply chain is the movement of the created materials or products through different processes and activities on the network of organizations with the upstream and downstream connections to reach the end customers [1]. Supply chain Management is to optimize the performance of the chain by linking all the supply chain parties to jointly cooperate within the firm so that the total cost of the chain minimizes, or on the other hand productivity in the

* **Corresponding Author.** (✉)
E-mail: mmohammadnejad@razi.ac.ir (M. Mohammadnejad)

M. Mohammadnejad
PhD Candidate, Department of Industrial Engineering, Payame Noor University, Tehran, Iran.

I. Nakhai Kamalabadi
Professor, Department of Industrial Engineering, University of Kurdistan, Iran.

R. Sadeghian
Assistant Professor, Department of Industrial Engineering, Payame Noor University, Tehran, Iran.

F. Ahmadizar
Associate Professor, Department of Industrial Engineering, University of Kurdistan, Iran.

supply chain maximizes. Since the 1980s, the applications of the supply chain management in different industries have increased significantly. A comprehensive survey of supply chain management literature was performed by Cousins *et al*. [2, 3]. Recently, many researchers focused on issues of environmental protection and also the economic advantages of using returned goods. Due to these studies, they have achieved significant success in designing and executing reverse logistics networks and closed-loop supply chain networks [4, 5]. A forward supply chain includes the movement of services and goods from raw material suppliers, to manufacturers and assemblers, to retailers and end-consumers linked by shipping and storage processes [6]. In a closed-loop supply chain, the reverse flow of products contains after-sale activities and issues for recovery, recycling or safe disposal of the used products [7, 8]. The structure of closed-loop supply chain network is categorized into four types including the reuse, remanufacturing, recycling, and business returns. By growing public awareness about the supply chain environmental potentials, initial attempts for closing the loop of the supply chain has been initiated [9, 10]. Many companies found that mixing activities of closed-loop supply chain not only reduces the environmental impact but leads to reduced cost and increased productivity by providing services and new products which are achieved from recycling products.

The study is organized as follows. Section 2 gives the literature review of a closed-loop supply chain. Section 3 describes the problem and the related assumptions. Section 4 consists of the proposed algorithms for finding good solutions. Section 5 reports data generation and computational results. Finally, section 6 presents the conclusions and directions for future research.

2 Review of the Related Literature

Some researchers investigated the main forces of three industry parts including automotive, consumer, and electronic appliances [11]. The main aim was to close the supply chain loop in the product lifecycle. Four generic recycling options (recycling with or without disassembly in combination with outsourcing recycling or active intercommunity in recycling processes) and their effects were explored by Pagell *et al*., [12]. They identified existing recycling options to managers and their strategic implications. Hsu *et al*., [13] explored the business activities of distribution centers to estimate the business process of reverse logistic. Also, a model was developed to survey the interactions and data exchanges between different elements of the reverse logistics process. Rubio *et al*., [14] conducted a case study on the steel industry in Spanish. They presented a new packaging system which may be recovered via a reverse logistics system. Moreover, the economic and environmental advantages of the proposed system have been indicated. Concentrating on the Spanish automotive sector, barriers to the implementation of environmentally oriented reverse logistics were investigated by González *et al*., [15]. Using empirical evidence and robust statistical analysis, classification, and estimation barriers to environmentally oriented reverse logistics was done. For the first time, Halabi *et al*., [16] studied reverse logistic practices in Colombian enterprises especially in the plastic sector. They provided several conceptual models for the enterprises under study. After analysis of the obtained results, suggestions to reduce a negative impact on the environment were provided. A closed-loop supply chain network design under uncertainty and risk conditions were considered by Pishvaee and Torabi [17]. They formulated the problem as a bi-objective possibility mixed integer programming model and presented an interactive fuzzy solution method for solving the proposed possibility optimization model. In the presented solution approach, several efficient solution methods were combined. Pishvaee and Razmi [18] provided a multi-objective fuzzy optimization model for environmental supply chain network design under inherent uncertainty of input data. The objective functions were the minimization of the traditional cost and the multiple environmental impacts. For assessing and quantifying the environmental impact of different scenarios, a life cycle assessment-based method was used. Furthermore, they presented an interactive fuzzy solution approach to solve the problem. Pishvaee *et al*., [19] considered the problem of sustainable medical supply chain network design under epistemic uncertainty of input data. They presented a multi-objective possibility programming model for the proposed problem with conflicting economic, environmental and social objectives. An accelerated Benders decomposition algorithm with three acceleration mechanisms was used for solving the proposed model. Wei *et al*., [20] concentrated on a closed-loop supply chain with symmetric and asymmetric information structures for which the game theory was used for making the decisions on pricing and collecting. The aim was to make optimal decisions about wholesale price, retail price, and collection rate for the manufacturer and the retailer under symmetric and asymmetric information conditions. Four different game decision scenarios were provided to study the strategies of each company and the role of the manufacturer and the retailer in these scenarios. He [21] studied on acquisition pricing and remanufacturing decisions in a closed-loop supply chain with a manufacturer and recycle and reliable supply channels. The proposed problem was considered for two cases: with deterministic demand and with the stochastic demand. Also, two recycle channels for closed-loop supply chain were examined: the centralized (integrated) recycle channel and the decentralized recycle channel. A closed-loop supply chain network design operating in a competitive environment and with price-dependent demand was presented by Rezapour *et al*., [22]. They investigated the impacts of strategic facility location decisions of the studied supply chain on the tactical/operational transport and inventory decisions and formulated the proposed problem as a bi-level mathematical model. Also, they presented a modified projection solution approach for solving the proposed problem. Dondo *et al*., [23] studied a multi-echelon vehicle routing problem with cross docking in supply chain management. The aim was to satisfy customer demands at a minimum total transportation cost. They formulated the proposed problem as an integrated mixed-integer linear mathematical formulation and examined it for several problem instances. Agustina *et al*., [24] focused on food supply chains and studied vehicle scheduling and routing at a cross-docking center. The objective has been to deliver food just on time and with minimum costs of delivery. These costs contain inventory holding and transportation costs and the penalty costs due to early or tardy deliveries. They provided an integrated mixed-integer linear programming model for the proposed problem and solved it in CPLEX. Two-level vehicle routing with cross-docking in a three-echelon supply chain was studied by Ahmadizar *et al*., [25]. they formulated the problem as a mixed-integer nonlinear programming model. The objective function was to determine the optimal allocation of products to suppliers and cross-docks, the optimal scheduling, and routing of vehicles and to consolidate products so that the sum of the acquiring, transportation and holding costs is minimized. They presented a hybrid genetic algorithm for solving the problem. Hu *et al*. [26] considered a dynamic closed-loop vehicle routing problem under the uncertain pickup and deterministic delivery of incompatible goods where incompatibility between collected goods and goods for delivery has occurred. For measuring incompatibility, two strategies were presented. In the first strategy, the quantities of the goods to be collected and delivered were considered and in the second strategy, the vacant vehicle capacity based on the first strategy was considered. The aim was to minimize transportation cost, incompatibility and number of customers visited twice. They presented a solution approach based on variable neighborhood search algorithm for solving the proposed model. For showing the effects of considering the incompatibility, a case study in China's catering industry was conducted.

3 Statement of the Problem

In this Study, we consider multi-period, Closed-Loop Supply Chains (CLSCs) with two echelons consisting of producers and customers. In order to fulfill the demands, the producers' order for the materials at the beginning of each period and repeats for one or more periods. A fleet of heterogeneous vehicles is routed in order to deliver the products from producers to customers. They also pick up defective products from the customers and move them to the collection-repair center. The objective is the maximization of the profit, which comes from the total cost that is subtracted from income. The problem is elaborated by the following assumptions. Figure 1 illustrates the proposed problem.

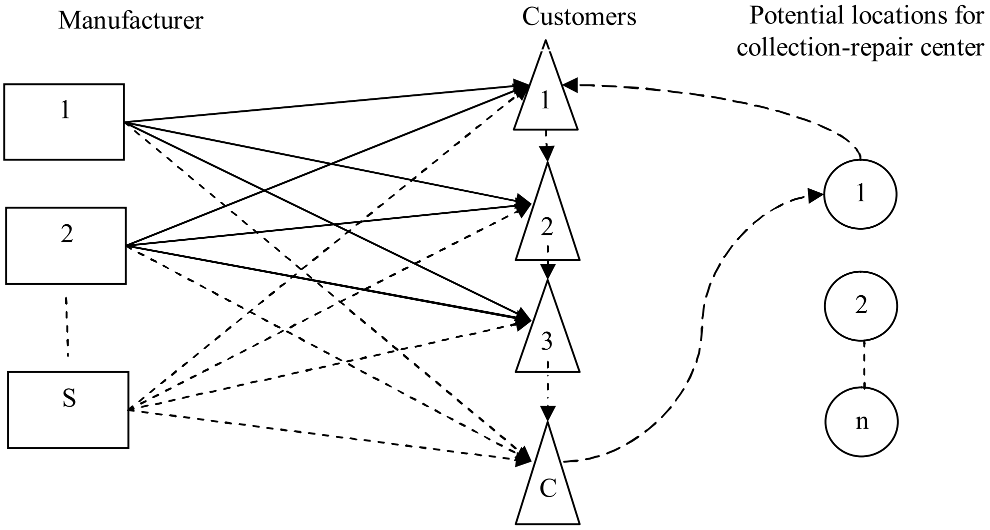

Fig. 1 Illustration of the presented problem.

3.1 Assumptions

- The problem is planned for the horizon of several periods.
- The chain consists of two echelons of producers and customers.
- The manufacturer can order for materials at the beginning of each period.
- Defective products are picked up from the customers and transported to the collection-repair center.
- The collection-repair center is placed in one of the several potential locations.
- Defective products might be returned to the distribution system in the next period or sold as a waste.
- The rate of defective products is related to the price; in other words, the more expensive the products, the less rate of the defect.
- Transportation between the manufacturer and the customer is directed, and at most, a vehicle is assigned to each pair of them.

- In order to pick up the defective products, a vehicle is sent to the customers in every period. The vehicle can also deliver repaired products to them after the first period.

Indices, parameters, decision variables, mathematical model, objective function, and constraints are presented as follows:

3.2 Indices

S: Set of manufactures
N: Set of locations containing collection-repair potential centers (Set L, n first nodes of N nodes) and customers (Set C, N-n remaining nodes)
V: Set of vehicles
T: Set of planning periods

3.3 Parameters

n: Number of candidate potential locations for establishing the collection-repair center.
γ : Rate of defective products; it is dependent on the price.
λ : Price of products with highest quality
φ : Rate of defective products that can be repaired.
FP_j : Fixed cost for establishing the collection-repair center in node j
FV_l : Fixed cost of vehicle l
DV_l : Unit shipping cost of vehicle l
CV_l : Capacity of vehicles l
Pt_t : Price of un-repairable defective product at period t
CR_t : Unit cost of repair at period t
α_{jt} : Mean demand, which is independent from price for customer j at period t
β_{jt} : Rate of price-dependent demand of customer j at period t
h'_{kt} : Unit storage cost in location k at period t
A_{it} : Ordering cost for manufacturer i at period t
Pb_{it} : Material cost of each unit of product for manufacturer i at period t
h_{it} : Unit storage cost in the warehouse of manufacturer i at period t
$Dist_{ij}$: Distance between nodes i and j
M : An arbitrary large number

3.4 Decision Variables

LR_t : Amount of loading of the vehicle when it leaves the collection-repair center
Ps_t : Sales price of the product at period t
RW_t : Number of products repaired at period t

W_{jt} : Auxiliary variables in order to eliminate sub-tours in node *i* at period *t*

DE_{jt} : Demand of customer *j* at period *t*

D_{jt} : Amount of repaired products delivered to customer *j* at period *t*

P_{jt} : Amount of backward defective products from customer *j* at period *t*

LC_{jt} : Amount of vehicle loading at the time before leaving customer *j* at period *t*

I'_{kt} : Amount of warehouse inventory in location *k* at period *t*

I_{it} : Amount of warehouse inventory in manufacturer *i* at period *t*

Q_{it} : Amount of ordering of manufacturer *i* at period *t*

X_{ijlt} : Amount of product moved from manufacturer *i* to customer *j* by vehicle *l* at period *t*

$Z_j : \begin{cases} 1 & \text{if the collection-repair center is opened in location j} \\ 0 & \text{else} \end{cases}$

$B_{jt} : \begin{cases} 1 & \text{if costomer i at period recieves repaired product or has backward} \\ 0 & \text{else} \end{cases}$

$O_{it} : \begin{cases} 1, & \text{if manufacturer i orders for material at period t} \\ 0 & \text{else} \end{cases}$

$V_{ijlt} : \begin{cases} 1, & \text{if vehicle l is used for transfering the products from manufacturer i to customer j at period t} \\ 0 & \text{else} \end{cases}$

$V'_{lt} : \begin{cases} 1, & \text{if vehicle l is used in the collection-repair center at period t} \\ 0 & \text{else} \end{cases}$

$Y_{jklt} : \begin{cases} 1, & \text{if vehicle l traveles from node j to k at period t} \\ 0 & \text{else} \end{cases}$

3.5 Mathematical Model

$$\begin{aligned} MaxZ = & \sum_{t\in T}\sum_{j\in C} DE_{jt}Ps_t - \left(\sum_{t\in T}\sum_{j\in C} P_{jt} - \sum_{t\in T} RW_t\right)\left(Ps_t - Pt_t\right) \\ & -\sum_{t\in T}\sum_{i\in S} O_{it}A_{it} - \sum_{t\in T}\sum_{i\in S} Pb_{it}Q_{it} - \sum_{t\in T}\sum_{i\in S} I_{it}h_{it} - \sum_{t\in T}\sum_{k\in L} I'_{kt}h'_{kt} \\ & -\sum_{t\in T}\sum_{l\in V}\sum_{i\in S}\sum_{j\in C} V_{ijlt}FV_l - \sum_{t\in T}\sum_{l\in V} V'_{lt}FV_l \\ & -\sum_{t\in T}\sum_{l\in V}\sum_{i\in S}\sum_{j\in C} X_{ijlt}DV_lDist_{ij} - \sum_{t\in T}\sum_{l\in V}\sum_{j\in N}\sum_{k\in N} Y_{jklt}DV_lDist_{jk} \\ & -\sum_{k\in L} Z_kFP_l - \sum_{t\in T}\sum_{j\in C} RW_{jt}RC_t \end{aligned} \tag{1}$$

s.t.

$$DE_{jt} \geq \alpha_{jt} - \beta_{jt}Ps_t \quad j\in C,\ t\in T \tag{2}$$

$$DE_{jt} \leq \alpha_{jt} - \beta_{jt}Ps_t + 1 \quad j\in C,\ t\in T \tag{3}$$

$$D_{jt} + \sum_{l\in V}\sum_{i\in S} X_{ijlt} \ge DE_{jt} \quad j\in C,\ t\in T \tag{4}$$

$$I_{it} = I_{it-1} + Q_{it} - \sum_{l\in V}\sum_{j\in C} X_{ijlt} \quad i\in S,\ t\in T \tag{5}$$

$$Q_{it} \le O_{it}M \quad i\in S,\ t\in T \tag{6}$$

$$X_{ijlt} \le V_{ijlt}CV_l \quad i\in S, j\in C,\ l\in V,\ t\in T \tag{7}$$

$$P_{jt} \ge \left(\gamma + (1-\frac{Ps_t}{\lambda})\right)\sum_{l\in V}\sum_{i\in S} X_{ijlt} \quad j\in C,\ t\in T \tag{8}$$

$$P_{jt} \le \left(\gamma + (1-\frac{Ps_t}{\lambda})\right)\sum_{l\in V}\sum_{i\in S} X_{ijlt} + 1 \quad j\in C,\ t\in T \tag{9}$$

$$P_{jt} \le B_{jt}M \quad j\in C,\ t\in T \tag{10}$$

$$D_{jt} \le B_{jt}M \quad j\in C,\ t\in T \tag{11}$$

$$\sum_{l\in V}\sum_{j\in N} Y_{jklt} = B_{kt} \quad k\in C,\ t\in T \tag{12}$$

$$\sum_{j'\in N} Y_{j'jlt} = \sum_{j''\in N} Y_{jj''lt} \quad j\in N,\ l\in V,\ t\in T \tag{13}$$

$$\sum_{t\in T}\sum_{l\in V}\sum_{k\in C} Y_{j(k+n)lt} \le Z_j M \quad j\in L \tag{14}$$

$$\sum_{j\in N}\sum_{k\in N} Y_{jklt} \le V'_{lt}M \quad l\in V,\ t\in T \tag{15}$$

$$\sum_{j\in L} Z_j = 1 \tag{16}$$

$$w_{kt} > w_{jt} - (1-Y_{jklt})M \quad j\in N,\ k\in C,\ l\in V,\ t\in T \tag{17}$$

$$\sum_{l\in V}\sum_{k\in C} Y_{j(k+n)lt} \le 1 \quad j\in L,\ t\in T \tag{18}$$

$$RW_t \ge \varphi \sum_{j\in C} P_{jt} \quad t\in T \tag{19}$$

$$RW_t \le \varphi\left(\sum_{j\in C} P_{jt}\right) + 1 \quad t\in T \tag{20}$$

$$I'_{kt} = I'_{kt-1} + RW_t - \sum_{j\in C} D_{jt} \quad k\in L,\ t\in T \tag{21}$$

$$\sum_{j\in C} D_{jt} \le I'_{kt-1} + (1-Z_k)M \quad k\in L,\ t\in T \tag{22}$$

$$LR_t = \sum_{j\in C} D_{jt} \quad t\in T \tag{23}$$

$$LC_{kt} \ge LR_t - D_{kt} + P_{kt} - (1-Y_{j(k+n)lt})M \quad k\in C, j\in L,\ t\in T \tag{24}$$

$$LC_{kt} \ge LC_{kt} - D_{kt} + P_{kt} - (1-Y_{j(k+n)lt})M \quad j,k\in C,\ t\in T \tag{25}$$

$$LR_t \le CV_l + (1-V'_{lt})M \quad l\in V,\ t\in T \tag{26}$$

$$LC_{kt} \le CV_l + (1-V'_{lt})M \quad k\in C,\ l\in V,\ t\in T \tag{27}$$

$$Z_j \in \{0,1\} \quad j\in L \tag{28}$$

$$Y_{jklt} \in \{0,1\} \quad j,k\in N,\ l\in V,\ t\in T \tag{29}$$

$$B_{jt} \in \{0,1\} \quad j\in C \tag{30}$$

$$O_{jt} \in \{0,1\} \quad j \in C \tag{31}$$

$$V_{ijlt} \in \{0,1\} \quad i \in S, j \in C, l \in V, t \in T \tag{32}$$

$$V'_{lt} \in \{0,1\} \quad l \in L, t \in T \tag{33}$$

$$DE_{jt}, P_{jt}, RW_t \text{ are integer} \quad j \in C, t \in T \tag{34}$$

3.6 Describing the Objective Function and Constraints

The objective function of the proposed mathematical model is to maximize profit. Profit is calculated from the total cost subtracted from the income. All the income comes from selling the products. However, cost function includes nine parts, which are waste cost (including the products that are sold as waste), ordering cost, material purchasing cost, storage cost in the manufacturers' places, storage cost in the collection-repair center, fixed cost of employing vehicles, travelling cost that is dependent on distance, establishing cost of the collection-repair center, and repair cost of the defective products. Constraints (2) and (3) represent the amount of demand of customers at the beginning of each period, which is dependent on the price. Constraint (4) ensures that the demand of each customer should be satisfied at each period. Constraint (5) calculates the amount of inventory of each manufacturer at each period. Constraint (6) ensures that a manufacturer can only order for materials when the ordering has been completed. Constraint (7) ensures the vehicles not to load more that their capacities. Constraints (8) and (9) calculate the number of backward products of each customer at each period that is dependent on the price. Constraints (10) and (11) determine if each customer requires a vehicle from the collection-repair center. Constraint (12) guarantees that the vehicles from the collection-repair center only meet the customers that need to be repaired products to be delivered or defective products to be picked up. Constraint (13) guarantees that if a vehicle enters a node in a period, it should leave it immediately after its mission is finished. Constraint (14) ensures that at the first of each period, a vehicle only comes out of the location in which the collection-repair center has been established. Constraint (15) illustrates the types of vehicle used at the collection-repair center in each period. Constraint (16) ensures that only one location must be selected as the collection-repair center. Constraint (17) eliminates sub-tour elimination constraint and ensures that no route is apart from the distribution center node. Constraint (18) ensures that each vehicle cannot travel more than one time at each period. Constraints (19) and (20) determine the number of repaired products in each period. Constraint (21) calculates the inventory level in the collection-repair center at each period. Constraint (22) shows the number of backward for each customer at each period. Constraint (23) calculates the loading amount of each vehicle when leaving the collection-repair center at each period. Constraint (24) calculates the loading amount of every vehicle when leaving the first customer after the collection-repair center through its route. Constraint (25) calculates a load of each vehicle when leaving each customer in its route. Constraints (26) and (27) ensure that the loading level never exceeds the capacity of the vehicle. Finally, constraints (28) and (34) show the kind of variables used in the model.

4 Method
4.1 Genetic Algorithm (GA)

Genetic algorithm (GA), one of the most applicable evolutionary algorithm, has been introduced first time by John Holland [27] which is based on Darwin's evolution theory. This algorithm looks for the best solution among a population of potential solutions through biological operations such as crossover, mutation and so on. Many examples which have been solved by Dengiz *et al.*, [28] Illustrates that Genetic algorithm can be applied to variety of problems. In order to adapt a problem to be solved by the Genetic algorithm, some parts of the Genetic algorithm have to be adapted according to the problem. The most common parts which require being adjusted are encoding, crossover, and mutation that are presented for the proposed problem in the following sections.

4.1.1 Solution Representation

In the proposed genetic algorithm, encoding contains six parts and each of them determines certain part of a solution and all of them together present a complete solution. The first section of the chromosome is related to the price which is presented by a string with the length of a number of periods. Each element has a value that presents the price of the product in the related period. The second section of the chromosome illustrates the place where the collection-rework center should be located. This part is demonstrated by a string with the length of L (L is the number of potential location) that each of them is relevant to a potential location and is presented by a real number in [0 1] which showed the merit of the related location to be a collection-rework center. Among potential locations, the highest value would be chosen as the center. The third section of the chromosome determines assigned vehicle and its routing for each period by a matrix with rows (T is the number of a period) and columns (C is the number of the customers). Each row is related to a period in which its first column assigns a vehicle with an integer value and C remaining columns are representatives of customers that show their priority with a real number in [0 1] to be visited by the determined vehicle through its route. The customer with the highest related value will be met at the beginning of the route and customer with the lowest value will be visited at the end of the route of the vehicle. The fourth section of the chromosome contains a matrix with the dimension of (S and V are the numbers of manufacturer vehicle respectively) that determines the product flows and assigned vehicles between manufacturer and customers. Each member is relevant to a customer, manufacturer, vehicle and period, it has a value in the range between [0 1] and shows the priority of related customer, manufacturer, vehicle and period to assign product flow. In order to satisfy customers' demands in each period, manufacturers and vehicles are assigned according to their priority value with considering their capacities. The fifth section of the chromosome is presented by a matrix with C rows and T columns that determine how high percent of demand of each customer in each period should be satisfied by the collection-repair center. If the amount that determined reworked product for a customer were more than the inventory of the collection-repair center, the customer would not receive more than the inventory level. The sixth section is relevant to the amount of materials that are ordered by manufacturers at the beginning of every period which is presented by a matrix with S rows and T columns. Values in this part are real numbers that are generated by the standard normal distribution function. The previous parts of the chromosome have determined the number of the product that each manufacturer must produce every period, and thus, the number of required materials for each manufacturer can be calculated. If a value in the sixth part of the chromosome is equal to a negative number, the related manufacturer in that period orders as many as the requirement of that period considering the inventory of materials from previous periods. On the other hand, if the value is bigger than zeros, the manufacturer orders material (1 + the proposed value) times more than the required number of material in that period.

4.1.2 Genetic Operations

Genetic operations play a significant role in genetic algorithms, and in this section, we introduce the applied operation in this research. In order to prevent uniformity in populations and to produce the wide range of solutions, two kinds of crossovers are implemented on the parents that are selected by the Roulette-wheel procedure. In the first one, there is guide metric for each part of a chromosome which is the same dimension as the related part and which has members with binary value. The offspring are produced according to their parent with different values that are exchanged for those elements that their related elements in the guide matrix are equal to one. For the second kind of crossover operator, a random number with uniform distribution function is generated for each element of every part. Suppose for one element the value in parent 1 and 2 are equal to a, b respectively, and is the generated random number. Therefore, if the values of the related element in the offspring are c, d, obtained by respectively. Figures 2 and 3 illustrate the crossover operators in the proposed algorithm.

Parent1

0.37	0.49
0.82	0.91

Parent2

0.86	0.31
0.77	0.53

Guide Matric

1	0
0	1

Offspring1

0.86	0.49
0.82	0.53

Offspring2

0.37	0.31
0.77	0.91

Fig. 2 First kind of crossover operation

Parent1

0.37	0.49
0.82	0.91

Parent2

0.86	0.31
0.77	0.53

α for the elements

0.15	0.65
0.42	0.78

Offspring1

0.43	0.37
0.79	0.61

Offspring2

0.78	0.42
0.79	0.82

Fig. 3 Second kind of crossover operation

The genetic operation that is extremely important to avoid local optimal solution is *mutation* that preserves diversity in each generation. In this algorithm, mutation is implemented by *reverse* operator in which two rows or two columns are chosen randomly and values in every column or row are reversed. Figure 4, shows performance of this operator.

0.39	0.31	0.53	0.71
0.57	0.29	0.47	0.13
0.97	0.40	0.62	0.27

0.39	0.71	0.53	0.31
0.57	0.13	0.47	0.29
0.97	0.27	0.62	0.40

Fig. 4 mutation operation

In order to ensure the feasibility of individuals, chromosomes must be evaluated after each generation in the first population or after applying genetic operations. If the generated chromosome produces a feasible solution which does not violate the constraints, it will be accepted, otherwise, it will be rejected and another chromosome will be generated until achieving a feasible one.

4.2 Imperialist Competitive Algorithm (ICA)

ICA is one of the newest methods in meta-heuristic field that was suggested and developed by [29]. This method is based on the human social and political behavior. Similar to GA, the ICA is a population-based algorithm and the population consisted of some countries which are classified in two categories: imperialists and colonies. Imperialist is a country that rules a number of countries which are called colonies. In other words, the policies, culture, religion and other social measurements of a colony is delineated by the imperialist in power. After producing initial population randomly, at first step each country must be specified to either imperialist or colony. The countries have several attributes including culture, language, religion, economic policy, etc. Next, the fitness value of countries will be calculated and those with lowest cost are determined as imperialists and other countries will be considered as colonies. Then the numbers of each imperialist's colonies are calculated by Eqs. (35)- (38):

$$c_i = Cost\ (country) \tag{35}$$

$$C_n = max_i \{c_i\} - c_n \tag{36}$$

$$P_n = \left| \frac{C_n}{\sum C_i} \right| \tag{37}$$

$$number\,of\ \ clonies_n = round\left(P_n . N_{col}\right) \tag{38}$$

where c_n and C_n are the cost of n^{th} imperialist and its normalized cost respectively. P_n is imperialist's power and imperialists with lower cost have higher power and it increases their chance to get more colonies. After specifying imperialists and their colonies, ICA devices assimilation policy and revolution operators to search for better countries. Assimilation policy is performed on all colonies to form new ones. In this policy, each imperialist absorbs colonies by making changes in their attributes such as social, cultural, regional etc. Next; the cost of new colonies that are absorbed to the current imperialist must be recalculated. If the new colony is better than its imperialist, they will be exchanged with each other immediately. The second operator is revolution that creates diversification in countries. This operator randomly selects two attributes in a country and exchanges their values. Then, the power of each emperor is calculated by Eqs. (39)- (41):

$$T.C_n = Cost\left(Imperialist_n\right) + \zeta . mean\left\{Cost\left(Colonies\,of\ \ Empire_n\right)\right\} \tag{39}$$

$$N.T.C_n = max_i \{T.C_i\} - T.C_n \tag{40}$$

$$P_{Pn} = \left| \frac{N.T.C_n}{\sum_{i=1}^{Nimp} N.T.C_i} \right| \tag{41}$$

where $T.C_n$equivalent to total is cost of nth empire and ζ is a positive number which is considered lower than1, $N.T.C_n$ is power of *nth* empire and P_{Pn} is the possession possibility of each emperor. The emperor with the lowest cost will be considered as the weakest emperor. Then the other emperors compete with each other to take possession of the weakest colonies of the weakest emperor. ICA uses a selection process to choose an emperor that will pick up the mentioned colonies. The vector R created uniformly distributed random number as following:

$$R = \left[r_1, r_2, \ldots, r_{Nimp} \right]$$

From vector D in eq. (42), the emperor with highest value will be selected and the weakest colony of the weakest emperor will be assigned to it.

$$D = P - R = \left[D_1, D_2, \ldots, D_{Nimp} \right] = \left[p_{P1} - r_1, p_{P2} - r_2, \ldots, p_{p_{Nimp}} - r_{p_{Nimp}} \right] \tag{42}$$

The stopping criterion of the algorithm indicates the remaining of one emperor. In order to adapt the ICA with the proposed problem, the solution representation is as the same as the section 4.1.1 However, the elements that have discrete value are rounded before encoding the representation to a solution.

5 Computational Results

The required data to analyze the performance of the random generated test problems are shown in Table1. The data is introduced by [30] and has been adopted as reference and modified in order to illustrate the application of the multi-period model.

Table 1 Problems' factor range [30]

Factor	Range
Price	Unif(3750,5000)
Fixed cost for establishing the collecting-repair center	Unif(100000,1000000)
Fixed cost of each vehicle	Unif(60000,400000)
Unit shipping cost of each vehicle	Unif(200,500)
Capacity of each vehicle	Unif(600,14000)
The sales price of un-repairable defective product	Unif(500,1000)
Unit cost of repair	Unif(500,1500)
Mean price-independent demand	Unif(0, 3000)
Rate of price-dependent demand	Unif(0.3,0.5)
Unit storage cost	Unif(150,300)
Ordering cost for each manufacture	Unif(100000,500000)
Unit purchasing cost for each manufacture	Unif(1500,2500)
Unit storage cost in warehouse of each manufacture	Unif(50,100)

The required data to analyze the performance of the problem includes five factors, namely: number of customer, number of manufacture, number of vehicle, number of period and number of possibility of location. These factors have several levels which are illustrated in Table2.

Table 2 Problems' factor level

Factor	Level
Number of customers	10,15,30,50
Number of manufactures	5,10,15
Number of possibility of locations	2,4,6
Number of vehicles	3,4
Number of periods	3,5,7

Parameter of the proposed GA and ICA is experimentally tuned to increase their quality to reach a good solution for the random generated test problems. Computational result for proposed algorithms is illustrated in Table3. Performance of the proposed GA and ICA are compared by average relative percent deviation (RPD) criterion and computational time. Each test problem computed five times and average of each metrics (RPD and Time) is listed in Table3. RPD is calculated from the formula:

$$RPD = \frac{(Objective\,value\,of\;\;the\;metaheuristic - Best\;objective\,value)}{(Best\;objective\,value)} \tag{43}$$

Table 3 Evaluation of proposed GA and ICA based on *RPD* and Time metrics

Problem. No	Customer. No	Manufacture. No	Location. No	Period. No	Vehicle. No	$\overline{RPD}_{GA}$	$\overline{TIME}_{GA}$ (Second)	$\overline{RPD}_{ICA}$	$\overline{TIME}_{ICA}$ (Second)
1	10	5	2	3	3	0.0237288	425.407	0.0406863	376.333
2	10	5	2	7	3	0.0234023	844.909	0.0800137	785.251
3	10	5	2	5	3	0.0049064	742.751	0.1153327	755.300
4	10	5	2	3	4	0.0271916	386.694	0.0359364	407.896
5	10	15	2	7	4	0.0418422	249.498	0.0699423	422.447
6	15	5	4	3	3	0.0544567	440.584	0.1143359	546.721
7	15	5	4	7	3	0.0624784	924.552	0.0498192	1170.33
8	15	10	4	5	3	0.0119512	1058.131	0.0382464	940.571
9	15	10	4	3	4	0.0637660	1053.607	0.0755459	1026.25
10	15	15	4	7	4	0.0491737	3363.753	0.0313403	2165.78
11	30	5	6	3	3	0.0154657	1972.122	0.0187021	1080.34
12	30	5	6	7	3	0.0325618	3831.096	0.0150003	1461.72
13	30	10	6	5	3	0.0420129	3409.721	0.0150219	1278.78
14	30	15	6	3	4	0.0062571	2526.404	0.0227787	1172.51
15	30	15	6	7	4	0.0185432	6943.777	0.0043170	2180.83
16	50	5	2	5	3	0.0153439	3447.590	0.0037656	1682.52
17	50	5	2	3	3	0.0219868	1937.583	0.0270462	1243.36
18	50	10	2	7	4	0.0378207	7172.907	0.0060285	5438.20
19	50	15	2	5	4	0.0178107	7964.289	0.0691935	3401.86
20	50	15	2	3	4	0.0418206	8430.917	0.0170096	2208.37
		Mean				0.0306260	2856.31	0.042503	1487.27

The computational results are graphically illustrated in figures 5 which. Fig 5 shows that GA performs better than ICA in problems 10 and 15 customers. In problems 30 and 50 customers both in ICA and GA have a same behavior.

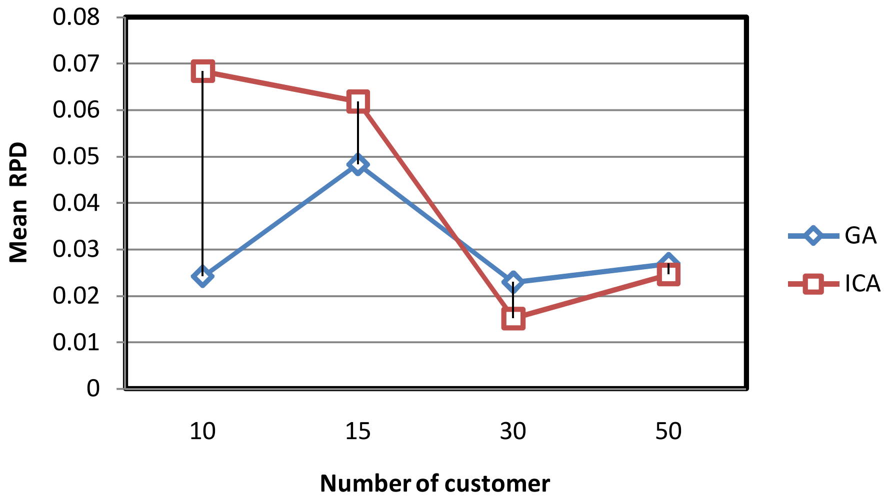

Fig. 5 Average Relative Percent Deviation ($\overline{RPD}$) for different value of customer

Figure 6. demonstrates that GA performs better than ICA based on RPD metric in problems 5 and 15 manufactures and ICA in problem with 10 manufactures is better.

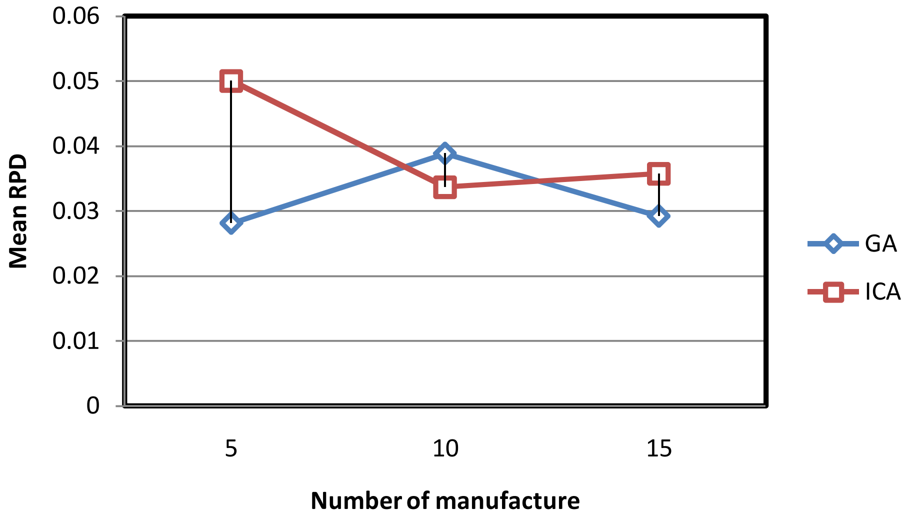

Fig. 6 Average Relative Percent Deviation ($\overline{RPD}$) for different value of manufacture

Figure 7. shows that GA performs better than ICA based on RPD metric in problems 2 and 4 locations and ICA is better in problem with six manufactures.

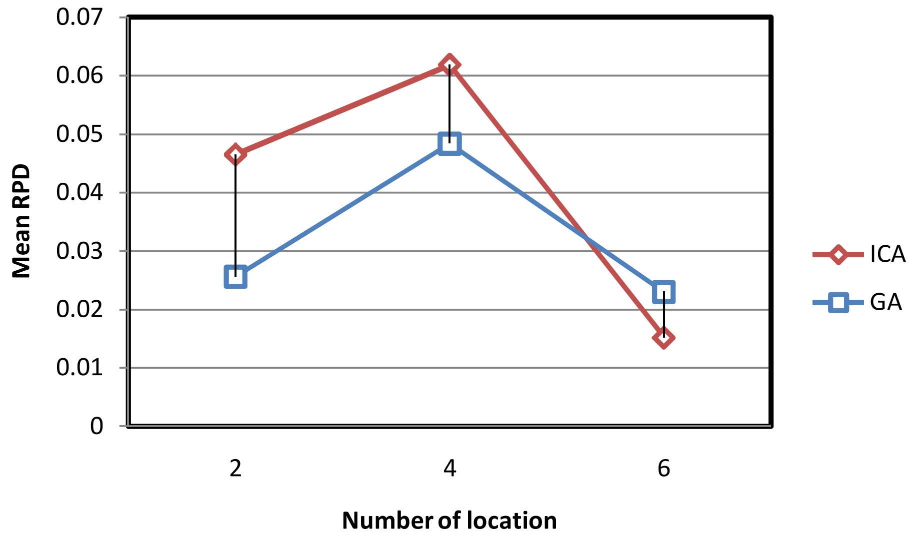

Fig. 7 Average Relative Percent Deviation ($\overline{RPD}$) for different value of possibility location

The interaction between (Number of vehicle, RPD) and (Number of period, RPD) are illustrated in Figures 8 and 9 respectively. These figures demonstrate that in all of the problems GA is better than ICA in quality of solution.

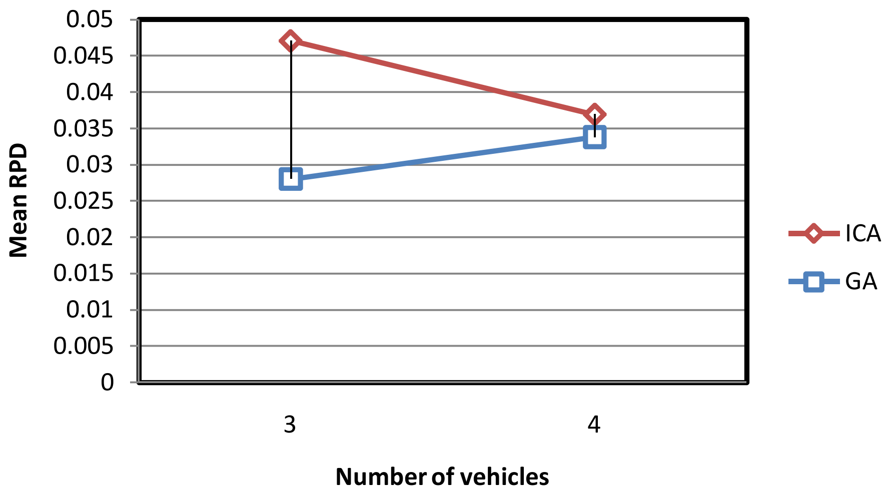

Fig. 8 Average Relative Percent Deviation ($\overline{RPD}$) for different value of vehicles

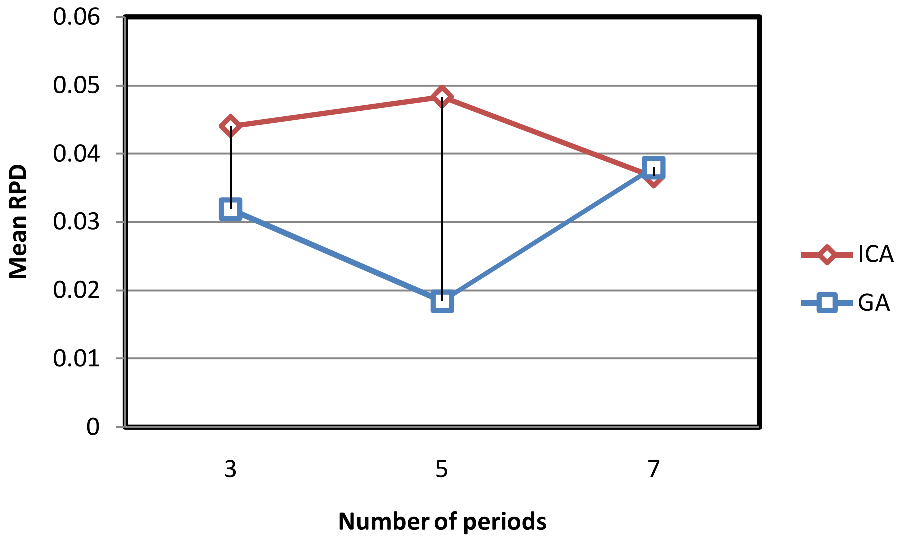

Fig. 9 Average Relative Percent Deviation ($\overline{RPD}$) for different value of period

6 Conclusions

In this study, a multi-period closed-loop supply chain problem with pricing policy has been considered. There are two echelons contain manufacturers and customers that are connected by a heterogeneous fleet of vehicles. In this paper, some of the delivered products to customers might be defective; therefore, they are picked up and collected in the collection-repair center in order to repair and return to the chain or to sell as wastes. As it has been mentioned in the literature review, the problem belongs to Np-hard problem; therefore, a genetic algorithm (GA) and an Imperialistic Competitive Algorithm (ICA) are applied so that we generated randomly generated test problems and solved them to evaluate their efficiency. In addition, the algorithms are compared by average relative percent deviation (RPD) criterion for the different number of customer, manufacturer, potential location, vehicle, and period and computational results are graphically have been illustrated. Although GA performance is better in a majority of the test problems but there is no significant difference between GA and ICA in general. However, average CPU time of ICA is less than GA in all cases. Thus, when time is important to achieve a solution, the ICA would be the choice with waiving the nuance between the two algorithms.

There are some guidelines for future research; first, this paper has not considered suppliers while as a significant player in supply chain management and an effective supplier selection can enhance its productivity. Second, we considered a problem when products are sent from manufacturers to customers directly that require a separated vehicle in each path, and thus, transportation cost increases dramatically. However, cross-duck can be located as the connector between manufacturers and customers and used as a temporary stock in order to reduce transportation costs and improve service level to the customers by delivering products on time.

References

1. Christopher, M., (2011). Logistics and supply chain management: Creating value-adding networks, Pearson Education Limited.
2. Sachan, S., Subhash D., (2005). Review of supply chain management and logistics research. International Journal of Physical Distribution & Logistics Management, 35(9), 664–705.
3. Storey, J., Emberson, C., Godsell, J., Harrison, A., (2006). Supply chain management: theory, practice and future challenges. International Journal of Operations & Production Management, 26 (7), 754–774.
4. Meade, L., Sarkis, J., Presley, A., (2007). The theory and practice of reverse logistics. International Journal of Logistics Systems and Management, 3, 56–84.
5. Petek, J., Glavic, P., (1996). An integral approach to waste minimization in process industries. Resource, Conservation and Recycling, 17, 169–188.
6. Fahimnia, B., Sarkis, J., Ali Eshragh, A., (2013). A Tradeoff Model for Greesn Supply Chain Planning: A Leanness-versus-Greenness Analysis. Omega, 54, 173–190.
7. Fleischmann M., Krikke H., Dekker, R., (2000). A characterization of logistics network for product recovery. Omega, 28(6), 653–666.
8. Govindan, K., Nicoleta Popiuca, M., (2014). Reverse supply chain coordination by revenue sharing contract: A case for the personal computers industry, European Journal of Operational Research, 233(2), 326-336.
9. Fahimnia, B., Sarkis, J., Hoda Davarzani, H., (2015). Green Supply Chain Management: A Review and Bibliometric Analysis. International Journal of Production Economics 162, Retrieved 2015, May 12, from: DOI: 10.1016/j.ijpe.2015.01.003.
10. Georgiadis, P., Besiou, M., (2008). Sustainability in electrical and electronic equipment closed-loop supply chains: A System Dynamics approach. Journal of Cleaner Production, 16(15), 1665-1678.
11. Kumar, S., Putnam, V., (2008). Cradle to cradle: Reverse logistics strategies and opportunities across three industry sectors. International Journal of Production Economics, 305–315.
12. Pagell, M., Wu, Z., N. Murthy, N., (2007). The supply chain implications of recycling. Business Horizons, 50, 133-143.
13. Hsu, S., Alexander, C., Zhiwei, Z., (2009). Understanding the reverse logistics operations of a retailer: a pilot study. Industrial Management & Data Systems, 109 (4), 515–531.
14. Rubio, S., Miranda, F. J., Chamorro, A., Valero, V., (2009). Implementing a reverse logistics system: a case study. International Journal of Procurement Management, 2(4), 346-357.
15. González, T., Álvarez, M., Sarkis, J., (2010). Barriers to the Implementation of Environmentally Oriented Reverse Logistics: Evidence from the Automotive Industry Sector. British Journal of Management, 21, 889–904. Retrieved 2015, May 12, from: DOI: 10.1111/j.1467-8551.2009.00655.X.
16. Halabi, A. X., Montoya-Torres, J. R., Pirachicán, D. C., Mejía, D., (2013). A modelling framework of reverse logistics practices in the Colombian plastic sector. International Journal of Industrial and Systems Engineering, 13(3), 364-387.
17. Pishvaee, M., Torabi, S., (2010). A possibilistic programming approach for closed-loop supply chain network design under uncertainty. Fuzzy Sets Syst. 161(20), 2668–2683.
18. Pishvaee, M., Torabi, S., Razmi, J., (2012). Credibility-based fuzzy mathematical programming model for green logistics design under uncertainty. Computer Industrial Engineering, 62, 624–632.
19. Pishvaee, M., Razmi, J., Torabi, S., (2014). An accelerated Benders decomposition algorithm for sustainable supply chain network design under uncertainty: A case study of medical needle and syringe supply chain. Transportation Research Part E, 67, 14–38.
20. Wei, J., Govindan, K., Li. Y., Zhao, J., (2015). Pricing and collecting decisions in a closed-loop supply chain with symmetric and asymmetric information. Computers and Operations Research, 54, 257–265.
21. He, Y., (2015). Acquisition pricing and remanufacturing decisions in a closed-loop supply chain. International Journal of Production Economics, 163, 48-60.
22. Rezapour, S., Farahani, R., Fahimnia, B., Govindan, K., Mansouri, Y., (2015). Competitive Closed-Loop Supply Chain Network Design with Price-Dependent Demands, Journal of Cleaner Production. Retrieved 2015, May 13, from: doi: 10.1016/j.jclepro.2014.12.095.
23. Dondo, R., Méndez, C. A., Cerdá, J., (2011). The multi-echelon vehicle routing problem with cross docking in supply chain management. Computers & Chemical Engineering, 35(12), 3002-3024.
24. Agustina, D., Lee, C. K. M., Piplani, R., (2014). Vehicle scheduling and routing at a cross docking center for food supply chains. International Journal of production economics, 152, 29-41.
25. Ahmadizar, F., Zeynivand, M., Arkat, J., (2015). Two-level vehicle routing with cross-docking in a three-echelon supply chain: A genetic algorithm approach. Applied Mathematical Modelling, 39(22), 7065-7081.

26. Hu, Z., Sheu J., Zhao, L., Lu, C., (2015). A dynamic closed-loop vehicle routing problem with uncertainty and incompatible goods. Transportation Research Part C, Emerging Technologies 55, 273-297.
27. Holland, J. H., (1975). Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor.
28. Dengiz, B., Altiparmak, F., Smith, A., (1997). Local search genetic algorithm for optimal design of reliable networks. IEEE Transactions on Evolutionary Computation,1, 179–88.
29. Atashpaz-Gargari, E., Lucas, C., (2007). Imperialist Competitive Algorithm: An algorithm for optimization inspired by imperialistic competition. IEEE Congress on evolutionary Computation,4661–4666. Retrieved 2015, May 12, from: http://www.icasite.info/icasite/ica_papers/new_code//icapap_2007_en_esmae_imperialis.pdf.
30. Zeballos, L., Méndez, A., Barbosa-Povoa, A., Novais, A., (2014). Multi-period design and planning of closed loop supply chains with uncertain supply and demand. Computers and Chemical Engineering, 66, 151–164.