JJMIE

Volume 12 Number 2, September. 2018
ISSN 1995-6665
Pages 77 - 91

Jordan Journal of Mechanical and Industrial Engineering

Optimization of a Closed Loop Green Supply Chain using Particle Swarm and Genetic Algorithms

Mojtaba Rahimi [a], Hamed Fazlollahtabar [b,*]

[a]Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran
[b]Department of Industrial Engineering, School of Engineering, Damghan University,Damghan, Iran

Received OCT 20 2017 *Accepted SEP 01 2018*

Abstract

Nowadays, due to increase of environmental hazards and legislation in this context by governments and also restriction of manufacturing resources, researchers paid special attention to the design of closed-loop green supply chain network. To establish better coordination between the components of the supply chain and gain more profits in the network, special decisions are required during the product lifecycle. The network presented in this study consists of four layers in the forward chain including suppliers, manufacturers, distribution centers and customer markets, and it also includes three facilities containing collection, dismantler and disposal centers in reverse chain. A mixed integer linear programming model proposed to optimize closed-loop green supply chain by considering the level of quality for constituent components of manufacturing parts along with the pricing policy and product life cycles to maximize profits. Genetic algorithm and particle swarm optimization are used to find the optimal solutions. Having analyzed the results and due to the relative percentage deviation and solution time, it was found that genetic algorithm performs better compared with the particle swarm optimization.

Keywords: *Closed-loop supply chain (CLSC); Green supply chain (GrSC); Mathematical programming; Particle swarm optimization (PSO); Genetic algorithm (GA).*

1. Introduction

Recently, much research in the field of closed-loop and green supply chain is done. A closed-loop logistics model for remanufacturing has been studied by Jayaraman et al. (1999) in which decisions relevant to shipment and remanufacturing of a set of products, as well as establishment of facilities to store the remanufactured products, were taken into consideration. The model was in the form of a 0–1 integer programming formulation and minimizes a total cost function of shipment, remanufacturing, and inventory. Fleischmann et al. (2001) considered a reverse logistics (RL) network design problem in which they analyzed the impact of product return flows on logistics networks. Krikke et al. (2003) considered minimization of facility set-up, processing, and distribution costs in the CLSC network design, while designing a GrSC with support from both product design and logistics networks. Sarkis (2003) provided a strategic decision framework with the help of an analytical network process for making decisions within the GrSC. Debo et al. (2006) studied the effects of new and remanufacturing products in the same market over the life cycle. In addition, they examined the production system when demand for new and remanufactured products is segmented into same and secondary markets. Ko and Evans (2007) presented a mixed-integer nonlinear programming (MINLP) model to configure forward and return networks. Moreover, they utilized genetic algorithm to solve the problem. Salema et al. (2007) presented a general model for reverse logistics network where capacity limits, multiproduct management, and uncertainty on product demands and returns exist.

While reverse logistic activities in a CLSC can improve the competence of enterprises, customer service level, and reduce the production costs, they should also provide a green image to the enterprises by increasing the demand of conscious customers for their products (Demirel and Gokcen 2008). Selim and Ozkarahan (2008) proposed a fuzzy goal programming approach for a reverse logistics (RL) network. The uncertainty in demand and decision makers' aspiration levels for the goals are taken into account. Lee et al. (2009) proposed a model for minimizing shipment costs of a CLSC and opening costs of disassembly centers and processing centers. In other words, the model can determine the optimal numbers of disassembly and processing centers. But, it does not include inventory costs such as holding costs. In addition, the model is designed for single supplier. Guide and Van Wassenhove (2009) categorized product returns according to product life cycle. Besides, they linked product return types to specific recovery activities. However, they did not examine the effects of returns pair on network configuration. Commercial returns are products that are returned by consumers within a certain period of time (for instance, 60 days after buying). These returned products often are repaired. End-of-use returns happen when a

* Corresponding author e-mail: hfazl@du.ac.ir; hfazl@alumni.iust.ac.ir.

functional product is replaced by a technological upgrade. The majority of these products are remanufactured. End-of-life returns are available when the product becomes technically obsolete or no longer contains any utility for the current user. The option of recycling is more suitable for this kind of return. Cell phone industry is a good example of three types of returns.

Pishvaee et al. (2010) developed a bi-objective MILP model to minimize the total costs and maximize the responsiveness of a logistics network. They applied a memetic algorithm. El-Sayed et al. (2010) proposed a multi-period forward and reverse logistics network. They considered both deterministic and stochastic demands. Paksoy et al. (2010) emphasized the reuse of recovered and recycled material while considering the minimization of carbon emissions of transporting vehicles through multi-objective mixed integer linear programming problems. Kannan et al. (2010) proposed a multi-period closed loop supply chain network for the optimum usage of recovered material in terms of lead recovered from lead-acid batteries. Their purpose was to develop a multi-echelon, multi-period, and multi-product CLSC to determine optimum distribution and inventory level decisions through a heuristics-based genetic algorithm (GA).

Pishvaee et al. (2011) proposed a robust optimization model for handling the inherent uncertainty of input data in a CLSC network problem. While first, a deterministic mixed integer programming model is developed for designing the CLSC network, finally the robust counterpart of the proposed model was presented by using the recent extensions in robust optimization theory. Shi et al. (2011) studied a production-planning problem for a multi-product closed-loop system, in which the manufacturer has two channels for supplying products: producing brand-new products and remanufacturing returns into as-new ones. The problem is to maximize the manufacturer's expected profit by jointly determining the production quantities of brand-new products, the quantities of remanufactured products, and the acquisition prices of the used products, subject to a capacity constraint. Ramezani et al. (2013) proposed a stochastic multi-objective model for the integrated forward and reverse supply chain network under uncertain environments. In their study, uncertainty referred to the return rate of used products. They aimed at maximization of profits, customer service levels in both forward and reverse networks, and sigma quality levels by minimizing defects in raw materials. Ozkır and Baslıgil (2013) proposed a multi-period, multi-commodity and capacitated CLSC network design with the help of a multi-objective optimization model.

Devika et al. (2014) proposed a mixed integer linear programming model to design a CLSC network to capture the triple bottom line of the sustainability. They considered recovering, remanufacturing, recycling, and disposal facilities under treatment centers of the reverse logistics network. Ozceylan et al. (2014) proposed an integrated model that jointly optimizes the strategic and tactical decisions of a closed-loop supply chain (CLSC). The strategic level decisions relate to the amounts of goods flowing on the forward and reverse chains. The tactical level decisions concern balancing disassembly lines in the reverse chain. The objective is to minimize costs of transportation, purchasing, refurbishing, and operating the disassembly workstations. A nonlinear mixed integer programming formulation is described for the problem.Soleimani and Kannan (2015) proposed a hybrid algorithm based on particle swarm optimization (PSO) and genetic algorithm (GA) for a CLSC network design problem.Accorsi et al. (2015) provided a tool to assess the enabling economic, environmental, and transport geography conditions to design sustainable closed-loop networks for the management of a generic product along its life-cycle. The proposed tool is built through a mixed-integer linear programming (MILP) model for the strategic design of a multi-echelon closed-loop network. The model minimizes a cost-based and a carbon-based function to determine the optimal geographic location of the nodes of the network and the allocation of transport flows.On the other hand, Diabat et al. (2015) address the single echelon case for both the forward and backward logistics of a closed-loop location-inventory problem, but develop an exact two phase Lagrangian relaxation to solve it.Garg et al.(2015) proposed a multi-objective mixed integer nonlinear programming model that extending the traditional supply chain to a closed-loop supply chain for to control the environmental issues has been achieved in terms of increased transport activities and to solve it offered an interactive multi-objective approach and Lingo software.

Zohal and Soleimani (2016) developed a model for green closed-loop supply chain in a gold industry. A green approach based on the CO2 emission function was regarded in the proposed model. A new ant colony optimization algorithm was proposed to solve generated and real instances.

Soleimani et al. (2017) addressed a design problem of a closed-loop supply chain regarding various echelons of a supply chain. Sustainability and green approaches were considered in the modeling and solving the proposed closed-loop supply chain. Fuzzy type of uncertainty was regarded for customer demands. A developed genetic algorithm was also proposed in order to solve the presented model.

Ghomi-Avili et al. (2018) presented a bi-objective model for green closed-loop supply chain network design considering disruption and operational risks with a fuzzy price-dependent demand. Also, environmental issues by minimizing CO2 emission in production process were addressed and a bi-level programming method was applied to model Stackleberg game in the problem.

To sum up, an overview of the most significant past works' contributions and the gap handled by this paper are summarized in Table 1.

Table 1: Summary of past works and research gap

	Authors	Year	Topic	Approach
1	Demirel and Gokcen	2008	remanufacturing in reverse logistics environment	mixed integer programming
2	El-Sayed et al.	2010	forward-reverse logistics network design	Mathematical programming
3	Abdallah et al	2012	Green supply chains with carbon trading	Mathematical formulation
4	Amin and Zhang	2012a	closed-loop supply chain configuration	Multi-objective
5	Demirel et al.	2014	closed-loop supply chain network	genetic algorithm
6	Garg et al.	2015	environmental issues in closed loop supply chain network	multi-criteria optimization
7	Zohal and Soleimani	2016	green closed-loop supply chain network	ant colony
8	Soleimani et al.	2017	sustainable and green closed-loop supply chain network	Fuzzy multi-objective and GA
9	Ghomi-Avili et al.	2018	green competitive closed-loop supply chain	Game theory and fuzzy optimization
10	The proposed problem	-	Green closed loop supply chain (considering quality, life cycle and pricing)	GA and PSO

As it is concluded from the reviewed past works the emphasis on more tactical and strategic levels of CLSC were neglected. Most of the reviewed works concentrated on operational variables of supply chain in mathematical formulations. Also, other works mainly used an evolutionary algorithm and the comparison of the methods to find the most efficient one was not investigated.In this paper, we intend to present a mixed integer linear programming model for a green closed-loop supply chain network design problem with respect of pricing, quality of the components and products life cycle that are effective tactical and strategic level decisions, under certain conditions of demand and rate of return. Furthermore, two evolutionary algorithms are adapted for the problem and their performance to find solutions are compared and analyzed.

The remainder of the paper is organized as fallows. Next, the proposed problem is described and justified. In Section 3, the corresponding mathematical formulations are given.In Section 4, particle swarm optimization (PSO) and genetic algorithm (GA) are implemented to optimize the proposed mathematical model as solution approaches. Results for implementation and discussions are presented in Section 5. We conclude in Section 6.

2. Problem description

We configured a closed-loop green supply chain (CLGSC) network as shown in Figure 1. Network facilities can be classified into two groups namely, forward supply chain and reverse supply chain facilities. The forward supply chain, which is the same as the traditional supply chain consists of raw material supplier facilities, manufacturing facilities, and distribution centers to serve their end customers. The reverse supply chain consists of three facilities: collection centers, dismantling centers and the disposal site location. The forward supply chain begins with the procurement of raw material from suppliers. Plant facilities are well equipped with required technology and responsible for manufacturing various components and then assembling them into products. From there, finished products move towards the end customers via distribution centers and customer zones. In the reverse chain of the proposed CLGSC network, returned products are collected from their users through a take back scheme. Users will be paid incentives for returning their end of life (EOL) and end of use (EOU) consumed products at the company operated collection center. Returned products collected will be transferred to the dismantling centers. There separated components will be inspected based on their quality and classified into two categories namely reusable and non-reusable components. The first category is that their use is terminated but due to possession of good and acceptable quality being used again and returned to manufacturing centers. The second category is considered to be waste and transferred to the disposal site. In this supply chain three types of products are produced that are called grade 1, grade 2, and grade 3. Grade 1 products are such products that it’s all constituent components and raw materials are original and directly procured from suppliers. Then, the components produced and assembled in manufacturing centers. Finally, the product grade 1 is delivered to the customer. In the second grade products, all its constituent parts are the reusable components that are sent to the manufacturing centers through the reverse chain and the dismantling centers. These components are then assembled and form product grade 2.In the third grade products, the components are a combination of original and reusable components.

Seeing all these issues, a mixed integer linear programming model, depicting the requirement of the proposed CLGSC is formulated. A model corresponding to the proposed multi-echelon CLGSC is configured for a multi type product and a multi period to determine the optimum flow of material, product and component in the network, while maximizing the total profit. Moreover, during the course of model formulation, the following assumptions are postulated:

1. Demand at customer end is deterministic; there is no shortage.
2. Facility locations are known a priori and they are fixed.
3. The flow of products, parts, and materials can occur only in between two consecutive stages; inter stage flow is not allowed.
4. All cost parameters are deterministic and all operations of CLSC are to be carried under capacity limitations.
5. Set-up cost of facilities is considered to be a part of the operations cost of the respective facilities.
6. Quality testing is done in the dismantling center and operational expense of this center, including the cost of the test is also.
7. Products quality grade 2 and grade 3 is different from the grade 1. Therefore, the selling price is considered to be different.
8. Demand and the rate of return for each type of product are considered to be different.

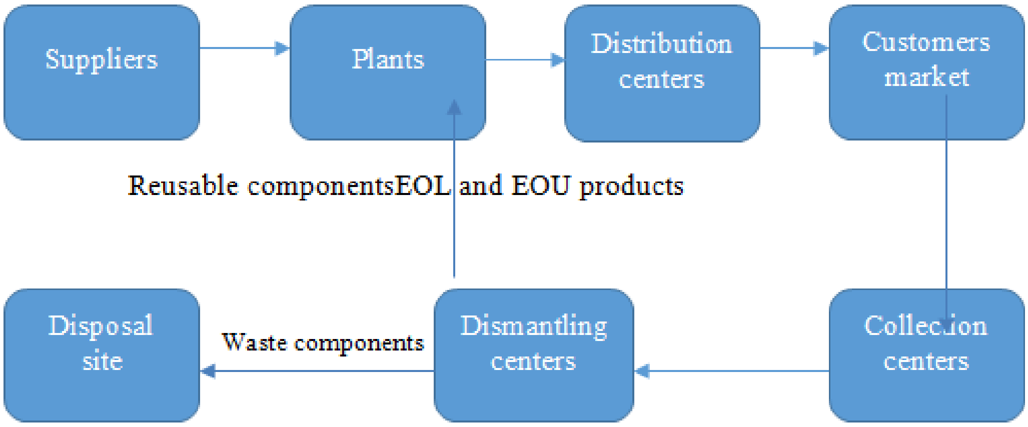

Figure 1: Closed loop green supply chain network

3. Mathematical formulation

Here, the mathematical notations proposed for the mathematical presentation of the problem are listed and defined.

Sets:

I: Set of raw material supplier, indexed by *i, i=1, 2… I*

J: Set of manufacturing plant, indexed by *j, j=1,2,…J*

K: Set of distribution center, indexed by *k, k=1,2..K*

L: Set of customer market, indexed by *l, l=1,2..L*

C: Set of collection centers, indexed by *c, c=1, 2.., C*

p: Set of dismantling centers, indexed by*p,p=1, 2.., P*

f: Set of disposal sites, indexed by*f,f=1, 2.., F*

T: Set of time period, indexed by*t, t=1, 2… T*

R: Set of raw materials, indexed by*r, r=1, 2… R*

M: Set of components, indexed by*m, m=1, 2… M*

$$Q = \begin{cases} 1 & \text{quality of reusable components} \\ 2 & \text{quality of wastes components} \end{cases}$$

Cost parameters:

Pur_{ijt}^{r} *Per unit purchasing cost of rth material from ith supplier for jth plant in period t*

HA_{mjt} *Production cost of mth component at jth plant in period t*

HM_{jt} *Assembling cost of a product at jth plant in period t*

OP_{kt} *Per unit operating cost at kth distribution center in period t*

KB_{t} *Incentive paid for a return in period t (fixed regardless of the condition)*

PC_{pt} *Dismantling cost of a returned product at pth dismantling center in period t*

HD_{ft} *Disposal cost of a fth disposal site for each component in period t*

TC_{rt}^{ij} *Cost of transporting of rth raw material from ith supplier to jth plant in period t*

TC_{t}^{jk} *Cost of transporting a unit of product from jth plant to kth distribution center in period t*

TC_{t}^{kl} *Cost of transporting a unit of product from kth distribution center to lth customer in period t*

TC_{t}^{cp} *Cost of transporting a unit of returned product from cth collection center to pth dismantling center in period t*

TC_{mt}^{pj} *Cost of transporting a unit of mth component from pth dismantling center to jth plant in period t*

TC_{mt}^{pf} *Cost of transporting a unit of mth component from pth dismantling center to fth disposal site in period t*

Other parameters:

D_{lt} *Demand of customer l for grade1 product in period t*

D'_{lt} *Demand of customer l for grade2 product in period t*

D''_{lt} *Demand of customer l for grade3 product in period t*

α_{lt} *Rate of return for grade1 product from customer l in period t*

α'_{lt} *Rate of return for grade2 product from customer l in period t*

α''_{lt} *Rate of return for grade3 product from customer l in period t*

β_{m} *Utilization rate of mth component in the product*

μ_r^m *Utilization rate of rth material per unit of mth component*

MI *Great number*

QF_{lt} *Unit selling price of grade1 product for the customer market l in period t*

$Q^{'}F_{lt}$ *Unit selling price of grade2 product for the customer market l in period t*

$Q^{''}F_{lt}$ *Unit selling price of grade3 product for the customer market l in period t*

Cap_i^r *Capacity of ith supplier for supplying rth material*

Cap_j *Production capacity of plant j*

Cap_k *Capacity of kth distribution center*

δ_t *Rate of return for reusable components from dismantling centers in period t*

Decision variables:

X_{ijrt} *Quantity of raw material r shipped from supplier i to plant j in period t*

X_{mjt} *Quantity of mth original component that is produced at plant j in period t*

X_{jkt} *Quantity ofgrade1 product shipped from plant j to distribution center k in period t*

$X^{'}_{jkt}$ *Quantity of grade2 product shipped from plant j to distribution center k in period t*

$X^{''}_{jkt}$ *Quantity of grade3 product shipped from plant j to distribution center k in period t*

X_{klt} *Quantity of grade1 product shipped from distribution center k to customer market l in period t*

$X^{'}_{klt}$ *Quantity of grade2 product shipped from distribution center k to customer market l in period t*

$X^{''}_{klt}$ *Quantity of grade3 product shipped from distribution center k to customer market l in period t*

X_{lct} *Quantity of used product returned from customer market l to collection center c in period t*

X_{ct} *Quantity of product shipped from collection center c to dismantler centers in period t*

X_{mpjqt} *Quantity of mth component with quality q=1 that considered reusable components and shipped from dismantler center p to plant j in period t*

X_{mpfqt} *Quantity of mth component with quality q=2 that considered waste components and shipped from dismantler center p to disposal center j in period t*

$$A_{lc} = \begin{cases} 1 & \text{if collection center } c \text{ is opened to collect return goods from costumer market } l \\ 0 & otherwise \end{cases}$$

$$B_{kl} = \begin{cases} 1 & \text{if costumer market } l \text{ to be catered by distribution center } k \\ 0 & \text{otherwise} \end{cases}$$

In terms of the sets indices, parameters, and decision variables defined above, the multi-echelon, multi-product and multi-period green closed loop supply chain design problem can be formulated as follows.

Objective functions:

The objective is to maximize the total profit generated in the CLGSCN. The profit is to be obtained by subtracting the total cost incurred to the system from the income earned in the network. The sources of income in the CLSC network are the customer market where the finished products with each type are to be sold. The mathematical representation of total income generated in the CLSC is:

$$\sum_k \sum_l \sum_t (QF_{lt} * X_{klt} + Q^{'}F_{lt} * X^{'}_{klt} + Q^{''}F_{lt} * X^{''}_{klt}) \quad \text{(I)}$$

In equation (I), the first term shows the multiplication of unit selling price of grade1 product to quantity ofgrade1 product leading to the earned income from product grade 1. The second and the third terms are also the earned income from grade 2 and 3 products, respectively.

Various costs borne by the company including the costs of maintaining effective functioning of each facility and the flow between the facilities need to be considered. Thus the total cost includes operational costs and transportation costs. Furthermore, the operational costs incurred in the forward chains are due to the purchasing of raw material, the production of original components, product assembly and on-time delivery of the products to their customers. The reverse chain requires the company to pay incentives to their customers under a take back scheme for returning EOU and EOL products, and the company also bears various costs in the reverse chain such as dismantling cost that including quality testing , and disposal cost. The mathematical representation of operational costs incurred in the network follows in equation (II).

Equation (III) represents the transportation cost which includes the cost of transporting material from suppliers to plants, products from plants to distribution centers and distribution centers to customers market in the forward chain, the cost of shipping returned products from collection centers to the dismantling centers, and the cost of shipping components from the dismantlers to plants and disposal centers.

$$\sum_r\sum_j\sum_i\sum_t Pur_{ijt}^r * X_{ijrt} + \sum_m\sum_j\sum_t HA_{mjt} * X_{mjt}$$
$$+\sum_j\sum_k\sum_t HM_{jt} * \left(X_{jkt} + X_{jkt}^{'} + X_{jkt}^{''}\right) + \sum_k\sum_l\sum_t OP_{kt} * \left(X_{klt} + X_{klt}^{'} + X_{klt}^{''}\right) \quad \text{(II)}$$
$$+\sum_l\sum_c\sum_t KB_t * X_{lct} + \sum_p\sum_c\sum_t PC_{pt} * X_{ct} + \sum_p\sum_f\sum_m\sum_t HD_{ft} * X_{mpfq2t}$$

$$\sum_r\sum_j\sum_i\sum_t TC_{rt}^{ij} * X_{ijrt} + \sum_j\sum_k\sum_t TC_t^{jk} * \left(X_{jkt} + X_{jkt}^{'} + X_{jkt}^{''}\right)$$
$$+\sum_k\sum_l\sum_t TC_t^{kl} * \left(X_{klt} + X_{klt}^{'} + X_{klt}^{''}\right) + \sum_p\sum_c\sum_t TC_t^{cp} * X_{ct} \quad \text{(III)}$$
$$+\sum_p\sum_j\sum_m\sum_t TC_{mt}^{pj} * X_{mpjq1t} + \sum_p\sum_f\sum_m\sum_t TC_{mt}^{pf} * X_{mpfq2t}$$

Therefore, the objective function is (I)-(II)-(III):

$$MaxZ = \sum_k\sum_l\sum_t (QF_{lt} * X_{klt} + Q^{'}F_{lt} * X_{klt}^{'} + Q^{''}F_{lt} * X_{klt}^{''})$$
$$-(\sum_r\sum_j\sum_i\sum_t Pur_{ijt}^r * X_{ijrt} + \sum_m\sum_j\sum_t HA_{mjt} * X_{mjt}$$
$$+\sum_j\sum_k\sum_t HM_{jt} * \left(X_{jkt} + X_{jkt}^{'} + X_{jkt}^{''}\right) + \sum_k\sum_l\sum_t OP_{kt} * \left(X_{klt} + X_{klt}^{'} + X_{klt}^{''}\right)$$
$$+\sum_l\sum_c\sum_t KB_t * X_{lct} + \sum_p\sum_c\sum_t PC_{pt} * X_{ct} + \sum_p\sum_f\sum_m\sum_t HD_{ft} * X_{mpfq2t}$$
$$+\sum_r\sum_j\sum_i\sum_t TC_{rt}^{ij} * X_{ijrt} + \sum_j\sum_k\sum_t TC_t^{jk} * \left(X_{jkt} + X_{jkt}^{'} + X_{jkt}^{''}\right)$$
$$+\sum_k\sum_l\sum_t TC_t^{kl} * \left(X_{klt} + X_{klt}^{'} + X_{klt}^{''}\right) + \sum_p\sum_c\sum_t TC_t^{cp} * X_{ct}$$
$$+\sum_p\sum_j\sum_m\sum_t TC_{mt}^{pj} * X_{mpjq1t} + \sum_p\sum_f\sum_m\sum_t TC_{mt}^{pf} * X_{mpfq2t} \quad)$$

Constraints:

Constraints under which we need to optimize the above objective are as follows.

$$\sum_i X_{ijrt} = \sum_m \mu_r^m * X_{mjt} \quad \forall j,r,t \quad (1)$$

Constraint (1) represents the quantity of each raw material shipped from suppliers to plant, and it depends on the number of components manufactured there.

$$\sum_j X_{ijrt} \le Cap_i^r \quad \forall r,i,t \quad (2)$$

Constraint (2) shows that the total quantity of each raw material shipped from any supplier cannot exceed the supplier's supplying capacity.

$$\sum_j X_{jkt} = \sum_l X_{klt} \quad \forall k,t \quad (3)$$

$$\sum_j X_{jkt}^{'} = \sum_l X_{klt}^{'} \quad \forall k,t \quad (4)$$

$$\sum_j X_{jkt}^{''} = \sum_l X_{klt}^{''} \quad \forall k,t \quad (5)$$

Constraints (3)-(5) represents that for each type of the product the flow entering each distribution center is equal to the flow exiting from the distribution center.

$$\sum_l \left(X_{klt} + X_{klt}^{'} + X_{klt}^{''}\right) \le Cap_k \quad \forall k,t \quad (6)$$

Constraint (6) ensures that the flow of the product exiting from each distribution center does not exceed the capacity of the distribution center.

$$\sum_k X_{jkt} * \beta_m \le X_{mjt} \quad \forall m,j,t \quad (7)$$

Constraint (7) shows the quantity of the original components that are required for the production of the grade1 product.

$$\sum_k X_{jkt}^{'} * \beta_m \le \sum_p X_{mpjq1(t-1)} \quad \forall m,j,t \quad (8)$$

Constraint (8) shows the quantity of the reusable components that are required for the production of the grade2 product.

$$\sum_k X''_{jkt} * \beta_m \leq \left(X_{mjt} - \left(\sum_k X_{jkt} * \beta_m \right) \right) + \left(\sum_p X_{mpjq1(t-1)} - \left(\sum_k X'_{jkt} * \beta_m \right) \right) \forall m, j, t \tag{9}$$

Constraint (9) shows the quantity of the original and reusable components that are required for the production of the grade3 product.

$$\sum_k \left(X_{jkt} + X'_{jkt} + X''_{jkt} \right) \leq Cap_j \quad \forall j, t \tag{10}$$

Constraint (10) ensures that the flow of the product exiting from each plant does not exceed of the production capacity of the plant.

$$\sum_k X_{klt} \geq D_{lt} \quad \forall l, t \tag{11}$$

$$\sum_k X'_{klt} \geq D'_{lt} \quad \forall l, t \tag{12}$$

$$\sum_k X''_{klt} \geq D''_{lt} \quad \forall l, t \tag{13}$$

Constraints (11)-(13) ensures no shortages of each type of the product at demand point.

$$\sum_c X_{lct} = (\alpha_{lt} * D_{lt}) + (\alpha'_{lt} * D'_{lt}) + (\alpha''_{lt} * D''_{lt}) \ \forall l, t \tag{14}$$

Constraint (14) describes the relationship between the demand and quantity of return products transferred from customers to collection centers.

$$X_{ct} = \sum_l X_{lct} \quad \forall c, t \tag{15}$$

Constraint (15) calculates the quantity of the total returned product at each collection center in each period.

$$\sum_p \sum_j X_{mpjq1t} = \sum_c \delta_t * X_{ct} * \beta_m \ \forall t, m \tag{16}$$

Constraint (16) shows the quantity of the total reusable components that flow of each component exiting from dismantling center to plant in each period.

$$\sum_p \sum_f X_{mpfq2t} = \sum_c (1 - \delta_t) * X_{ct} * \beta_m \ \forall t, m \tag{17}$$

Constraint (17) shows the quantity of the waste components that flow of each component exiting from dismantling center to disposal center in each period.

$$\left(X_{klt} + X'_{klt} + X''_{klt} \right) \leq MI * B_{kl} \ \forall k, l, t \tag{18}$$

$$X_{lct} \leq MI * A_{lc} \ \forall l, c, t \tag{19}$$

Constraint (18) represents that a distribution center can only serve the customers market assigned to it. Similarly, Constraint (19) says that a collection center can only collect the returned product from the customer market assigned to it.

$$B_{kl}, A_{lc} \in \{0, 1\} \ \forall k, l, c \tag{20}$$

$$(X_{ijrt}, X_{mjt}, X_{jkt}, X'_{jkt}, X''_{jkt}, X_{klt}, X'_{klt}, X''_{klt}, X_{lct}, X_{ct}, X_{mpjqt}, X_{mpfqt}) \geq 0 \tag{21}$$

and Integer $\forall i, j, k, l, c, p, f, m, r, q, t$

Constraints (20) and (21) impose the binary, non-negativity and integer restrictions on the corresponding decision variables.

4. Proposed algorithms

4.1. Particle Swarm Optimization (PSO)

PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy(1995), inspired by the social behavior of bird flocking or fish schooling. The algorithm was further developed (Poli et al., 2007). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike the GA, the PSO has no evolution operators such as crossover and mutation. PSO is one of the swarm intelligent techniques.In the idea of PSO, each particle in the swarm has the same characteristics and behaviors. However, each particle has a random of the position and velocity parameter. The position of particles is explained by a possibility that is a solution of the optimization problem. In this algorithm, each bird is a possible answer in the search space ofthe problem. At first by a group of birds that have been produced randomly, the algorithm begins searching to obtain the best solution. At each step of the iteration, the bird moves to the better position. The next opportunity for each bird is to consider the two values: the first value is the best position so far that bird has got (*pbest*) and the second value is the best position that all birds have won (*gbest*). In other words, *gbest* can be considered the best *pbest* in the whole group. This process continues until the algorithmreaches the termination condition. Termination condition in the algorithm tends the birds speed to zero or the number of repetitions that have been considered. According to *pbest*and *gbest* values, each bird uses the following formula to determine the next location:

$$v_i^{k+1} = w v_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k \right) + c_2 rand_2 \times \left(gbest - s_i^k \right) \tag{22}$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{23}$$

where v_i^k is the current velocity of particle i at iteration k, v_i^{k+1} the new velocity of particle i at iteration k, c_1 the adjustable cognitive acceleration constant, c_2 the adjustable social acceleration constant, $rand_{1,2}$ the random number between 0 and 1, s_i^k the current position of particle i at iteration k, s_i^{k+1} the new position of particle i at iteration k, $pbest_i$ the personal best of particle i, and

$gbest$ is the global best of population. Note that, $pbest_i$ is the best location of individual particle while $gbest$ is the best location of the swarm.

4.2. Genetic Algorithm (GA)

Genetic Algorithms (GAs) are adaptive heuristic search algorithms based on the evolutionary ideas of natural selection and genetic processes. The basic principles of GAs were first proposed by John Holland (1975), inspired by the mechanism of natural selection where stronger individuals are likely the winners in a competing environment. The GA assumes that the potential solution to any problem is an individual and can be represented by a set of parameters. These parameters are regarded as the genes of a chromosome and can be structured by a string of values in binary form. A positive value, generally known as a fitness value, is used to reflect the degree of "goodness" of the chromosome for solving the problem, which is highly related with its objective value.A GA starts with a random population of solutions (called chromosomes) and then tries to improve solutions through manyiterations called generations. Each solution's performance is evaluated by a fitness function corresponding to the objective function of the optimization problem. Following parental selection, crossover and mutation operators are applied. Crossover combines materials from parents to produce children. On the other hand, mutation makes small local changes in feasible solutions to provide population diversity for a wider exploration of feasible solutions. The mutation operator is defined to ensure that generated solutions are not trapped in some local optima. As the final solution is independent of initial solutions, the basic population is randomly generated in most cases (Michalewicz, 1996).

4.2.1. Chromosome structure

In this algorithm,based on the type of facilities available for the proposed network and the relationships between them, showing thechromosome is composed of seven parts. All these sectors of a multidimensional matrix and elements with real value in the interval [0,1] are formed.Together they create a solution to the problem that the values of the variables and objective function are calculated accordingly.The following matrix (Table 2) displaysdimensionsof each section.

For example, the first part of a four-dimensional matrix with dimensions (K*L*Q'*T) has been formed. This section determines that each customer in eachperiod will receivethe required product with anylevel of quality from each distributor. Suppose in a sample with 3customers and 2 distributors, first part of chromosome for product with quality level 1 in period 2 is as shown in Table 3.

In this section of the chromosomes, to assign each customer demand to distributor, the element assignment with the highest value is begun. In this case, theelement regarding to customer 1 and distributor 2 is the highest and thuscustomer's demand 1 is supplied through distributor 2, and the assigned demand is reducedfrom distribution's capacity.If one distribution's capacity was less than the corresponding customer's demand,then that distributor devotes its capacity and the remainder is supplied by another distributor.

4.2.2. Crossover operator

Crossoveroperator employed inthis algorithm is based on a guide matrix.This matrix has binary elements and for each individual element the chromosome size is the same. In this way, to select parents cross over operator is applied using roulette wheel.Thus, for each of the elements in each of the four sections of chromosomes a corresponding element of the guide matrix exists.In order to generate new offspring, if the value of the corresponding element in the guide matrix is 1, the corresponding element valueis changed between twoparents; otherwise, the element is left unchanged.Figure 2 impliesa small example of this approach.

Table2: Matrixdimensions of each section

Section1	Section2	Section3	Section4	Section5	Section6	Section7
$K \times L \times Q' \times T$	$J \times K \times Q' \times T$	$I \times J \times R \times T$	$L \times C \times T$	$C \times P \times T$	$P \times J \times T$	$P \times F \times T$

Table3: An example of the first part of chromosome structure

Distributor \ Customer	1	2	3
1	0.27	0.81	0.46
2	0.99	0.46	0.17

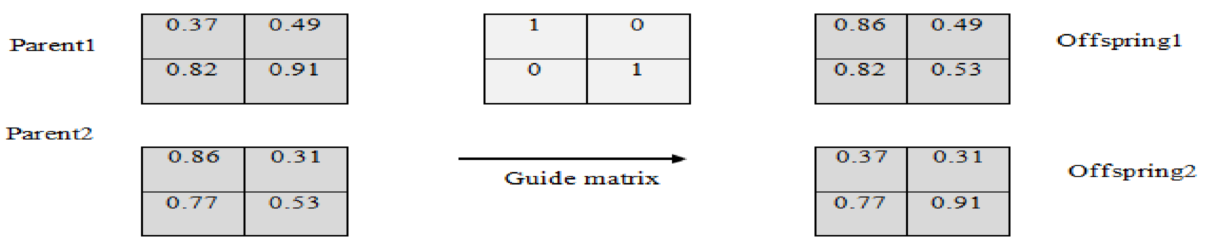

Figure 2: Proposed Crossover operator

4.2.3. Mutation operator

In this algorithm, for mutation in each section of chromosome, randomlytwo rows or two columns are chosen and the elements are pasted between them upside down.For parts of chromosomes that have more than one dimension, the operation is applied for all of them. Figure 3 shows how to apply mutation operator.

4.3. Parameters setting

Performance of anymeta-heuristic algorithm is directly influenced by parameters and operators setting, so that the wrong choiceof algorithm parameters will lead to ineffectiveness of the solutions. Based on paststudies and experimental considerations, the parameters are defined as shown in Tables 4 and 5 for GA and PSO algorithms, respectively.

5. Results of the proposed algorithms

In this section, a total of 30 sample problems were selected and each problem is repeated 5 times. Dimensions of sample problems are presentedinTable6.

Table4: GA Parameters

Population size	Number of iterations	Crossover Rate	Mutation Rate	Elitism Rate
350	150	0.9	0.1	0.1

Table5: PSO Parameters

Population size	Number of iterations	v	w	C_1	C_2
350	150	0.9	0.75	2	2

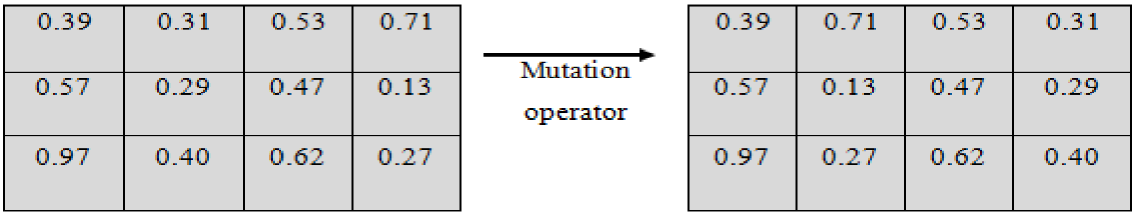

Figure 3: ProposedMutation operator

Table6: Dimensions of sample problems

problem size	suppliers	Manufacturers	distribution centers	Customers market	period	collection centers	dismantling centers	disposal site	components	Raw material
1	3	2	2	4	2	4	1	1	4	10
2	3	2	2	5	2	4	1	1	4	10
3	3	3	2	5	2	5	1	1	4	10
4	4	3	2	5	2	5	1	1	4	10
5	4	3	3	6	2	5	1	1	4	10
6	4	4	3	6	2	5	1	1	4	10
7	5	2	2	5	3	5	2	1	4	10
8	5	3	3	4	3	4	2	1	4	10
9	5	3	4	6	3	6	2	1	4	10
10	5	4	3	5	2	4	1	1	4	10
11	5	4	4	6	3	6	2	1	4	10
12	5	5	4	5	3	5	2	1	4	10
13	5	5	4	6	3	5	1	1	4	10
14	6	5	4	5	3	5	2	1	4	10
15	6	4	4	5	4	5	2	1	4	10
16	6	4	4	6	4	6	2	1	4	10
17	6	4	4	7	4	6	2	1	4	10
18	6	5	4	7	4	7	3	2	4	10
19	7	5	5	7	4	7	3	2	4	10
20	7	6	5	7	4	7	3	2	4	10
21	7	6	6	7	5	7	3	2	4	10
22	7	6	5	8	5	7	3	2	4	10
23	8	6	5	8	5	8	3	2	4	10
24	8	6	6	8	6	8	4	2	4	10
25	8	7	5	8	5	8	3	2	4	10
26	8	7	5	9	5	8	4	2	4	10
27	8	7	5	9	6	9	4	3	4	10
28	9	7	6	9	6	9	4	3	4	10
29	9	8	6	10	6	9	4	3	4	10
30	9	8	6	10	6	10	4	3	4	10

The values of the parameters used in the model are randomly generated based on the given probability distribution functions in the following table (Table 7) and is used in each stage.

Table7: Parameter values in the model

Parameter Number	Parameter	probability functions
1	QF_{lt}	U[1955,11700]
2	$Q^{'}F_{lt}$	U[1562,11500]
3	$Q^{''}F_{lt}$	U[1750,11755]
4	D_{lt}	U[1120,1210]
5	$D_{lt}^{'}$	U[0,148]
6	$D_{lt}^{''}$	U[0,190]
7	α_{lt}	U[0.52,0.75]
8	$\alpha_{lt}^{'}$	U[0.28,0.56]
9	$\alpha_{lt}^{''}$	U[0.47,0.68]
10	Pur_{ijt}^{r}	U[4,18]
11	HA_{mjt}	U[40,58]
12	HM_{jt}	U[40,50]
13	OP_{kt}	U[45,55]
14	KB_{t}	U[95,105]
15	PC_{pt}	U[35,44]
16	HD_{ft}	U[51,61]
17	TC_{rt}^{ij}	U[20,35]
18	TC_{t}^{jk}	U[20,33]
19	TC_{t}^{kl}	U[20,33]
20	TC_{t}^{cp}	U[20,32]
21	TC_{mt}^{pj}	U[20,32]
22	TC_{mt}^{pf}	U[20,32]
23	Cap_{i}^{r}	U[61300,130200]
24	Cap_{j}	U[13450,16250]
25	Cap_{k}	U[13000,15000]
26	δ_{t}	U[0.43,0.57]

5.1. Measures of algorithm performance

To study the effectiveness of the proposed algorithms and compare them with each other, a measure of the relative percentage deviation (RPD) used that is calculated by the following equation:

$$RPD_{ab} = \left| \frac{(Mean_{sol})_{ab} - Best_{sol}}{Best_{sol}} \right| \quad (24)$$

where $Best_{sol}$ is the best result for a problem between all performances of the problem and $(Mean_{sol})_{ab}$ is the mean of the best results for a problem in an algorithm. Obviously, a lower value of (RPD) represents the algorithm has better performance.It isalso known that an important feature of each algorithm is the computational time. Clearly, the proper use of meta-heuristic algorithm reduces the computational time for a problem.In Table 8 the results of the two algorithms are shown.

Table8: The results of the GA algorithm and PSO algorithms

Problem number	GA algorithm				PSO algorithm			
	Mean	Best	Time	RPD	Mean	Best	Time	**RPD**
1	25727176.8	25728321	108.8207	0.0471	26613903	26998222	162.9818	0.0142
2	27533283.8	27726698	124.1821	0.007	27205304.2	27644764	203.6378	0.0188
3	9081762	9116236	154.2433	0.1132	9975214.4	10240851	530.0432	0.0259
4	26529593.7	26569450	211.408	0.0381	26952338	27581159	350.6616	0.0228
5	-2344434.2	-1898141	257.4556	0.2351	-2222085.2	-2097766	457.3326	0.1707
6	11732358.9	12097469	299.743	0.0849	11997137.2	12821131	508.9971	0.0643
7	-1608452.6	-1355601	276.9875	0.4116	-1354632.3	-1139461	478.0214	0.1888
8	29336463.6	29605973	345.59	0.066	30449607.6	31410818	853.2278	0.0306
9	78485567.6	78877074	514.1089	0.0195	77349956.2	80048327	697.574	0.0337
10	9333445.8	9710196	406.3376	0.2724	10814956.2	12828595	712.0418	0.157
11	56793521.4	57442661.6	568.0022	0.05	58471076.7	59784232.3	829.1311	0.022
12	29983902.7	31362475.6	1058.045	0.044	29016879.6	31269455	837.8348	0.0748
13	54815452	55484178.3	1871.012	0.0121	53045156.2	55300421	893.5983	0.044
14	35166080.7	35517962.3	931.0291	0.0955	37623726.5	38879316	928.1525	0.0323
15	97649910	98706250	3821.869	0.02	96964262.5	99643729	1066.032	0.0269
16	25087706.1	26229566	862.7388	0.0435	18752074.3	20385899	1242.021	0.2851
17	30476547.4	31817281	915.8037	0.0421	22536321.4	23841114	1336.709	0.2916
18	143653590	144095563	1057.302	0.0031	138624146	143276556	1719.556	0.038
19	195785782	78779223	1228.755	0.0041	193338178	194259465	1748.414	0.0166
20	76168864.6	78779223	1426.445	0.0331	69261453.5	71516008.3	1950.664	0.1208
21	193426387	195292564	2290.256	0.0096	185913567	188937311	2442.267	0.048
22	-8106671.6	-6728674	2281.183	0.2048	-23279928	-20904265	2670.729	2.4598
23	103144435	103949997	2187.646	0.0077	90706818.2	94289903	2551.266	0.1274
24	144808109	147738949	2792.341	0.0198	137857166	141438086	3636.245	0.0669
25	117983938	122360844	2538.078	0.0358	110521973	113351132	3181.979	0.0968
26	185026377	187772817.6	2580.784	0.0146	176280127.4	179896662.3	3159.592	0.0612
27	277832644	282025518.5	3402.463	0.0149	268122134.2	269976107.7	4330.511	0.0493
28	216991612	222083769	3851.312	0.229	196093058	205698700	4460.662	0.117
29	123408828	126849792	4504.353	0.0271	109017654	113135257	5402.177	0.1406
30	62046948.7	70148233	4528.834	0.1155	4717958.6	53718567	5652.2	0.3274

In Table8 by "the best" we mean the best solution among the optimum solutions for each algorithm and the "mean", "time" and "RPD" stand for average optimum solutions, time and calculated RPD to 5 times run of any problem, respectively. Figure 4showssolution for problem 27 in replication 1(27-1).

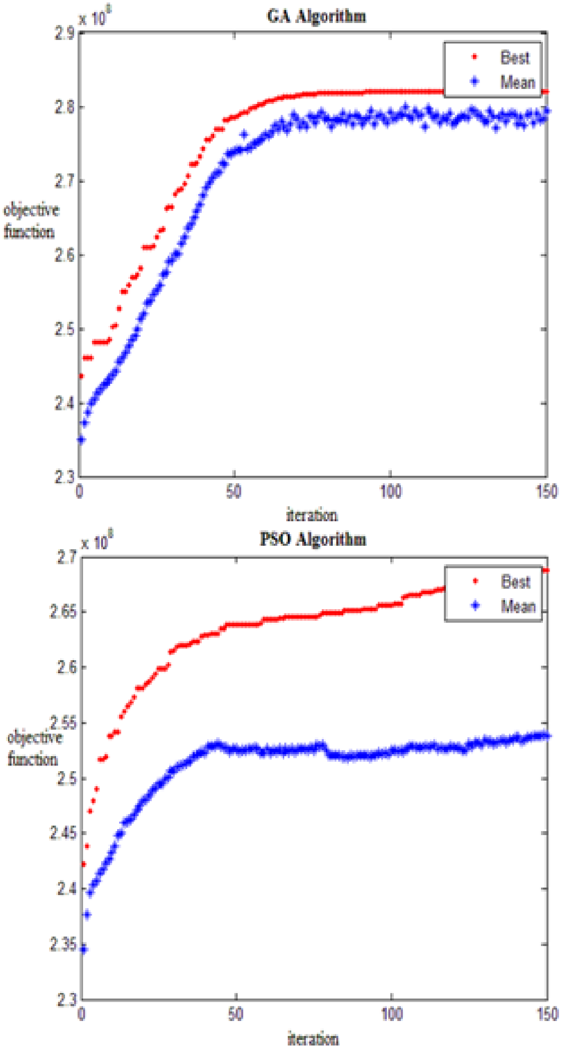

Figure 4: Solution graph for problem 27-1 using GA and PSO algorithms

As mentioned in the past section, to check the performance of the proposed algorithm RPD criterion is used.Supply chain issues are usually more sensitive in specific variables.In this study, the efficiency of algorithms is analyzed for closer examination of these issues with respect to variables including suppliers, manufacturers, distribution centers, customers and periods RPD graph is drawn.For example, in the graph shown below (Figure 5) by changing the number of suppliers the analysis is performed. When the number of suppliers is between 3 and 9, supplier RPD variations for both algorithms are depicted.

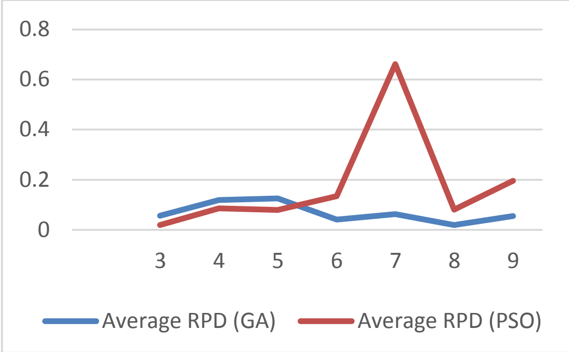

Figure 5: Algorithms RPD graph with thedifferent number of suppliers

As it is clear from Figure 5, for problems until 5 suppliers, the PSO algorithm's RPD is less. But by increasing the number of suppliers, GA algorithm outperforms PSO with respect to RPD and therefore has a better performance.

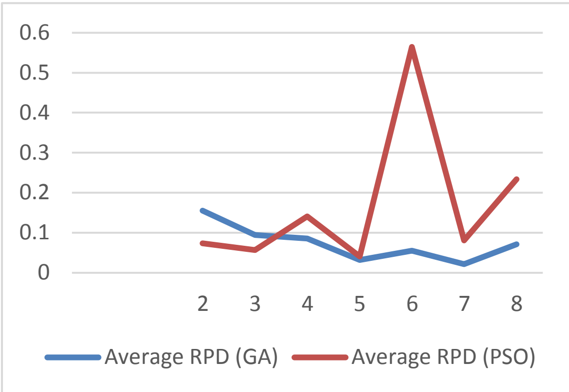

Figure 6.RPD graph with thedifferent number of manufacturers

As it is clear from Figure 6, for problems until 3manufacturers,the PSO algorithm's RPD is less. But by increasing the number of manufacturers, GA performs better.

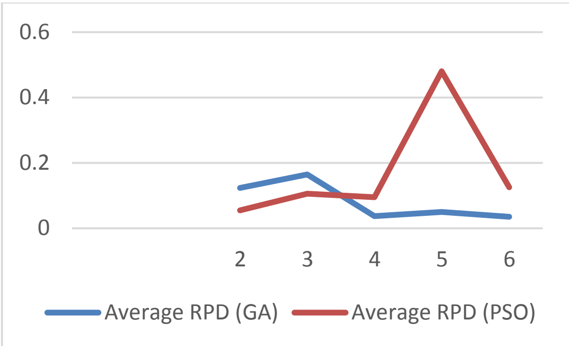

Figure 7.RPD graph with the different number of distribution centers

According to Figure 7, for problems until 3distribution centers, the PSO algorithm's RPD is less. But by increasing the number of distribution centers, GA performs better.

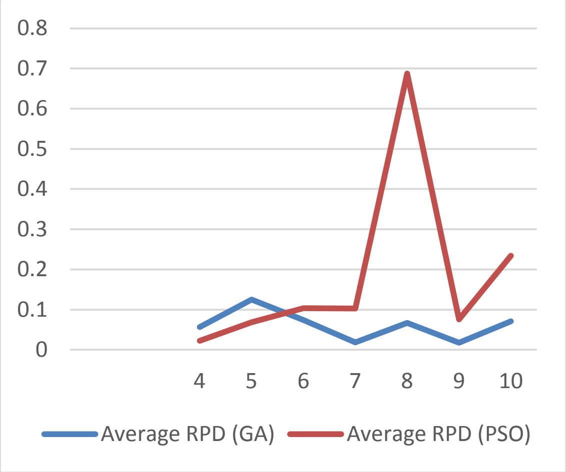

Figure 8.RPD graph with thedifferent number of customers

As it is clear from Figure 8, for problems until 5customers,the PSO algorithm's RPD is less. But by increasing the number of customers, GA performs better.

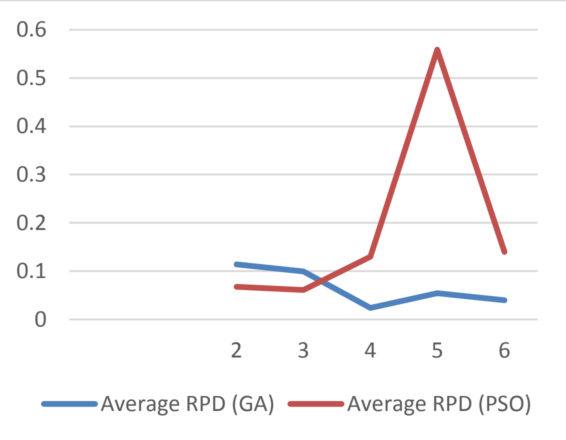

Figure 9.RPD graph in different time periods

As it is clear from Figure 9, for problems until 3 periods, the PSO algorithm's RPD is less. But by increasing the number of periods, GA performs better.

Another measure to evaluate the performance of the proposed algorithms is solution time. In Figure 10 the solution time comparison of GA versus PSO with respect to different problem sizes is depicted.

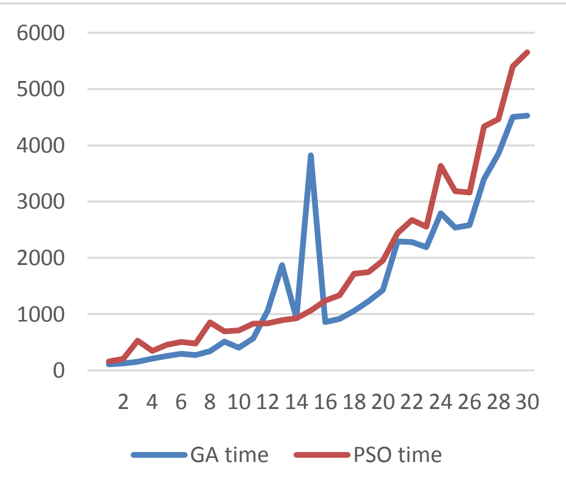

Figure 10.The proposed algorithms solution times graphs

According to the solution time, it is implied that except in instances 13, 14, and 15, GAneeds shorter solution timein comparison with PSO.

According to the results of algorithms and analyzes made by the RPD and solution time graphs it can be interpretedthat genetic algorithm has better performance and the resultsobtained are more efficient compared with particle swarm optimization algorithm.

6. Conclusions

Product life cycle development and products return through a reverse logistic network provide reduction in wastes and job opportunities. Design of a closed-loop supply chain network enforces enterprises to decide about end of life or end of use products. In this research, a four-layer forward supply chain and a three-layer reverse one is considered. A mixed integer linear mathematical model is proposed to maximize the total profit with respect to product quality classification, pricing policy and product life cycle. As solution approaches GAand PSO were proposed and implemented. The required modifications and parameters adjustment with respect to the proposed problem and mathematical formulations were performed. Two criteria of RPD and computational time were considered for comparing GA and PSO for different problemsettings. RPD was handled separately for suppliers, manufacturers, distribution centers and customers. The results show better performance of GA in different problem sizes considering the solution time and relative percentage deviation.

As for future research directions, the following are suggested; Considering uncertainty in parameters like demand and rate of return could help the decision makers to include uncertainty of real world cases; including inventory and warehouse issues in the model lead to a more comprehensive problem which is complex and need to develop efficient solution methods; More emphasis on environmental aspect of green supply chain by including gas emission parameters in the model makes the problem more environment friendly; Considering game theory based pricing strategies for pricing segment of the model helps to develop a competitive model for the peers in each stage of the supply chain.

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