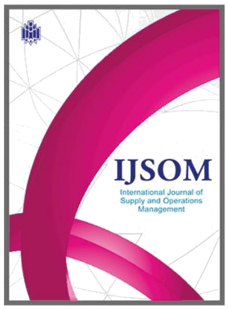
International Journal of Supply and Operations Management

IJSOM

May 2017, Volume 4, Issue 2, pp. 115- 132
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



Design of a Forward/Reverse Logistics Network with Environmental Considerations

Masoud Rabbani [*, a], Niloufar Akbarian Saravi [a], Hamed Farrokhi-Asl [b]

[a] *School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran*
[b] *School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran*

Abstract
An increase in environmental issues has encouraged the consideration of various factors that influence the environment. In this regard, the green supply chain has attracted the attention of researchers because of its considerable impacts on the environment. This study, therefore, was an attempt to design a forward/revers logistics network by putting emphasis on some environmental issues like the quantity of CO2 emission in its model. In this logistics network, three objective functions including minimizing the total cost and quantity of CO2 emission as well as maximizing the satisfaction of customers are considered simultaneously. This persuaded the researchers to adopt multi-objective optimization methods. Thus, Non-dominated sorting genetic algorithms (NSGA-II) and Multi-objective particle swarm optimization (MOPSO) are proposed to cope with the problem. Finally, the results of the experiments on several test problems are verified by GAMS software. They confirm the superiority of NSGA-II over MOPSO in terms of all comparison metrics.

Keywords: Green supply chain; CO2 emission; Forward/reverse logistics; Environmental issues; Multi-objective optimization.

1. Introduction

Nowadays, global warming and fluctuation in oil prices make protection of the environment a primary concern. Various factors including greenhouse gases increase the temperature of the earth and in turn lead to global warming. Greenhouse gases (GHGs), as one of the most important factors, are produced by human activities and industrial activities in both developed and developing countries. Since there has been a rise in the amount of these gases, global warming has become a major issue all over the world. It leads to an increase in the number of hurricanes and floods, accelerates the ice melt at the poles, and causes other environmental problems. Therefore, it is important to consider environmental factors besides social and economic factors to design a logistics network and to determine an appropriate allocation of facilities in order to decrease the greenhouse gases emitted from factories and vehicles.

Recently, many researchers have focused on the concept of supply chain management (SCM), which dates back to the early 1990, as well as increasing profitability and staying competitive in firms as the most significant role of the supply chain (Choon Tan et al., 2002; Li et al., 2006; Pasandideh et al., 2015). Forward/reverse logistics is one of the sub-branches of the field of supply chain management which has captured the attention of researchers regarding environmental, social, and economic factors (Govindan et al., 2015). Resource restrictions along with the increasing costs of logistics networks, and tendency towards using new products instead of consumed products in the environment promote designing logistic networks with considering both forward and reverse flows (Saffari et al., 2015).

Passengers and freight transport generate a number of activities which impact on sustainability and international economy. Also, these activities have their own consequences, especially those related to the environment (Wang et al., 2011). As such, governmental and environmental regulations and the increasing demands of customers for products and services force companies to reconsider how they can administer their supply chains with regard to environmental issues. Thus, in order to reduce environmental effects and achieve environmental efficiency, an increasing emphasis is being placed on green aspects (Kumar et al., 2017)

*Corresponding author email address: mrabani@ut.ac.ir

Green supply chain has gained in popularity among firms and research companies due to the importance of industrial ecology (Graedel et al., 1995). Industrial ecology is described as a systematic organizing framework associated with aspects of environmental management (Lowe, 1993). Carbon dioxide (CO2), one of the most important greenhouse gases, is produced from human activities. An increase in the CO2 emission, for a considerable portion of which human activities are responsible, has a negative impact upon the natural cycle. On the other hand, supply chain comprises different activities including production, transportation, recovery, and so forth. Thus, considering environmental factors has significant effects on designing supply chain networks (Saffar and Razmi, 2014). Designing facilities in logistics networks and designing suitable forward/reverse logistics have a profound impact on the profitability of systems which depend on many factors with social, economic, and environmental aspects.

In this regard, taking economic factors into consideration influences determining an appropriate allocation and designing suitable logistics networks. The establishment cost of each center as well as the transmission cost of each unit among each center affect the design of logistics networks.

It is also necessary to take social factors into account due to the increasing requirements of customers. Customer responsiveness, an important factor related to the quality of products and delivery time, is increased by both enhancing products' quality and timely delivery of products.The rest of this paper is organized as follows: A brief literature review is provided in Section 2. It is followed by the problem and the methodology to tackle it in Section 3. Section 4 is devoted to the parameters tuning for NSGA-II and MOPSO algorithms. Experimental results and sensitivity analyses are given in section 5. Finally, conclusions and future research directions are provided in Section 6.

2. Literature Review

In recent years, researchers have studied various topics related to supply chain. As a result, a mixed-integer linear programming for designing reverse logistics network models is presented. In addition to considering demand as a deterministic parameter, the economic aspects which influence logistics networks are studied (El Saadany and El-Kharbotly). A memetic algorithm is introduced by Pishvaee et al. (2010) in order to design an integrated forward/reverse logistics network. In this study the objective functions are related to customer responsiveness and total cost which are maximized and minimized respectively. An impressive memetic algorithm is fostered to discover a set of non-dominated solutions. Moreover, a mixed integer linear programming model is presented by Pishvaee et al. (2011) to design a closed-loop supply chain network. Because of the growing concern for transformation in the business environments like demands of customers and transportation cost, the robust optimization model is considered for supply chain. The model utilizes the intrinsic uncertainty of input data in closed-loop supply chain network design problems. A mixed integer linear optimization is presented to select appropriate sources, CO2 storage sites, and the optimal total minimum cost in supply chain management frameworks (Pishvaee and Razmi, 2012). Diabat et al. (2013) also introduced a multi-echelon multi-commodity facility location problem dealing with the cost of carbon emission and cost of preparation.

In another study, Mousazadeh et al. (2014) considered the green supply chain and reverse logistics simultaneously to reduce the environmental pollution. Fuzzy environment through analyses of the previous literature and systematic review is used to design and plan reverse and green logistics. Choudhary et al. (2015) presented a quantitative optimization model for the forward/reverse logistics which consider CO2 emission in order to facilitate layout decision. The aim of the proposed model was to minimize carbon footprint and total cost by a genetic algorithm (Kumar et al.). In the same vein, Soysal et al. (2015) introduced a multi-period model for inventory routing which includes the evaluation of CO2 emission and fuel consumption. The model showed that when the requirement of service level is satisfied and a better support system is proposed, a considerable saving in the overall cost is achieved. Kalyanarengan et al. (2016) also proposed a multi-objective fuzzy mathematical model to design a supply chain by considering environmental factors of different alternatives for supply chain network. In addition to the traditional cost, the life cycle method was applied to evaluate and quantify the environmental factors. In fact, optimization of the network design is a key factor in improving economic, environmental, and social efficiency (Ghaderi et al., 2016). Soleimani et al. (2016) designed a closed-loop multi-period, multi-product supply chain network. They assumed demand and price to be stochastic by using mixed integer linear programming, studied forward/reverse logistics models which include multi-period, multi-echelon and vehicle routing, and considered particle swarm optimization and artificial immune system algorithms. The aim was to maximize the total expected profit and to obtain an appropriate route for the vehicle corresponding to an optimal solution (Kumar et al., 2017). Significant features of the mentioned studies and this study about different environmental, economic, and social aspects are listed in Table 1.

The main contribution of this study which distinguishes it from the existing relevant research can be presented as follows: To have satisfactory and favorable environmental conditions, it is necessary to consider the amount of CO_2 emitted through vehicles and factories in the forward/reverse logistics networks and we did so. To the best of authors' knowledge, this study is the first study which considers environmental, social, and economic aspects simultaneously. In addition, two applicable algorithms are used in the study in order to obtain the best approach to solve the proposed problem.

Table 1. Significant features of this study and different relevant aspects of other studies

Study	Solution methods	Type of network [a]		Factors [b]			Objective [c]		
		F L	RL	EV	EC	SC	C	QC	RS
Pishvaee et al. (2010)	Memetic algorithm	✓	✓		✓	✓	✓		✓
Pishvaee et al. (2011)	MILP	✓	✓	✓	✓		✓		
Pishvaee and Razmi (2012)	LCA	✓		✓	✓		✓		
Diabat et al. (2013)	MILP	✓	✓	✓	✓		✓	✓	
Mousazadeh et al. (2014)	Fuzzy mathematical programming		✓	✓	✓		✓		
Choudhary et al. (2015)	GA	✓	✓	✓				✓	
Soysal et al. (2015)	MILP	✓	✓	✓		✓	✓		✓
Soleimani et al. (2016)	MILP	✓	✓		✓		✓		
Kalyanarengan et al. (2016)	MILP			✓			✓	✓	
Kumar et al. (2017)	PSO, AIS	✓	✓	✓	✓		✓		
This study	NSGA-II,MOPSO	✓	✓	✓	✓	✓	✓	✓	✓

[a]FL : forward logistics, RL: reverse logistics
[b]EV : environmental, EC: economic, SC: social
[c]C: cost, QC: quantity of CO_2 emission, RS: responsiveness

3. Problem definition

In this paper, the integrated forward/reverse logistics network (IFRLN) is a multi-category logistics network containing production, distribution, customer zones, collection/inspection, recovery and disposal centers with multi-level capacities. First, in the forward flow, new products are shipped from production centers to customer zones through distribution centers to meet the demand of each customer. Then, in the reverse flow, returned products are collected in collection/ inspection centers. Our strategy in this model is to minimize the total costs and maximize the responsiveness of the logistics network. The returned products can be transported directly to the suitable facilities. Because the recoverable products are sent to recovery facilities and scrapped products are sent to disposal centers after testing, the total cost will be minimized. Furthermore, considering hybrid processing facilities with both distribution and collection centers established at the same location decreases the total cost. In addition to minimizing the total cost, maximization of the responsiveness is considered in the study. It is important to save the resulting cost with regard to separate distribution and collection centers. Also, in response to the increase in global warming, a crucial strategy is to consider and control the quantity of greenhouse gases such as CO_2 emitted through vehicles and factories. To this end, shipping of products through various centers is accomplished by three types of vehicles, namely CNG, gasoline, hybrid. Using these vehicles influences the release of greenhouse gases. Therefore, the model intends to consider the quantity of CO_2 emission per units shipped from different centers. Using hybrid-collection facilities is a decision variable, and as mentioned before, we considered a three-transport system between the centers. This study aims to design a model between these transport systems to recognize which system is better in terms of pollution and environmental issues besides traditional costs and customer responsiveness. The resulting network of supply chain is shown in Figure 1. Forward and revers flows are demonstrated by dark and dotted arrows, respectively. It should be pointed out that customer zones are assumed to be predetermined and constant in this network. Other assumptions are as follows:

- Emission from transportation is assumed to be proportional to the type of vehicle.
- It is assumed that emission from facilities is relevant to production centers and it is not considered for other centers.
- Emission from transportation is assumed to be proportional to the distance of both centers between which products are shipped.
- All of the parameters are assumed to be deterministic.
- The total amount of products carried by a vehicle does not exceed its capacity.
- Shortage is not allowed and all demands of customers and centers should be satisfied.

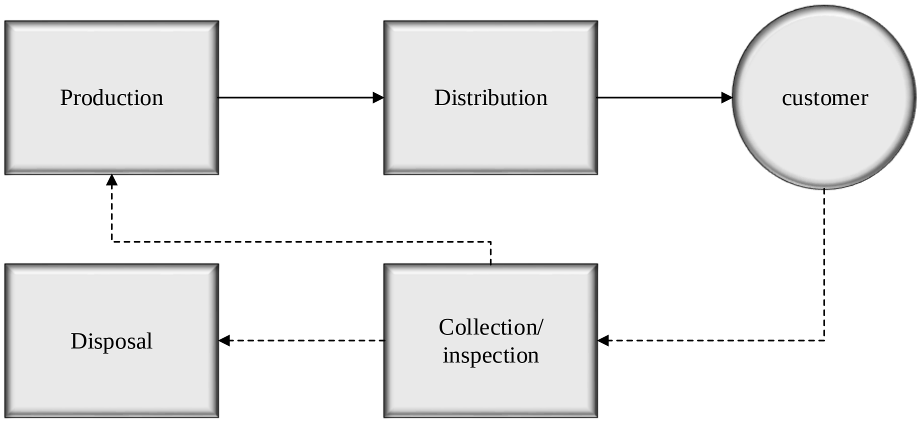


Figure 1. A generic form of forward/reverse logistics

The following notations are used in the formulation of the integrated forward/reverse logistics model according to the schematic form of logistics:

Sets:

B potential number of distribution centers $b \in B$

P potential number of production/recovery centers $p \in P$

C potential number of customer zones $c \in C$

I potential number of collection/inspection centers $i \in I$

G potential number of disposal centers $g \in G$

F set of capacity level available for facilities $f, f' \in F$

K set of vehicle types, namely CNG, hybrid, gasoline, $k \in \{1,2,3\}$

J set of joint potential sites between collection/inspection centers and distribution centers $j \in J$ $J \in B$ $J \in I$

Parameters:

d_c Demand of customer zone c

r_c Rate of the return of used products from customer zone c

w Average disposal fraction

fi_{fp} fixed cost of opening production/recovery center p with capacity level f

oc_{fb} fixed cost of opening distribution center b with capacity level f

h_{fi} fixed cost of opening collection/inspection center i with capacity level f

a_{fg} fixed cost of opening disposal center g with capacity level f

$fc_{ff'j}$ fixed saving cost associated with opening distribution center with capacity level f and collection/inspection center at joint potential site j with capacity level f'

cx_{pbk} shipping cost per unit of products from production/ recovery center p to distribution center b by vehicle k

cu_{bck} shipping cost per unit of products from distribution center b to customer zone c by vehicle k

cq_{cik} shipping cost per unit of returned products from customer zone c to collection/inspection center I by vehicle k

cp_{ipk} shipping cost per unit of recoverable products from collection/inspection center i to production/recovery center p by vehicle k

cs_{igk} shipping cost per unit of scrapped products from collection/inspection center i to disposal center g by vehicle k

∂_{fp} capacity of production with level f for production/ recovery center p

φ_{fb} capacity with level f for distribution center b

ω_{fi} capacity with level f for collection/inspection center i

γ_{fg} capacity with level f for disposal center g

τ_k capacity for each transportation vehicle k

e_{pbk} quantity of CO_2 emission from production center p to distribution center b by transportation vehicle k

e_{bck} quantity of CO_2 emission from distribution center b to customer zone c by transportation vehicle k

e_{cik} quantity of CO_2 emission from customer zone c to inspection/collection center i by transportation vehicle k

e_{ipk} quantity of CO_2 emission from inspection/collection center i to production center p by transportation vehicle k

e_{igk} quantity of CO_2 emission from customer zone c to inspection/collection center i by transportation vehicle k

e'_p quantity of CO_2 emission per unit of product from center p

tf_{bc}	delivery time from distribution center *b* to customer zone *c*
tr_{ci}	collection time from customer zone *c* to collection/ inspection center *i*
del_f	expected delivery time in the forward network
del_r	expected delivery time in the reverse network
DL_{fc}	$=\{\mathrm{b} \mid tf_{bc} \leq del_f\}$
DL_{rc}	$=\{\mathrm{i} \mid tr_{ci} \leq del_r\}$
α	a sufficient large number ($\alpha \geq w * \sum_{c\epsilon C} r_c d_c$)
λ	weighting factor (importance) for the forward responsiveness in second objective function; ($1-\lambda$)denotes the weight of the reverse responsiveness

Variables:

x_{pbk}	quantity of products shipped from production/recovery center *p* to distribution center *b* by transportation vehicle *k*
u_{bck}	quantity of products shipped from distribution center *b* to customer zone *c* by transportation vehicle *k*
q_{cik}	quantity of returned products shipped from customer zone *c* to collection/inspection center *i* by transportation vehicle *k*
cl_{ipk}	quantity of recoverable products shipped from collection/inspection center *i* to production/recovery center *p* by transportation vehicle *k*
y_{igk}	quantity of scrapped products shipped from collection/ inspection center *i* to disposal center *g* by transportation vehicle *k*

$$Z_{fp}:\begin{cases} 1 & \textit{if a production and recovery center with capacity level } f \textit{ is opened at location } p \\ 0 & \textit{otherwise} \end{cases}$$

$$O_{fb}:\begin{cases} 1 & \textit{if a distribution center with capacity level } f \textit{ is opened at location } d \\ 0 & \textit{Otherwise} \end{cases}$$

$$M_{fi}:\begin{cases} 1 & \textit{if a collection inspection center with capacity level } f \textit{ is opened at location } i \\ 0 & \textit{otherwise} \end{cases}$$

$$N_{fg}:\begin{cases} 1 & \textit{if a disposal center with capacity level } f \textit{ is opened at location } g \\ 0 & \textit{otherwise} \end{cases}$$

$$t_{ff'j}:\begin{cases} 1 & \textit{if a distribution and collection centers are located at the same location} \\ 0 & \textit{otherwise} \end{cases}$$

$$\begin{aligned} \text{Min } W1= & \sum_{p\in P}\sum_{f\in F} fi_{fp} Z_{fp} + \sum_{f\in F}\sum_{b\in B} oc_{fb} O_{fb} + + \sum_{f\in F}\sum_{i\in I} h_{fi} M_{fi} \\ & + \sum_{f\in F}\sum_{g\in G} a_{fg} N_{fg} + \sum_{p\in P}\sum_{b\in B}\sum_{k\in K} cx_{pbk} x_{pbk} + \sum_{c\in C}\sum_{b\in B}\sum_{k\in K} cu_{bck} u_{bck} \\ & + \sum_{c\in C}\sum_{i\in I}\sum_{k\in K} cq_{cik} q_{cik} + \sum_{i\in I}\sum_{g\in G}\sum_{k\in K} cs_{igk} y_{igk} \\ & + \sum_{i\in I}\sum_{g\in G}\sum_{k\in K} cp_{ipk} cl_{igk} - \sum_{f\in F}\sum_{f'\in F}\sum_{j\in J} cfi_{ff'j} T_{ff'j} \end{aligned} \tag{1}$$

$$\text{Max} W2 = \lambda\left(\sum_{b\in B}\sum_{c\in C}\sum_{k\in K} u_{bck}\right)/\left(\sum_{C\in DL_{fc}} d_c\right) + (1-\lambda)\left(\sum_{c\in C}\sum_{i\in I}\sum_{k\in K} q_{cik}\right)/\left(\sum_{C\in DL_{rc}} r_c d_c\right) \tag{2}$$

$$\text{Min} W3 = \sum_{p\in P}\sum_{b\in B}\sum_{k\in k} x_{pbk} . e_{pbk} + \sum_{b\in B}\sum_{c\in C}\sum_{k\in K} u_{bck} . e_{bck}$$

$$+\sum_{c\in C}\sum_{i\in I}\sum_{k\in K} q_{cik}\,.\,e_{cik} + \sum_{i\in I}\sum_{p\in P}\sum_{k\in K} cl_{ipk}\,.\,e_{ipk} + \sum_{i\in I}\sum_{g\in G}\sum_{k\in K} y_{igk}\,.\,e_{igk} + \sum_{b\in B}\sum_{k\in K} x_{pbk}\,.\,e'_{p}$$

(3)

$$\sum_{b\in B}\sum_{k\in K} u_{bck} = d_c \quad \forall c \in C \tag{4}$$

$$\sum_{i\in I}\sum_{k\in K} q_{cik} = r_c d_c \quad \forall c \in C \tag{5}$$

$$\sum_{p\in P}\sum_{k\in K} x_{pbk} = \sum_{k\in K}\sum_{c\in C} u_{bck} \quad \forall b \in B \tag{6}$$

$$\sum_{k\in K}\sum_{g\in G} y_{igk} = W\sum_{c\in C}\sum_{k\in K} q_{cik} \quad \forall i \in I \tag{7}$$

$$\sum_{k\in K}\sum_{p\in P} cl_{ipk} = (1-W)\sum_{c\in C}\sum_{k\in K} q_{cik} \quad \forall i \in I \tag{8}$$

$$\sum_{k\in K}\sum_{b\in B} x_{pbk} \le \sum_{f\in F} Z_{fp}\,\partial_{fp} \quad \forall p \in P \tag{9}$$

$$\sum_{p\in P}\sum_{k\in K} x_{pbk} \le \sum_{f\in F} O_{fb}\,\varphi_{fb} \quad \forall b \in B \tag{10}$$

$$\sum_{k\in K}\sum_{c\in C} u_{bck} \le \sum_{f\in F} O_{fb}\,\varphi_{fb} \quad \forall b \in B \tag{11}$$

$$\sum_{c\in C}\sum_{k\in K} q_{cik} \le \sum_{f\in F} M_{fi}\,\omega_{fi} \quad \forall i \in I \tag{12}$$

$$\sum_{i\in I}\sum_{k\in K} y_{igk} \le \sum_{f\in F} N_{fg}\,\gamma_{fg} \quad \forall g \in G \tag{13}$$

$$\sum_{i\in I}\sum_{k\in K} cl_{ipk} \le \sum_{f\in F} Z_{fp}\,\partial_{fp} \quad \forall p \in P \tag{14}$$

$$\sum_{g\in G}\sum_{k\in K} y_{igk} + \sum_{p\in P}\sum_{k\in K} cl_{ipk} \le \sum_{f\in F} M_{fi}\,\omega_{fi} \quad \forall i \in I \tag{15}$$

$$\sum_{i\in I}\sum_{p\in P} cl_{ipk} \le \alpha \sum_{p\in P}\sum_{b\in B} x_{pbk} \quad \forall i \in I \tag{16}$$

$$\sum_{p\in P}\sum_{b\in B} x_{pbk} \le cay_k \quad \forall k \in K \tag{17}$$

$$\sum_{b\in B}\sum_{c\in C} u_{bck} \le cay_k \quad \forall k \in K \tag{18}$$

$$\sum_{i\in I}\sum_{p\in P} cl_{ipk} \le cay_k \quad \forall k \in K \tag{19}$$

$$\sum_{c\in C}\sum_{i\in I} q_{cik} \leq cay_k \qquad \forall k \in K \tag{20}$$

$$\sum_{i\in I}\sum_{g\in G} y_{igk} \leq cay_k \qquad \forall k \in K \tag{21}$$

$$\sum_{f\in F} Z_{fp} \leq 1 \quad \forall p \in P \tag{22}$$

$$\sum_{f\in F} O_{fb} \leq 1 \quad \forall b \in B \tag{23}$$

$$\sum_{f\in F} M_{fi} \leq 1 \quad \forall i \in I \tag{24}$$

$$\sum_{f\in F} N_{fg} \leq 1 \quad \forall g \in G \tag{25}$$

$$2t_{ff'j} \leq m_{f'j} + o_{fj} \qquad \forall j \in J \ ,\forall f \in F, \quad \forall f' \in F \ , \tag{26}$$

$$Z_{fp}, O_{fb}, M_{fi}, N_{fg} \in \{0,1\} \forall g \in G, \forall i \in I, \forall b \in B, \forall p \in P \tag{27}$$

$$x_{pbk}, u_{bck}, q_{cik}, cl_{ipk}, y_{igk} \quad b\in B\ p\in P\ c\in C\ i \in I\ g \in G \tag{28}$$

Objective function (1) minimizes the total cost including fixed opening cost, transportation costs and the cost saving because of the collection and distribution centers allocated in the same location. Objective function (2) maximizes the forward and reverse responsiveness of the integrated network. Objective function (3) minimizes the dangerous CO_2 emission released from vehicles. Constraints (4) and (5) demonstrate that the demands of all customers are satisfied and the returned products from all customer zones are collected. Constraints (6)-(8) assure the flow balance at production/recovery, distribution, collection/inspection, disposal and customer centers. Constraints (9)-(16) are capacity constraints on facilities, which also prevent the units of products, returned products, recoverable and scrapped products from being transferred to facilities which are not open. Constraints (17)-(21) are capacity constraints on vehicles in terms of the quantity of products shipped from different centers by transportation vehicles. Finally, Constraints (22)-(25) ensure that a facility can be assigned at most one capacity level. The constraint (26) shows that the value of $t_{ff'j}$ could not be 1 in three conditions. Finally, Constraint (27) and (28) place the binary and non-negative restrictions on the corresponding decision variables.

4. Methodology

The proposed model in this research aims to not only minimize the total cost and CO_2 emission but also maximize the responsiveness of logistics network for the first, second, and third objective functions. Using multi-objective evolutionary algorithms is supported in this study because of the existence of contradiction between multiple objectives functions and the NP-hard nature of the problem (Davis and Ray, 1969).

Therefore, two well-known multi-objective evolutionary algorithms which have been investigated widely by researches are utilized in this study. In other words, the non-dominated sorting genetic algorithm (NSGA-II) and Multi-objective particle swarm optimization (MOPSO) algorithm are used in order to tackle the proposed problem. The next section explains these algorithms and the process of individual solution decoding.

4.1. solution representation

Complexity and calculating time considerably rely on a scheme of solution representation. The structure of the problem is based on the order recognized as the most efficient method to encode the solutions of problem.

To decode the problem, the chromosome is divided into several sections devoted to the number of node and related to each echelon of forward/reverse logistics network. Each section also determines components of systems. Each chromosome is described based on the order of the problems nodes and components. In this paper, the coding of this approach solution is considered as $3\,(B + P + C + I + G)$ matrix in which B, P, C, I and G denote the number of production center, number of distribution center, number of customer, number of inspection center, and number of disposal center, respectively (See Figure 2). In this structure, the characterization of the first, second and third rows of chromosome is determined respectively as follows:

- Generation of random numbers by uniform distribution is utilized in order to characterize the first row of the chromosome which shows the allocation of centers in terms of ranking the number of cells. In other words, each row is characterized by generating numbers in the range of 0 to 1. These numbers show the priority of nodes in descending order.
- The second row of the chromosome is devoted to the capacity level of facilities. Three levels have been considered for each facility. This level is generated randomly.
- Type of vehicles used for transporting goods is shown in the third row. Because of considering three types of vehicles, the number of this row is generated by integer numbers in the range of 1 to 3.

	Production center		Distribution center			Customer zone			Inspection center		Disposal center	
Order of system components	0.49	0.06	0.61	0.02	0.97	0.88	0.17	0.39	0.09	0.57	0.4	0.43
Capacity level	3	2	3	2	1	3	2	2	3	2	3	3
vehicle	1	3	3	3	2	1	2	2	3	3	3	1

Figure 2. Solution representation

The decoding procedure is then introduced in order to convert this structure into meaningful solutions and to extract the decision variables related to each solution representation. First, in the forward logistics the production and distribution center is devoted to customers. The ranking of customers obtained through sorting the number of first row is considered for selection. Then, by considering the demand of customers and assigning the appropriate customer, capacity of the distribution center is determined. After responding to all demands of customers and determining the distribution nodes, the production center is devoted and assigned through ranking the numbers. Similarly, in the reverse logistics, the first devotion is related to customers. Returned products are shipped to inspection by considering the rank and capacity of the node. The transportation systems are then assigned to all facilities by randomly-generated numbers and the capacity level considered for each center is assigned in terms of the generated number in each cell. Figure 2 illustrates this procedure. In the production center the customer with the higher rank order, that is equal to 0.46, is selected. Then, its capacity level and vehicle mode can be determined, and the remaining nodes of the concerned supply chain are specified.

Because of the straightforward implementation of this description scheme for two algorithms, namely NSGA-II and MOPSO, it seems that the same procedure should be used in presenting a chromosome.

4.2. proposed NSGA-II

The Non-dominated Sorting Genetic Algorithm (NSGA-II) is proposed which has been widely applied to multi-objective optimization problems with two or more conflicting objective functions (Farrokhi-asl et el. 2016). It is a genetic algorithm with the selection of characteristics in the phase of selection. Consequently, in such problems just one global optimum solution does not exist for optimizing objective functions simultaneously. The Pareto-optimal solution which is not dominated by any other solution has been utilized in this algorithm and improved by deteriorating at least one objective function.

A basic representation of NSGA-II algorithm is demonstrated in Figure 3. In NSGA-II algorithm, every solution is ranked by a fast sorting procedure. As is shown in the flowchart, the population P_0 with population size Np is initialized in NSGA-II randomly and the population P_0 is sorted in order to obtain the best population P_0. Selection is applied utilizing the value of the ranked Pareto and crowded distance to discriminate within the rank. Offspring population O_0 is generated according to the rate of crossover P_c and mutation P_m. Firstly, tournament selection operators are used to select the individuals as parents. Through this selection method, the individuals which have a better rank and less distance of crowding have a high probability of being selected. In accordance with sorting the non-dominated and crowded distance, union population $R_t = P_t \cup Q_t$ is formed. Then, using the best individuals of union population the next population P_{t+1} is constructed. This algorithm will be iterated until satisfying the criterion. Pareto optimal solutions are obtained through ranking the individuals of the last population. The first rank of the individuals is the Pareto solution.

4.3. NSGA- II operators

Two operators are employed in order to justify a much better spread of solutions. In other words, this makes us certain that total space of the solution has been fully explored. More specifically, mutation and crossover operators have been utilized to generate new individuals from their old chromosome. Then the pair of chromosomes recombine and influence continuity of the process of evolutionary algorithm. After the recombination, new chromosomes are bored which may

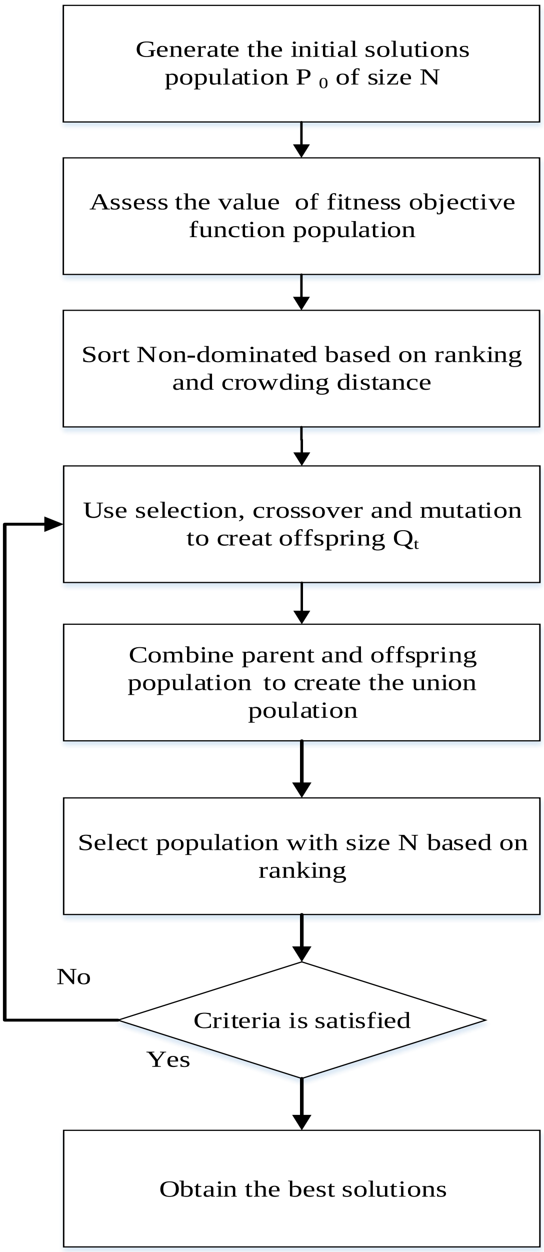


Figure 3. flowchart of NSGA-II

have better features compared with their parents. Local optimum has been obtained through diversity of solutions and prohibiting the process of search which have been guaranteed by the mutation operator. These operators are of many types. Details of the selected operators and how to implement them are explained below.

4.3.1. Crossover

The steps of crossover two parents and generating two new children are shown in Figure 4. Single point crossover technique is used by regarding the structure of the chromosomes. To put it another way, each row of the chromosome used single point crossover separately. First, one point of the chromosome is selected randomly. Then, the right information of the first parents is scanned from the beginning to the crossover point in the first child and the left information is copied in the second child. The right information of the second parents is copied in the second child and the left information is scanned in the first child. The crossover approach guarantees the feasibility of the new populations.

4.3.2. Mutation

Figure 5 shows the implementation of the mutation operator. In inversion mutation, we select a subset of genes like in scramble mutation, but instead of shuffling the subset, we merely invert the entire string in the subset.

Parent 1	0.49	0.06	0.61	0.02	0.97	0.88	0.17	0.39	0.09	0.57	0.4	0.43
	3	2	3	2	1	3	2	2	3	2	3	3
	1	3	3	3	2	1	2	2	3	3	3	1

Parent 2	0.27	0.57	0.5	0.02	0.64	0.98	0.78	0.17	0.73	0.27	0.57	0.15
	1	2	3	1	2	1	3	2	3	3	1	3
	1	1	2	1	1	1	2	2	1	2	2	3

Offspring 1	0.49	0.06	0.61	0.02	0.97	0.88	0.78	0.17	0.73	0.27	0.57	0.15
	3	2	3	2	1	3	3	2	3	3	1	3
	1	3	3	3	2	1	2	2	1	2	2	3

Offspring 2	0.27	0.57	0.5	0.02	0.64	0.98	0.17	0.39	0.09	0.57	0.4	0.43
	1	2	3	1	2	1	2	2	3	2	3	3
	1	1	2	1	1	1	2	2	3	3	3	1

Figure 4. Single point crossover operator

parent	0.49	0.06	0.61	0.02	0.97	0.88	0.17	0.39	0.09	0.57	0.4	0.43
	3	2	3	2	1	3	2	2	3	2	3	3
	1	3	3	3	2	1	2	2	3	3	3	1

offspring	0.49	0.06	0.09	0.39	0.17	0.88	0.97	0.02	0.61	0.57	0.4	0.43
	3	2	3	2	2	3	1	2	3	2	3	3
	1	3	3	2	2	1	2	3	3	3	3	1

Figure 5 .Inversion mutation operator

4.4. MOPSO algorithm

An extension of Particle Swarm Optimization algorithm for solving multi-objective problems such as simplicity of implementation and coverage of search process to an acceptable solution is proposed by Coello et al. (2004) and is called Multi Objective Particle Swarm Optimization algorithm (MOPSO). The intelligence group is the main idea of this algorithm that includes knowledge of previous best position (x_{pbest})and the global best position of all swarm (x_{gbest}). Updating the velocity and the position of particle a for jh dimension at iteration $t+1$ explained by $v_{aj}(t+1)$ and $x_{aj}(t+1)$is done based on Equations (29) and (30).

$$v_{aj}(t+1) = w \times v_{aj}(t) + c_1 \times r_1 \times (x_{pbest}(t) - x_{aj}(t) + c_2 \times r_2 \times (x_{gbest}(\mathrm{t}) \text{-} v_{aj}(t)) \tag{29}$$

$$x_{aj}(t+1) = x_{aj}(t) + v_{aj}(t+1) \tag{30}$$

where r_1 and r_2 are random values, $x_{aj}(t+1)$ is the updated position, $v_{aj}(t+1)$ is the updated velocity, and w is the weight that is applied to adjust exploration and exploitation. c_1 and c_2 denote particles move closer to the (x_{pbest})or (x_{gbest}) positions. The flowchart of this algorithm is shown in Figure 6.

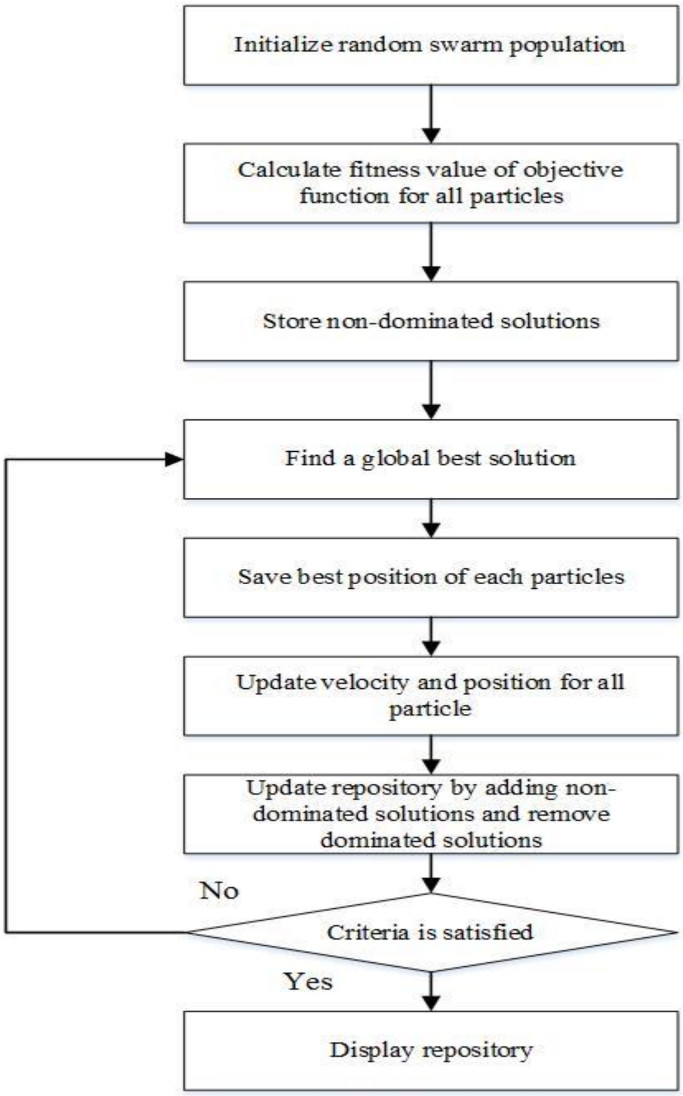


Figure 6. flowchart of MOPSO

5. Parametric tuning

Estimating tuning parameters has assumed importance because of the influence of these parameters on the efficiency and reliability of the evolutionary algorithms. The Taguchi method is adopted as an appropriate tool for parameter tuning in order to improve the experimental results of this study for both algorithms of NSGA-II and MOPSO. The Taguchi method enjoys the advantage of obtaining the largest amount of information with the least number of experiments. It is used to analyze the penetration of NSGA-II parameters such as population size and maximum iterations rate of crossover and mutation (Pc and Pm). Four levels of parameters are used in the Taguchi method which makes decision based on the best value of each objective function. The Taguchi design is used for medium-scale problems in Minitab software that is shown in Figure 7. Additionally, it is used to tune the optimal levels of swarm size (Np), the total number of iterations (Max Iteration), and repository size (Nr) for MOPSO algorithm shown in Figure 8. Results of the Taguchi design for both algorithm parameters are presented in Table 3.

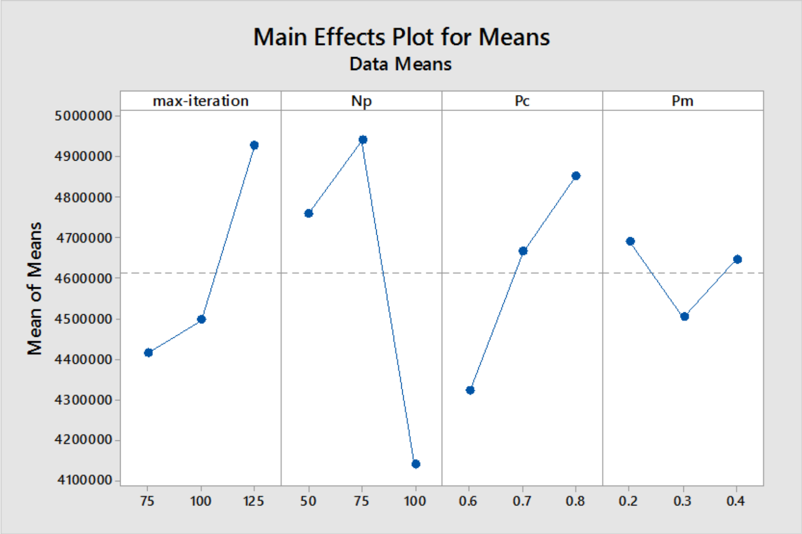


Figure 7. Analyses of NSGA- II based on the Taguchi Method

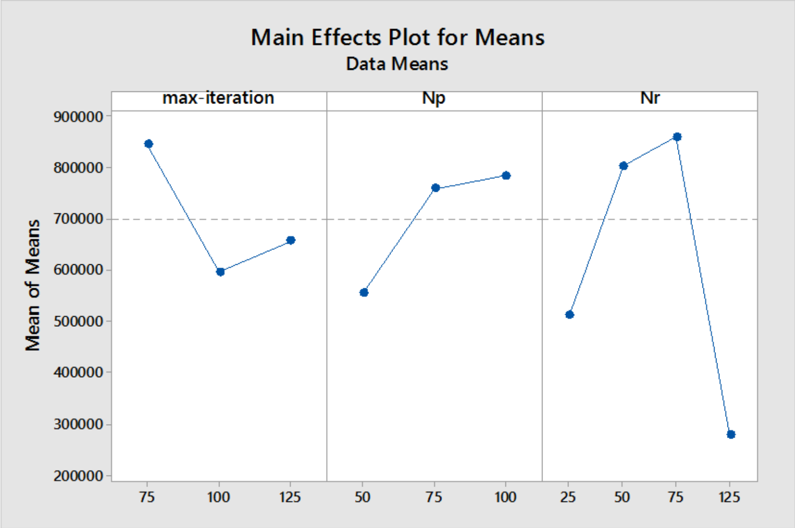


Figure 8. Analyses of MOPSO based on the Taguchi Method

Table 2. Parameter tuning for NSGA-II and MOPSO algorithm

Algorithm	parameters				
	Max-Iteration	N_P	P_c	P_m	N_r
NSGA-II	75	100	0.6	0.3	-
MOPSO	100	50	-	-	125

6. Computational results

6.1. Model validation

Several computational results are obtained in order to prove the validity of the proposed model. These solution results are presented in this section. The solution results are acquired through GAMS software and are indicated in Table 3. Due to the existence of multiple objective functions in the proposed formulation, the problem is solved through minimizing both the total cost and CO_2 emission as well as maximizing the responsiveness individually. For example, after minimizing the total cost, the objective functions related to CO_2 emission and responsiveness are obtained from the optimal solution of cost objective function and so on. As shown in Figure 9, the Pareto of three objective functions are designed. Also, the results of GAMS in Table 3 show the optimum state of the objective function, and that the quantities of objective functions such as CO_2 emission, responsiveness, and total cost are considered.

After validating and verifying the proposed model by GAMS software to find the best and most appropriate solution approach, some computational results are presented in this section. Both NSGA-II and MOPSO algorithms are coded in MATLAB R2014a software and execute an intel Corei7 with 8 GB.

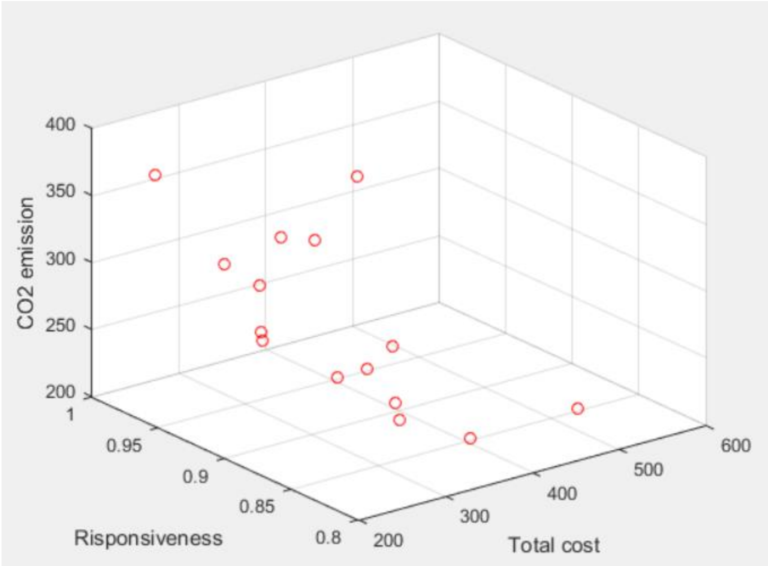


Figure 9. Pareto surface of solutions obtained from GAMS for three-objective functions problem

Table 3. Experimental results obtained from GAMS software

Desirable direction	Z_1	Z_2	Z_3
Min Z_1(total cost)	240	506	238
Max Z_2(responsiveness)	0.8	1	0.8
Min Z_3(CO_2 emission)	322	320	453
$\mathbf{z_i^{NIS}}$	506	0.8	453

z_i^{NIS}: Negative ideal value of the ith objective function

6.2. Comparison metrics

To specify strengths and weaknesses of multi-objective evolutionary algorithms, numerous criteria have been presented by researchers. This study employs four of the comparison metrics to assess the performance of the NSGA-II and MOPSO algorithms in order to obtain better solution sets. These metrics are as follows:

- Spacing metric

This metric determines the spread of solutions in the objective space, and is calculated by Equation 31 (Rabbani et al., 2010; Rabbani et al., 2016):

$$Spacing\ metric = \frac{\sum_{j=1}^{N-1}\left|dis_j - \overline{dis}\right|}{(N-1)\bar{dis}} \tag{31}$$

where d_i is the Euclidean distance between obtained solutions, $\bar{d}$ is the mean of Euclidean distance, and N is the number of non-dominated solutions.

- Quantity of metric
  The number of Pareto optimal solutions at the concurrent run for all solution approaches is evaluated by this metric. The high value of this metric reveals that the algorithm can converge to the real Pareto front.
- Diversity metric

This metric calculated the maximum Euclidean distance of Pareto optimal solutions. The algorithm with a high value of this metric could coverage a great space of solutions.

The computational results of solving various test problems are presented in Table 5. Also, Figures 10-13 compare both metaheuristic algorithms based on three comparison metrics. Based on them, NSGA-II algorithm has a better performance than MOPSO according to the computational time, diversity, spacing, and quantity. Two test problems of non-dominated solutions are shown in Figure 14.

Table 4. Comparison of problem instances in terms of different metrics

Problem number	Problem dimension	NSGA-II				MOPSO			
		CPU time	Quantity of Pareto	Spacing($\times 10^4$)	Diversity($\times 10^5$	CPU time	Quantity	Spacing($\times 10^4$)	Diversity($\times 10^5$
1	(2,3,5,2,2)	53.68	36	0.4516	2.68192	29.39	11	3.3038	3.70261
2	(8,12,20,8,8)	55.55	82	7.7091	27.21098	33.68	14	7.4439	16.41678
3	(10,15,25,10,10)	4.82	30	17.5918	27.73432	32.15	10	45.8112	32.39852
4	(14,21,35,14,14)	10.36	28	13.4710	30.81531	35.46	13	13.4462	23.38441
5	(18,27,45,18,18)	2.54	30	12.4679	31.82044	38.31	14	12.0613	29.73697
6	(20,30,50,20,20)	57.69	87	9.1225	25.10688	37.51	11	20.3498	26.90615
7	(24,36,60,24,24)	4.59	29	10.8580	25.07438	42.72	17	32.1251	48.40148
8	(30,45,75,30,30)	60.2	70	9.9258	46.85153	44.36	13	44.9496	49.51978
9	(40,60,100,40,40)	61.54	97	7.6405	52.64127	46.71	11	30.1601	41.76726
10	(50,75,125,50,50)	66.05	86	7.4789	78.5262	56.27	6	16.4585	30.33947
11	(60,90,150,60,60)	67.92	84	7.6199	35.27615	60.70	11	89.5426	54.27544
12	(70,105,175,70,70)	70.68	97	12.3475	80.79395	83.59	11	60.0069	72.46748
13	(80,120,200,80,80)	77.02	94	15.4812	66.81290	68.78	13	42.5058	73.76128
14	(90,135,225,90,90)	77.79	81	14.3615	103.42936	78.36	8	185.7784	61.97190
15	(100,150,250,100,100)	82.47	99	13.2908	128.84865	83.67	12	56.2866	99.84797
	Average	50.19	69	10.65	50.90	51.44	12	44.01	44.32

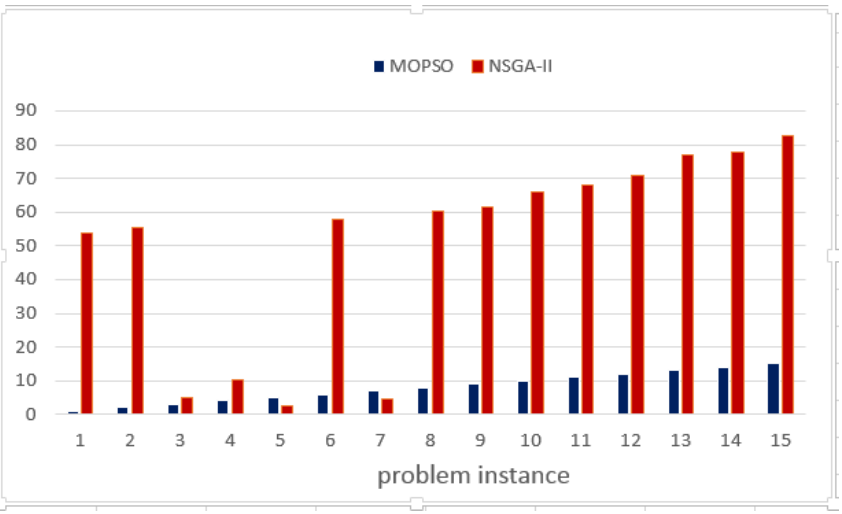


Figure 10. Comparison of NSGA- II and MOPSO in terms of the CPU metric

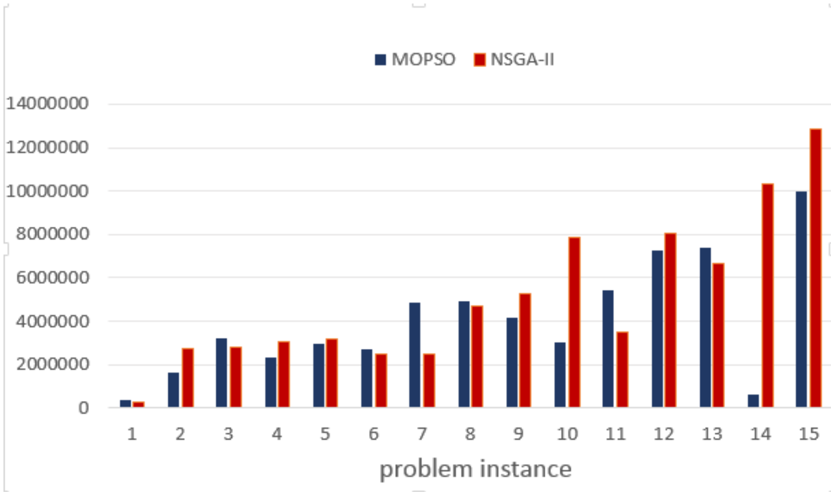


Figure 11. Comparison of NSGA- II and MOPSO in terms of the diversity metric

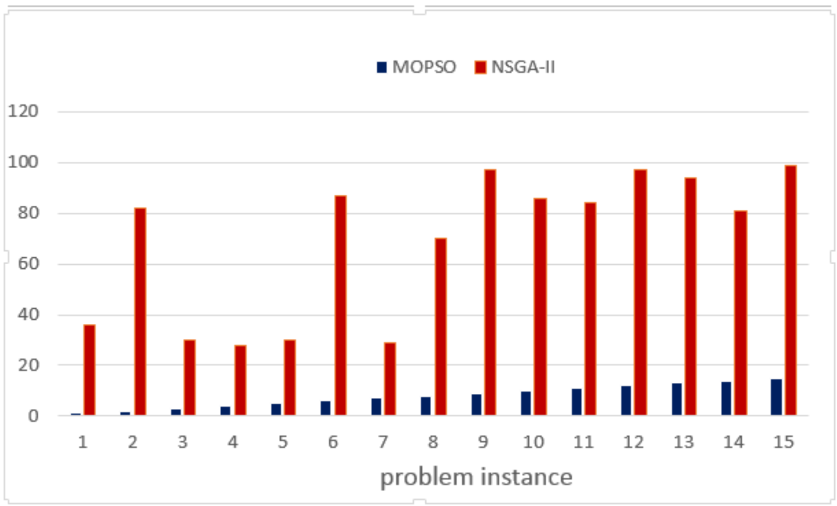


Figure 12. Comparison of NSGA- II and MOPSO in terms of the quantity metric

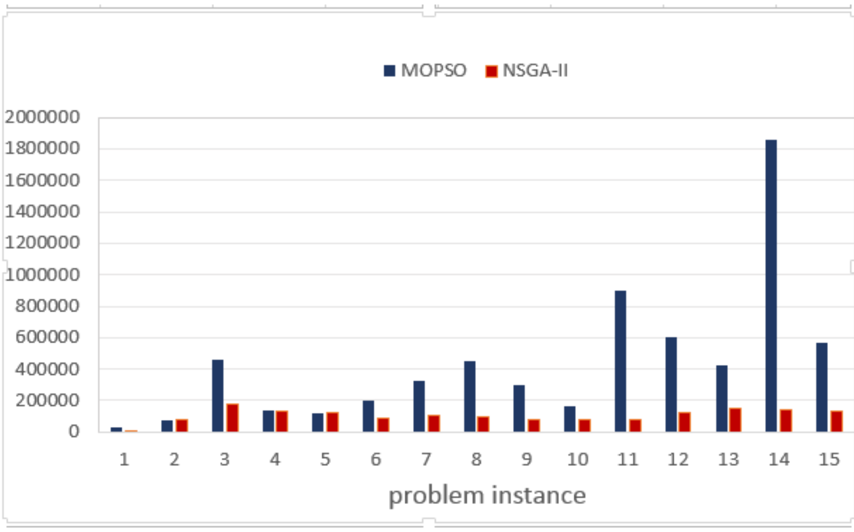
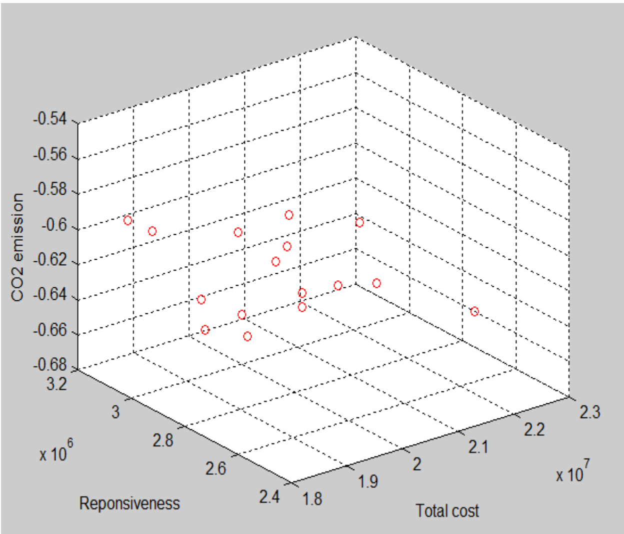
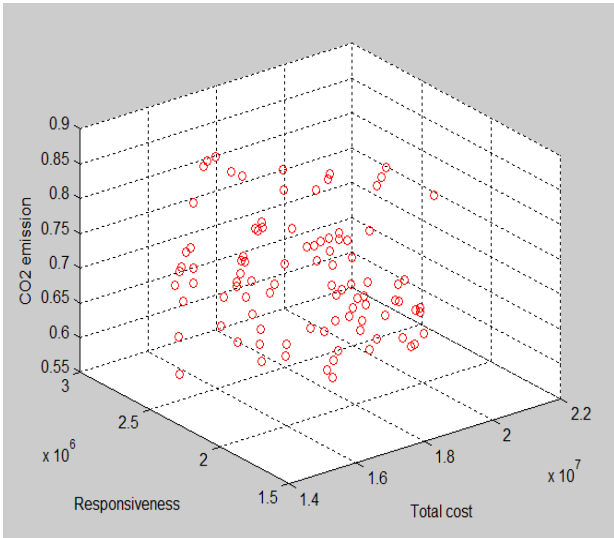


Figure 13. Comparison of NSGA- II and MOPSO in terms of the spacing metric



(b) MOPSO



(a) NSGA- II

Figure 14. Approximation of Pareto from instance 8

7. Conclusion

In the current study, the forward/logistics supply chain is presented with regarding environmental considerations. CO_2 emission is the most important issue which affects the environment. When the activities of human beings proliferate, the CO_2 emission increases too. Thus, finding solutions for decreasing costs and greenhouse gases has been deemed necessary. In this regard, in this research, a new mathematical model is developed to control the risks and dangers of environmental issues. Three objective functions are considered in the model to keep a balance and tradeoff between environmental, economic, and social considerations. The model is validated and supported through a small scale problem instance by using GAMS software. Another contribution of this paper is the applicability of two algorithms, namely NSGA-II and MOPSO. They were chosen to solve the various sets of the NP-hard problem efficiently. Finally, the comparison between these algorithms was made based on different metrics in order to evaluate the accuracy and performance of the solutions. The results demonstrated that with respect to four performance metrics including quantity, spacing, diversity, and computational time, NSGA-II had a better performance than the other approach.

References

Choon Tan, K., Lyman, S. B., and Wisner, J. D. (2002). Supply chain management: a strategic perspective. *International Journal of Operations & Production Management,* Vol. 22(6), pp. 614-631.

Choudhary, A., Sarkar, S., Settur, S., and Tiwari, M. (2015). A carbon market sensitive optimization model for integrated forward–reverse logistics. *International Journal of Production Economics,* Vol. 164, pp. 433-444.

Coello, C. A. C., Pulido, G. T., and Lechuga, M. S. (2004). Handling multiple objectives with particle swarm optimization. *IEEE Transactions on evolutionary computation,* Vol. 8(3), pp. 256-279.

Davis, P., and Ray, T. (1969). A branch-bound algorithm for the capacitated facilities location problem. *Naval Research Logistics (NRL),* Vol. 16(3), pp. 331-344.

Diabat, A., Abdallah, T., Al-Refaie, A., Svetinovic, D., and Govindan, K. (2013). Strategic closed-loop facility location problem with carbon market trading. *IEEE Transactions on engineering Management,* Vol. 60(2), pp. 398-408.

El Saadany, A. M., and El-Kharbotly, A. *K.(2004). Reverse logistics modeling.* Paper presented at the 8th international conference on production engineering and design for development, Alexandria, Egypt.

Farrokhi-Asl, H., Tavakkoli-Moghaddam, R., Asgarian, B., and Sangari, E. (2017). Metaheuristics for a bi-objective location-routing-problem in waste collection management. *Journal of Industrial and Production Engineering*, Vol. 34(4), pp. 239-252

Ghaderi, H., Pishvaee, M. S., and Moini, A. (2016). Biomass supply chain network design: An optimization-oriented review and analysis. *Industrial Crops and Products*, Vol. 94, pp. 972-1000.

Govindan, K., Soleimani, H., and Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research,* Vol. 240(3), pp. 603-626.

Graedel, T., Allenby, B., and COMRIE, P. (1995). Matrix approaches to abridged life cycle assessment. *Environmental Science & Technology,* Vol. 29(3), pp. 134A-139A.

Kalyanarengan, R. N., Zondervan, E. E., Fransoo, J. J., and Grievink, J. (2016). A Supply Chain Optimization Framework For CO2 Emission Reduction: Case Of The Netherlands.

Kumar, V., Kumar, V., Brady, M., Garza-Reyes, J. A., and Simpson, M. (2017). Resolving forward-reverse logistics multi-period model using evolutionary algorithms. *International Journal of Production Economics,* Vol. 183, pp. 458-469.

Lertworasirikul, S., Fang, S.-C., Joines, J. A., and Nuttle, H. L. (2003). Fuzzy data envelopment analysis (DEA): a possibility approach. *Fuzzy Sets and Systems,* Vol. 139(2), pp. 379-394.

Li, S., Ragu-Nathan, B., Ragu-Nathan, T., and Rao, S. S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega,* Vol. *34*(2), pp. 107-124.

Lowe, E. (1993). Industrial ecology—an organizing framework for environmental management. *Environmental Quality Management,* Vol. 3(1), pp. 73-85.

Mousazadeh, M., Torabi, S. A., and Pishvaee, M. S. (2014). Green and reverse logistics management under fuzziness *Supply Chain Management Under Fuzziness*, pp. 607-637, Springer Berlin Heidelberg.

Nikoo, M. B., and Mahinpey, N. (2008). Simulation of biomass gasification in fluidized bed reactor using ASPEN PLUS. *Biomass and Bioenergy,* Vol. 32(12), pp. 1245-1254.

Pasandideh, S. H. R., Niaki, S. T. A., and Asadi, K. (2015). Bi-objective optimization of a multi-product multi-period three-echelon supply chain problem under uncertain environments: NSGA-II and NRGA. *Information Sciences,* Vol. 292, pp. 57-74.

Pishvaee, M. S., Farahani, R. Z., and Dullaert, W. (2010). A memetic algorithm for bi-objective integrated forward/reverse logistics network design. *Computers & operations research,* Vol. 37(6), pp. 1100-1112.

Pishvaee, M. S., Rabbani, M., and Torabi, S. A. (2011). A robust optimization approach to closed-loop supply chain network design under uncertainty. *Applied Mathematical Modelling,* Vol. 35(2), pp. 637-649.

Pishvaee, M. S., and Razmi, J. (2012). Environmental supply chain network design using multi-objective fuzzy mathematical programming. *Applied Mathematical Modelling,* Vol. 8(36), pp. 3433-3446.

Rabbani, M., Bajestani, M. A., and Khoshkhou, G. B. (2010). A multi-objective particle swarm optimization for project selection problem. *Expert Systems with Applications,* Vol. 37(1), pp. 315-321.

Rabbani, M., Mousavi, Z., and Farrokhi-Asl, H. (2016). Multi-objective metaheuristics for solving a type II robotic mixed-model assembly line balancing problem. *Journal of Industrial and Production Engineering,* Vol. 33(7), pp. 472-484.

Saffar, M., and Razmi, J. (2014). A new bi-objective mixed integer linear programming for designing a supply chain considering co2 emission. *Uncertain Supply Chain Management,* Vol. 2(4), pp. 275-292.

Saffari, H., Makui, A., Mahmoodian, V., and Pishvaee, M. S. (2015). Multi-objective robust optimization model for social responsible closed-loop supply chain solved by non-dominated sorting genetic algorithm. *Journal of Industrial and Systems Engineering,* Vol. 8(3), pp. 42-59.

Soleimani, H., Seyyed-Esfahani, M., and Shirazi, M. A. (2016). A new multi-criteria scenario-based solution approach for stochastic forward/reverse supply chain network design. *Annals of Operations Research,* Vol. 242(2), pp. 399-421.

Soysal, M., Bloemhof-Ruwaard, J. M., Haijema, R., and van der Vorst, J. G. (2015). Modeling an Inventory Routing Problem for perishable products with environmental considerations and demand uncertainty. *International Journal of Production Economics,* Vol. *164*, pp. 118-133.

Wang, F., Lai, X., and Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision Support Systems,* Vol. 51(2), pp. 262-269.