Designing a New Multi-objective Model for a Forward/Reverse Logistic Network Considering Customer Responsiveness and Quality Level

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Abstract

The necessity for supply chain management (SCM) is more than ever in the competitive world of today. SCM aims to give their businesses a competitive edge and boost productivity since the goal of logistic difficulties is to reduce the expenses of organisation to create suitable times and places for the products. The integrated forward/reverse logistics network is a class of NP-hard problems, and this study provides a new multi-objective model with three goal functions. The primary goal is to reduce the overall cost of the supply chain network. The second goal aims to raise customer response to the maximum possible level in both forward and reverse networks. The third goal seeks to reduce the overall amount of flaws in the raw materials purchased from suppliers, ultimately raising the degree of quality. The non-dominated sorting genetic algorithm (NSGA-II) and non-dominated ranked genetic algorithm (NRGA) are utilised to solve the proposed model. To determine and estimate the appropriate values of GAs parameters for enhancing their performances, a Taguchi experimental design method was used. Also, certain numerical examples are generated and their performances are compared using a few measures to see which approach performs better. The one-way ANOVA and Tukey test are employed at a 0.95 confidence level to examine whether there is a significant difference between the performances of the algorithms. Lastly, an analysis of the algorithms' performance is conducted, and the findings are presented.

Keywords: Supply Chain Management, Logistic Network, Non-Dominated Sorting Genetic Algorithm (NSGA-II), Non-dominated Ranked Genetic Algorithms (NRGA).

1. Introduction

A supply chain network design issue involves the totality of the infrastructure set up to acquire, transform, and distribute completed goods, distribute those goods, and offer services to customers after sales. The number, location, capacity level, and technology of the facilities to be taken into consideration are all determined by this challenge.

An efficient, effective, and reliable logistics network gives businesses a long-term competitive advantage and enables them to handle the escalating environmental volatility and escalating competitive demands. The design of forward and reverse logistics networks is typically studied independently in the past studies, however the reverse logistics network's architecture significantly affects the forward logistics network, and vice versa. Splitting the designs could lead to less-than-ideal results, hence the forward and reverse logistics network designs should be combined (Ramezani et al, 2013). The design of the forward and reverse logistics networks should be connected because designing the forward and reverse logistics separately results in sub-optimal designs in terms of prices, service levels, and responsiveness.

Because it involves integrating similar optimization issues at the same decision level, this type of integration is known as "horizontal integration" (Jacobs and Chase, 2008). Based on the aforementioned factors, this study introduces a novel mixed integer programming model for an integrated forward/reverse logistics network with four objective functions: total profit, transportation costs, system service, and total pollution generated for product transfer, with customer responsiveness and quality level taken into account as the logistic network's goals. The remainder of this essay is organised as follows. A thorough literature assessment for the forward/reverse logistic network design is included in Section 2. In Section 3, we describe a new multi-objective model with three objective functions for an integrated forward and reverse logistics network. Section 4 describes the use of two meta-heuristic algorithms, NSGA-II and NRGA, to solve the suggested model. The computational experiments and the analysis of the results are covered in Section 5. In Section 6, some recommendations and findings are offered.

2. Literature Review

Previous research in the area of forward/ reverse and integrated logistics network design often limited itself to single-objective (minimizing the cost or maximizing the profit) in front logistic. But, real world network design problems are often characterized by multiple objectives. The minimization of total costs and maximization of network responsiveness are the most commonly used single objectives in the forward logistics network design. These objectives are, however, typically conflicting, and considering them concurrently is the most favorable option for most decision makers. Network responsiveness is an important issue in reverse logistics too, as it is undesirable for customers/retailers to keep used products for a long time because of the related holding costs.

Since customers have a tendency to discard used products as soon as possible, companies aiming to collect more used products from customers should also consider network responsiveness when minimizing costs. Erol and Ferrel (2004) proposed a multi-objective SC model for minimizing costs and maximizing the customer satisfaction level. Gen and Syarif (2005) took into account the total cost of forward logistic network as an objective in their works. They presented a genetic algorithm for facilities locating, distribution cost and risk management. Huijun et al (2008) presented a bi-level programming model for location of logistic distribution centers by considering benefits of customers and logistics planning departments. They suggested a solution based on genetic algorithm.

Franca et al (2009) presented a stochastic multi-objective model for a forward logistic network that uses the Six Sigma measure to evaluate the quality of raw materials acquired by suppliers. The objectives of the problem are to maximize the profit of SC and minimize the total number of defective raw material parts under demand uncertainty. A bi-objective integrated forward/reverse supply chain design model was suggested by Pishvaee et al (2010), in which the costs and the responsiveness of a logistic network are considered as objectives of the model. They developed an efficient multi-objective memetic algorithm by applying three different local searches in order to find the set of non-dominated solutions. El-Sayed et al (2010) presented a multi-period multi-echelon forward/reverse logistic network design model while the objective of their model is to maximize the profit of a supply chain. The suggested network structure include the three direct path level (suppliers, facilities centers and gathering) and two

In the context of reverse logistics various models have been developed in the last decade. Krikke et al. (2003) designed a MILP model for a two-stage reverse supply chain network for a copier manufacturer. In this model processing costs of returned products and inventory costs are noticed in the objective function for minimizing the total cost. Pishvaee et al (2010) analyzed the cost of logistic network in multi-period with combinational genetic algorithm. Rajagopal (2015) reviewed and identified the types of logistics and compared the Reverse Logistics with Forward Logistics for better understanding and gaining competitive advantages. Giri & Sharma (2015) develop algorithms for sequential and global optimization to study the closed-loop supply chain comprised of the raw material supplier, manufacturer, retailer, and collector. They account for product quality by determining a level of quality above which items are sent to remanufacturing, and they report good results of their proposed algorithms. Anne et al. (2016) explained about reverse logistics and the influence of competitiveness among the food processing industries in Kenya. They proposed a framework for reverse logistics practices.

From the analysis, they found that there is a positive relationship between reverse logistics and proper utilization of material and also reduces cost and enhance competitiveness of the firm. Binti et al. (2016) demonstrated the reverse logistics in the food and beverage industries in Malaysia. They have formed the framework based on five dimensions and collected the feedback. From that the feedback they highlight the present scenario and investigated the internal and external barriers of the industries. Yadegari et al. (2017) presented an integrated forward/reverse logistics model, while considering three kinds of transportation modes. They proposed a memetic algorithm to solve the model.

To structure the literature review of SCND problem and to show difference of this paper form others, we give a systematic state-of-the-art to review the existing works on the SCND problem corresponding to Tables 2 in terms of the network structure. The codes of this table are given in Table 1. As shown in Tables, a large part of papers consider a single objective in their studies, a smaller part is associated with optimization of multi-objective SCND.

Table 1. Network type code

Code	Detail	Category
FL	Forward Logistic	Network Types
RL	Reverse Logistic	
FR	Forward/Reverse Logistic	
MC	Production Centers	Network Layers
DC	Distribution Centers	
CC	Collection Centers	
RMC	Reproduction Centers	
RYC	Recycling centers	
DSC	Disposal centers	

Table 2. A summary of the review literature

Authors	Network			Network Layers						Objectives				
	FL	RL	FR	SC	MC	DC	CC	RMC	DSC	cost	profit	responsiveness	time	Quality
Sabri (2000)	×			×	×	×				×		×		
Syarif (2002)	×			×	×	×				×				
Miranda (2004)	×				×	×				×				
Guillen (2005)	×				×	×					×	×		
Melachrinoudi (2005)	×				×	×				×		×		
Amiri (2006)	×				×	×				×				
Altiparmak (2006)	×			×	×	×				×		×		
Gen (2005)	×				×	×				×				
Selim (2008)	×				×	×				×		×		
Tsiakis (2008)	×				×	×				×				
Franca (2009)	×			×	×	×					×			×
Listes (2005)		×					×			×				
Min (2008)		×					×	×		×				
Uster (2007)		×			×	×	×	×		×				
Demirel (2008)		×			×	×	×	×		×				
Du (2008)		×			×	×		×		×		×		
Pishvaee (2010)		×					×	×	×	×				
Fleischmann (2001)			×		×	×	×	×		×				
Salema (2006)			×		×	×	×	×		×				
Ko (2007)			×		×	×	×	×		×				
Salema (2007)			×		×	×	×	×		×				
Lee (2008)			×		×	×	×	×		×				
Min (2008)			×		×	×		×		×				
Lee (2009)			×	×	×	×	×	×	×	×				
El-Sayed (2010)			×		×	×	×	×	×		×			
Pishvaee (2010)			×	×	×	×	×	×		×		×		
Wang (2010)			×	×	×	×	×	×	×	×				
Rajagopal (2015)		×		×	×	×			×		×	×		
Giri (2015)		×			×	×	×			×		×		
Anne (2016)		×		×		×		×			×	×		
Binti (2016)		×			×		×	×		× ×				
Yadegari (2017)		×			×	×			×		×	×		
This paper			×		×	×	×	×	×	×	×	×		×

Contribution: Although a number of researches are performed in SCND problem, but to the best of knowledge, there is no study that addresses the issues of chain profit, supplier quality and customer responsiveness in context of a Forward/Reverse Logistic. Table 2 shows the distinctiveness of this paper from others in the literature.

3. Problem Description

The integrated logistics network (ILN) discussed in this paper including supply centers or factories, distributers, customer zones, collection centers and disposal centers with multi-level capacities. The general structure of the proposed closed-loop logistic network is illustrated in Fig. 1.

- In forward direction, the factories are responsible for providing the products to customers. The products are conveyed from factories to customers via distribution centers to meet the customer demands.

- In the reverse direction, returned products are collected in collection centers and, after testing, the recoverable products are shipped to factories, and scrapped products are moved to disposal centers. By means of this strategy, excessive transportation of returned products is prevented and the returned products can be moved directly to the factories.

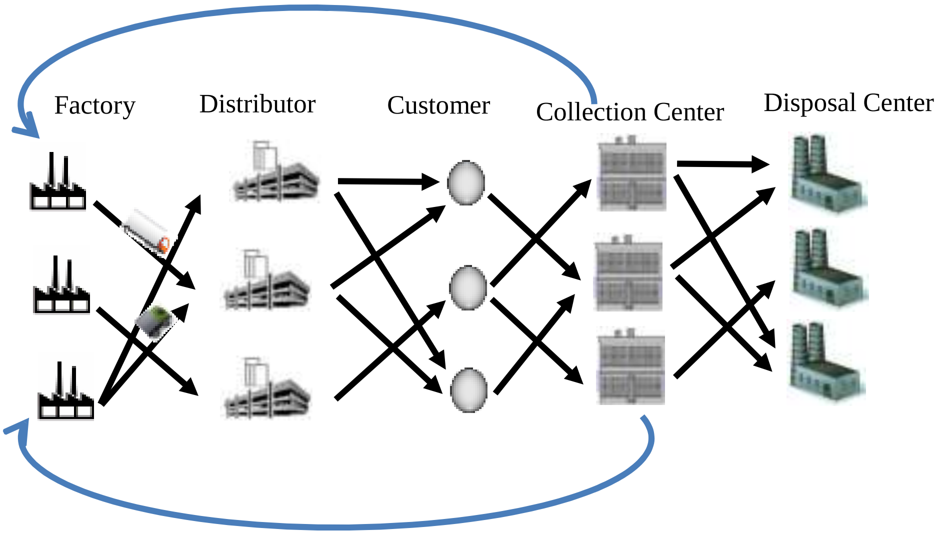

Figure 1. An integrated forward/reverse logistics network

In the forward network, products are pulled through a divergent network and in the reverse network, returned products are moved through a semi-convergent network according to push principles. A predefined percentage of demand from each customer zone is assumed to result in returned products and a predefined value is determined as an average disposal rate. The recovery process is performed in recovery centers and recovered products are inserted in the forward network and are considered identical to new products. Thus, the integrated forward/reverse logistics network is a closed-loop logistics network. It is important to note that the design of the integrated logistics network may involve a trade-off between the total costs and the network’s responsiveness. In some cases, factories may decide to open more facilities to increase the responsiveness for higher customer satisfaction, which may lead to a greater investment cost. Thus, the integrated forward/reverse logistics network is designed to jointly take network costs and network responsiveness into account.

Model Assumption

- Supply chain network includes three fronting level (supplier or factories, customers and distribution centers) and two levels in backing part (collection centers, disposal center).
- The model is designed for one period.
- All return products are provided from demand market in collection centers.
- The demand value of customers are specified.
- Factory locations and capacity, distribution centers, processing and disposal are specified.
- Customer situations are fixed and specified.
- The flow is only permitted to be transported between two consecutive stages. Moreover, there are no flows between facilities at the same stage.
- The quantity of price, production costs, operating costs, collection costs, disposal costs, demands and return rates are fixed and specified.

The proposed model consists of three objective functions. The first objective attempts to minimize the total cost of the supply chain network. The second objective attempts to maximize the customer service level (customer responsiveness) in both forward and reverse networks. The third objective tries to minimize the total number of defects of in raw material obtained from suppliers and thus increase the quality level.

Problem Parameters

i	Index of distributor type i, (i=1,…,m)
j	Index of customer type j, (j=1,…,n)
v	Index of vehicle type v, (v=1,...,V)
p	Index of product type p, (p=1,…,P)
N_i	Set of possible levels for making a distributor in Group i
l	Index of collection center type l, (l=1,…,L)
k	Index of quality level type k, (k=1,…,K)
s	Index of disposal center type s, (s=1,…,S)
cap_i^{np}	Capacity of distributor i for product type p with capacity level n
q_v^p	Capacity of vehicle v for product type p
$demand_j^p$	Demand of customer j for product type p
$cost_i^n$	Making Cost of distributor type i with capacity level n
$c1_{p,k}$	Production cost of product type p with using useful materials for the environment with quality type k
$c2_{s,k}$	Product processing cost on disposal center s with using clean technology with quality level k
Budget	Budget available to build distributors

$co1_v$	The amount of product pollution by carriers v per unit
$co2_{p,k}$	The amount of pollution produced of the product type p by manufacturer p with quality level k
$co3_{s,k}$	The amount of pollution produced of the product type p by disposal center s with quality level k
$sl_{p,k}$	The ratio of return redistribution average of p-type products are made with quality level k
$si_{p,k}$	The ratio of disposal average of p-type products are made with quality level k
$re_{p,j,l}$	The amount of product type p that is returned by customer type j to collection center l
$prod_p$	The amount of production of product type p
$d_{i,j}$	The distance between distributer i and j node
$d'_{i,p}$	The distance between distributer i and location of product type p
$d_{j,l}$	The distance between customer j and collection center type l
c_v	Operational cost of vehicle v per unit
$se_{p,k}$	Selling price of product type p (per unit) with quality level k

Problem Variables

$X^p_{i,j,v}$	A binary variable that indicates the distributer i located before node j in the path of vehicle v which carrier product type p
Y^n_i	A binary variable that indicates in the location of node i, a distributor with capacity level n be created
$Z^p_{i,j}$	A binary variable that indicates customer j get product type p from distributer i
$H^p_{i,v}$	A binary variable that indicates the product type p transferred to distributer i by vehicle v
$M_{p,k}$	A binary variable that indicates the manufacture of product type p uses useful material at quality level k
$N_{s,k}$	A binary variable that indicates the disposal center s uses clean technology at level k to disposal product
$S_{p,j,l}$	A binary variable that indicates the returned product type p from customer j be transferred to collection center l
$T_{p,l,s}$	A binary variable that indicates the collected product type p from collection center l be transferred to disposal center s
$W^p_{i,v}$	A Slack variable relating to sub tour elimination constraint

In terms of the above notation, the mixed integer multi-objective model for a forward/reverse logistic network with considering customer responsiveness and quality level can be formulated as follows:

$$\begin{aligned} \min OF_1 = &\sum_{i\in I}\sum_{v\in V}\sum_{p\in P} H^p_{i,v} \times c_v \times d'_{i,p} \\ &+ \sum_{i\in(I\cup J)}\sum_{j\in(I\cup J)}\sum_{v\in V}\sum_{p\in P} X^p_{i,j,v} \times c_v \times d_{i,j} \\ &+ \sum_{p\in P}\sum_{j\in J}\sum_{l\in L} re_{p,j,l} \times d_{j,l} + \sum_{n\in N_i}\sum_{i\in I} Y^n_i COST^n_i \\ &+ \sum_{p\in P}\sum_{k\in K} prod^p \times M_{p,k} \times c1_{p,k} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{j\in J}\sum_{s\in S} re_{p,j,l} \times si_{p,k} \times T_{p,l,s} \times N_{s,k} \\ &\times c2_{s,k} \end{aligned} \tag{1}$$

$$\max OF_2 = \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} Z^p_{i,j} \times demand^p_j \tag{2}$$

$$\begin{aligned} \min OF_3 = &\sum_{i\in I}\sum_{v\in V}\sum_{p\in P} H^p_{i,v} d'_{i,p} co1_v \\ &+ \sum_{p\in P}\sum_{k\in K} prod^p \times M_{p,k} \times co2_{p,k} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\sum_{j\in J}\sum_{s\in S} re_{p,j,l} \times si_{p,k} \times T_{p,l,s} \times N_{s,k} \\ &\times co3_{s,k} \end{aligned} \tag{3}$$

Subject to:

$$\sum_{i\in(I\cup J)} X^p_{i,j,v} - \sum_{i\in(I\cup J)} X^p_{j,i,v} = 0 \qquad \forall j \in I \cup J, v \in V, p \in P \tag{4}$$

$$\sum_{v\in V} H^p_{i,v} \times q^p_v \leq \sum_{n\in N_i} cap^{np}_i \times Y^n_i \qquad \forall i \in I, p \in P \tag{5}$$

$$\sum_{i\in(I\cup J)}\sum_{j\in J} X^p_{i,j,v} \times demand^p_j \leq q^p_v \qquad \forall v \in V, p \in P \tag{6}$$

$$\sum_{j\in J} Z^p_{i,j} \times demand^p_j \leq \sum_{v\in V} H^p_{i,v} \times q^p_v \qquad \forall i \in I, p \in P \tag{7}$$

$$\sum_{u\in(I\cup J)} X^p_{i,u,v} + \sum_{u\in(I\cup J)} X^p_{u,j,v} - Z^p_{i,j} \leq 1 \qquad \forall i \in I, j \in J, v \in V, p \in P \tag{8}$$

$$\sum_{n\in N_i}\sum_{i\in I} Y^n_i cost^n_i \leq budget \tag{9}$$

$$\sum_{i\in I}\sum_{v\in V} H^p_{i,v} \times q^p_v \leq prod^p \qquad \forall\, p \in P \tag{10}$$

$$\begin{aligned} re_{p,j,l} = &\sum_{i\in I}\sum_{k\in K} Z^p_{i,j} \\ &\times S_{p,j,l} \times demand^p_j \\ &\times sl_{p,k} \times M_{p,k} \end{aligned} \qquad \forall\, l \in L, j \in J, p \in P \tag{11}$$

$$\sum_{i\in(I\cup J)} \sum_{v\in V} X^{p}_{i,j,v} \leq 1 \qquad \forall j \in J, p \in P \qquad (12)$$

$$\sum_{n\in N_i} Y^{n}_{i} \leq 1 \qquad \forall i \in I \qquad (13)$$

$$\sum_{i\in I} Z^{p}_{i,j} \leq 1 \qquad \forall\, j \in J, p \in P \qquad (14)$$

$$\sum_{v\in V} H^{p}_{i,v} \leq 1 \qquad \forall\, i \in I, p \in P \qquad (15)$$

$$\sum_{k\in K} M_{p,k} \geq Z^{p}_{i,j} \qquad \forall\, i \in I, j \in J, p \in P \qquad (16)$$

$$\sum_{k\in K} N_{s,k} \geq T_{p,l,s} \qquad \forall\, p \in P, l \in L, s \in S \qquad (17)$$

$$\sum_{s\in S} T_{p,l,s} \geq \sum_{j\in J} S_{p,j,l} \qquad \forall\, p \in P, l \in L \qquad (18)$$

$$W^{p}_{i,v} - W^{p}_{j,v} + N X^{p}_{i,j,v} \leq N - 1 \qquad \forall i, j \in J, v \in V, p \in P \qquad (19)$$

$$X^{p}_{i,j,v}, Y^{n}_{i}, Z^{p}_{i,j}, H^{p}_{i,v}, S_{p,j,l}, M_{p,k}, N_{s,k}, T_{p,l,s} \in \{0, 1\} \qquad \forall i, j, p, v, n, l, k, s \qquad (20)$$

The first objective function (1) attempts to minimize the total cost of the supply chain network including: supply cost for purchasing the raw materials from factories, fixed cost for establishing the facilities, production cost for manufacturing the products in factories, inspection cost for the returned products in collection centers, operating cost in distribution centers, remanufacturing cost for recoverable products in factories and disposal costs for scrapped products. The second objective function (2) attempts to maximize the customer service level (customer responsiveness) in both forward and reverse networks. The third objective function (3) tries to minimize the total number of defects of in raw material obtained from factories and thus increase the quality level.

Constraint (4) insures that, for each product, the flow entering to each distribution center is equal to the flow exiting from this distribution center over each vehicle. Constraint (5) shows that the sum of the flow exiting from each distribution centers to all customers does not exceed the capacity of relevant vehicle. Constraint (6) shows that the sum of the flow entering to all customers by each vehicle does not exceed the capacity of relevant vehicle. Constraint (7) represents that the sum of the flow entering to each customer by various vehicles does not exceed the capacity of relevant vehicles. Constraint (8) shows the relation between allocation and routing in a model. Customer j allocates to the distributor i just if the vehicle v passes from customer j location, so it starts its journey from distributor i. Constraint (9) sets control the total budget. Constraint (10) ensures that the sum of the product type p which can moved by vehicle v does not exceed the capacity of production of it. Constraint (11) sets the returned products from customers to each collection center.

Constraint (12) ensures that each vehicle starts its movement from one distributor and finishes in another distributor. Constraint (13) ensures that each distributor can be created in one capacity level. Constraint (14) ensures that each customer receives all needs from one distributor maximally. Constraint (15) ensures that the sum of the product which can moved from each factory to distributers must be done by one vehicle maximally. Constraint (16) ensures that at least one of the products received by the customer from distributers, Must be produced with quality level type k.

Constraint (17) ensures that at least one of the collected products transferred to each disposal center from collection centers, Must be used with clean technology at level type k. Constraint (18) represents that if a product enters to a collection center, one disposal center should be allocated till returning the entering products to elimination center. Constraint (19) prevents the creation tour. Constraints (20) impose the binary restriction on the corresponding decision variables.

As the integrated forward/reverse logistics network design problem includes the capacitated plant location problem which is known to be NP-complete (Davis and Ray, 1969), the proposed model design problem is NP-hard. So, the performance of the proposed model is compared with two well-known multi-objective evolutionary Algorithms, namely NSGA-II and NRGA.

NSGA-II

Non–dominated sorting genetic algorithm II (NSGA-II) is one of the most well-known and efficient multi- objective evolutionary algorithms introduced by Deb et al. (2002). Ranking and selecting the population fronts are performed by non-dominance technique and a crowding distance. Also, the algorithm uses crossover and mutation operators to generate offspring are combined together. Finally, the best solution in terms of non-dominance and crowding distance is selected from combined population as the new population. The non-dominated technique, the calculation of crowding distance, and crowding selection operator will be explained as follows.

Assume that there are *r* objective functions. When the following conditions are satisfied, the solution X1 dominates solution X2. If X1 and X2 do not dominate each other, they are placed at the same front. For all objective functions, solution X1 is not worse than another solution X2. For at least one of the *r* objective functions X1 is really better than X2. Front number 1 is made by all solutions that are not dominated by any other solutions. Also front number 2 is built by all solutions that are only dominated by solutions in front number 1.

4. 1. 1. Crowding Distance

The crowding distance is a measure for density of solutions. The value of the crowding distance presents an estimate of density of solutions surrounding a particular solution. The solutions having a lower value of the crowding distance are preferred over solutions with a higher value of crowding distance.

4. 1. 2. Tournament Selection Operator

A binary tournament selection procedure has been applied for selecting solution for both the crossover and mutation operators. At first, select two solutions among the population size, then the lowest front number is selected if the two populations are from different fronts. If they become from the same front, the solution with the highest crowding distance is selected.

NRGA

NRGA was introduced by Al jadaan et al. (2008). But, In contrast to the NSGA-II, the difference between the NRGA and the NSGA-II is their different selection strategy. In NRGA, instead of binary tournament selection, roulette wheel selection is utilized. Al jadaan et al. (2008) applied roulette wheel selection algorithm. In that algorithm, a fitness value equal to its rank in the population is assigned to each individual. First, sort population according to fast non-domination sorting and choose the best solutions from the first ranked population. Then, according to their crowding distance criteria, individuals of eachfront are ranked. Now, two tiers ranked based roulette wheel selection are used (one tier to select the front and the other to select solution from the front).

The front probability obtained as Eq. (21).

$$P_i = \frac{2*rank_i}{N_F*(N_F+1)} \qquad \forall, i = 1,...,N_F \tag{21}$$

Where N_F show the number of fronts. In this equation, it is obvious that a front with highest rank has the highest probability to be selected. So the probability of individuals fronts based on their crowding distance criteria is calculated as follows:

$$P_{ij} = \frac{2*rank_{ij}}{M_i*(M_i+1)} \qquad \forall, i = 1,...,N_F \qquad \forall, j = 1,...,M_i \tag{22}$$

Where M_i show the number of individuals in the front i. In this equation individuals with more crowding distance have more selection probability. The diversity among non-dominated solutions is also considered. Next, roulette wheel selection is applied according to the two random numbers (indicate number of front and individual chromosome in selected front) in intervals [0, 1] and [0, 1] respectively. This process is repeated until the desired number of individuals has been selected.

5. Test problems

In order to assess the performance of the proposed model, a summary of experiments is provided in this section. Some authors mentioned that increasing the amount of model's parameters significantly increases the computational time with limited benefit in solution accuracy (Ramezani et al, 2013). Our experiments on the proposed model also confirm this judgment. Here to assess the performance of the proposed model, 30 test problems are selected which used 6 types of products. For each type, 5 test problems were designed which including various numbers of factory, distributers center, customer, collection location and disposal center. Test problems are solved with Matlab R2010b software on a Pentium dual-core 2.2 GHz computer with 2 GB RAM.

Parameter Tuning

Since the results of all meta-heuristics techniques are sensitive to their parameter setting, it is required to do extensive simulations to find suitable values for various parameters. The parameters of the NSGA-II and NRGA are *pop-size, Pc, Pm and iteration* (Al jadaan et al., 2008). The parameters of the two meta-heuristics algorithm are regulated using a Taguchi approach. In this approach, in the first stage, an L_{25} (55) orthogonal array experiment was arranged under Taguchi parameter standard setting values, in which no. 1 to no. 25 were Taguchi experimental data. Accordingly, the control factor's range was given four levels, as depicted in Table 3. For the second stage, it is similar to that of the first stage. An L_{25} (55) orthogonal array experiment was also utilized to perform the process. The multiple quality characteristics and energy efficiency are the performance of injection molding process. Accordingly, the control factor's range was given four levels, as depicted in Table 3. Overall, the range of factors in Table 3 covered the optima parameters under simulation (Maosheng et al., 2016). To achieve this aim using Taguchi, we carried out extensive experiments to determine effective parameters. In order to execute the procedure, we used MINITAB software for finding the relation between responses (objective functions) and effective factors on responses (*pop-size, Pc, Pm and iteration*) that results are presented in Table 3.

Table 3. NSGA-II and NRGA parameter sets

Algorithm	Parameters	Range	Level 1	Level 2	Level 3	Level 4
NSGA-II	Pop-size	50-200	50	100	150	200
	Pc	0.5-0.9	0.5	0.7	0.8	0.9
	Pm	0.05-0.2	0.05	1	0.15	0.2
	Iteration	200-500	200	300	400	500
NRGA	Pop-size	50-200	50	100	150	200
	Pc	0.5-0.9	0.5	0.7	0.8	0.9
	Pm	0.05-0.2	0.05	1	0.15	0.2
	Iteration	200-500	200	300	400	500

Comparison Metrics

Due to the conflicting nature of Pareto curves, we should use some performance measures to have a better assessment of multi-objective algorithms. So the following four performance metrics are considered (Tavakkoli-Moghaddam et al. 2011):

Number of Pareto Solution

The number of Pareto solution (NPS), which shows the number of Pareto optimal solutions that each algorithm can find.

Spacing Metric

We define the spacing (SM) metric by:

$$SM = \frac{\sum_{i=1}^{n-1} \left| \bar{d} - d_i \right|}{(n-1)\bar{d}} \tag{23}$$

where d_i is the Euclidean distance between consecutive solutions in the obtained non-dominated set of solutions and $\bar{d}$ is the average of these distances. This metric provides an ability to measure the uniformity of the spread of the solution set points. Due to the discontinuous test problem, the trade-off surface of these problems has some holes and leads to difficulty in interpreting this metric. Our approach with this metric is identical to the number of non-dominated solutions on using the ANOVA method, except that the effects are investigated on the spacing metric.

Diversification Metric

Diversification metric (DM) measures the spread of the solution set and is defined as:

$$DM = \sqrt{\sum_{i=1}^{N} \max(\|x_t^i - y_t^i\|)} \tag{24}$$

Where $\|x_t^i - y_t^i\|$ is the Euclidean distance between non-dominated solution x_t^i and non-dominate y_t^i.

Computational Time

The fourth metric is computational time of the algorithm (CPU) which indicates the computational time of each meta-heuristic algorithm.

Table 4. Results of the experiment of different size test problems

Num	Levels				NSGA-II				NRGA			
	Pop-size	P_c	P_m	*Iteration*	Spacing	NPS	D	Time	Spacing	NPS	D	Time
1	1	1	1	1	9760	23	82415	693	8886	25	77320	642
2	1	2	2	2	9502	22	52951	549	9352	23	73406	540
3	1	3	3	3	9716	23	41560	585	9480	17	61614	672
4	1	4	4	4	9150	23	67295	570	9452	21	66896	663
5	2	1	2	3	9524	24	62330	648	8476	21	61308	708
6	2	2	1	4	10444	34	68811	666	10556	27	70147	840
7	2	3	4	1	9330	36	76928	642	8520	33	70289	753
8	2	4	3	2	10338	34	75286	813	9698	30	76375	765
9	2	3	3	3	10512	33	78849	834	8464	26	70170	702
10	2	4	4	4	9576	40	87113	669	10242	28	75193	744
11	3	1	3	4	19374	47	117708	1191	16464	31	96821	1224
12	3	2	4	3	19310	50	119400	1245	16496	33	96708	1095
13	3	3	1	2	19236	43	107586	1296	19986	25	97773	1029
14	3	4	2	1	17726	49	110519	1263	16904	30	97197	1146
15	3	3	3	3	17568	44	115252	1125	18606	29	97434	1206
16	3	4	4	4	16098	64	226122	2130	19496	57	240106	1943
17	3	3	3	4	15798	62	191956	2145	18740	50	209969	1850
18	3	4	4	4	15310	55	296802	2100	17640	54	212390	1760
19	4	1	1	1	16712	56	142068	2127	19592	44	130644	1784
20	4	1	1	2	17588	61	196377	2169	16902	45	213090	1802
21	4	1	1	3	16546	68	228311	4827	20628	52	210668	4110
22	4	1	1	4	17532	61	321955	4548	21396	45	237904	3972
23	4	1	2	1	15982	65	283618	4701	19534	45	209799	4110
24	4	1	2	2	16210	67	359215	4791	20772	47	348703	4056
25	4	1	2	3	17458	57	327163	4746	18782	40	212591	3735
26	4	2	2	2	18270	87	345623	10235	21220	62	228204	8078
27	4	2	3	3	17154	85	458713	10547	22530	58	314728	7877
28	4	4	2	2	19560	85	372733	95390	22590	60	266970	8093
29	4	4	3	3	18590	91	398134	10223	23070	62	215457	7919
30	4	4	4	4	19286	92	377366	10106	20486	59	251417	8219

Computational Results

After defining the four performance metrics, the results of experiments and comparisons of meta-heuristic algorithms for their different sizes are presented in Table 4. Figure 2, shows the comparison between NSGA-II and NRGA performance in spacing index. As it can be seen in Figure 2, none of the algorithm are superior to each other.

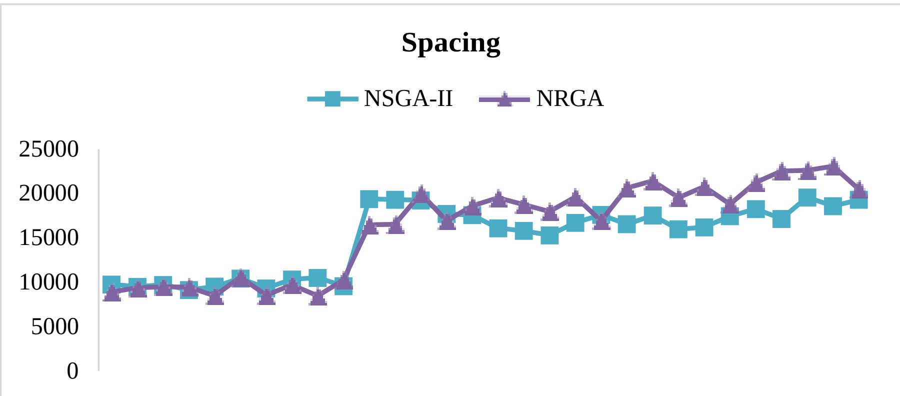

Figure 2. Performance comparison of the NSGA-II and NRGA based on spacing criteria

Figure 3, shows the comparison between NSGA-II and NRGA performance in diversity index. As it can be seen in this figure, NSGA-II has a better performance than NRGA.

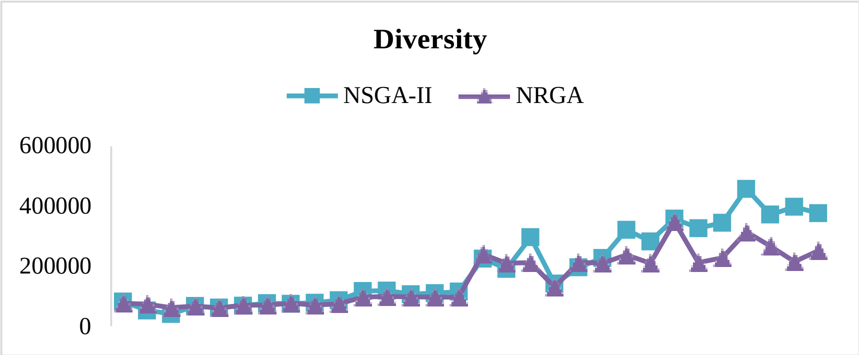

Figure 3. Performance comparison of the NSGA-II and NRGA based on diversity criteria

Figure 4, shows the comparison between NSGA-II and NRGA performance in number of Pareto solution index. As it can be seen in this figure, NSGA-II has a better performance than NRGA.

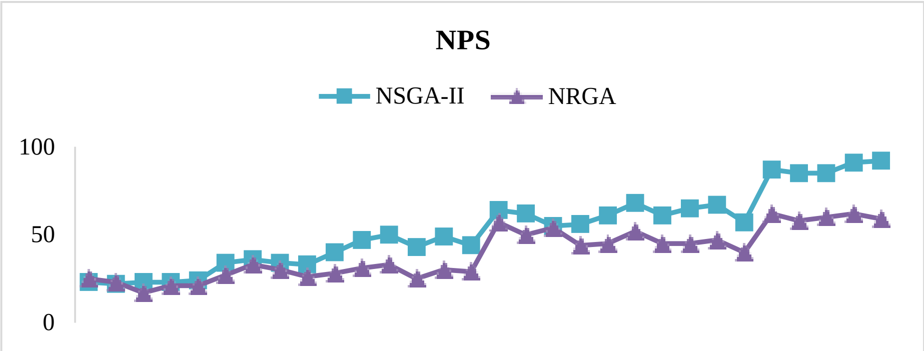

Figure 4. Performance comparison of the NSGA-II and NRGA based on NPS criteria

Figure 5, shows the comparison between NSGA-II and NRGA performance in CPU time index. As it can be seen in this figure, both algorithms have nearly identical performance on computational time.

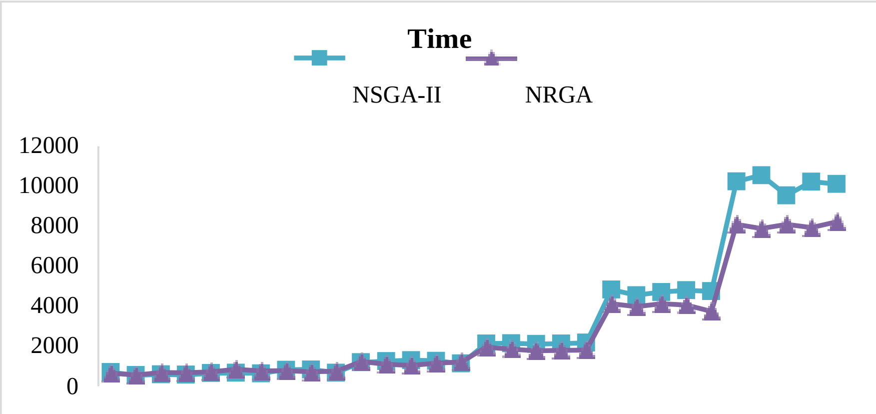

Figure 5. Efficiency comparison of the proposed algorithms based on computational time

Sensitivity Analysis

In addition, four one-way ANOVAs are used to statistically compare the performances of the two algorithms in terms of the four metric criteria. Tables 5-8 show the one-way ANOVA of the performance indices NPS, spacing, diversity, and CPU time at 95% confidence level along with the values of the corresponding *p*-values. Tables 5-8 show while there are significant differences between the two algorithms in terms of the means of NPS, spacing and diversity, and there are no significant differences among the two algorithms in term of the CPU time.

Table 5. The results of ANOVA for diversity criteria

Source	DF	SS	MS	F	P-value
Factor	1	1868	1868	15.34	0
Error	58	7062	122		
Total	59	8929			

Table 6. The results of ANOVA for NPS criteria

Source	DF	SS	MS	F	P-value
Factor	1	7871.2	7871.2	113.93	0
Error	58	4007.1	69.1		
Total	59	11878.3			

Table 7. The results of ANOVA for spacing criteria

Source	DF	SS	MS	F	P-value
Factor	1	559	559	7.39	0
Error	58	4387.6	75.6		
Total	59	4946.6			

Table 8. The results of ANOVA for computational time

Source	[1]DF	[2]SS	[3]MS	[4]F	P-value
Factor	1	2254.7	2254.7	35.44	0.0049
Error	58	3689.9	63.6		
Total	59	5944.6			

[1] Degree of Freedom
[2] Mean of Square error
[3] Sum of Square error
[4] F Distribution

Also, for comparing the performances of the two algorithms in terms of the four metric criteria, Tukey test is used. Figure 6 shows the Tukey test of the performance indices NPS, spacing, diversity, and CPU time. The results show NSGA-II has better performance than NRGA in terms of the means of NPS, spacing and diversity with confidence level 95% and in CPU time, the result is reversed.

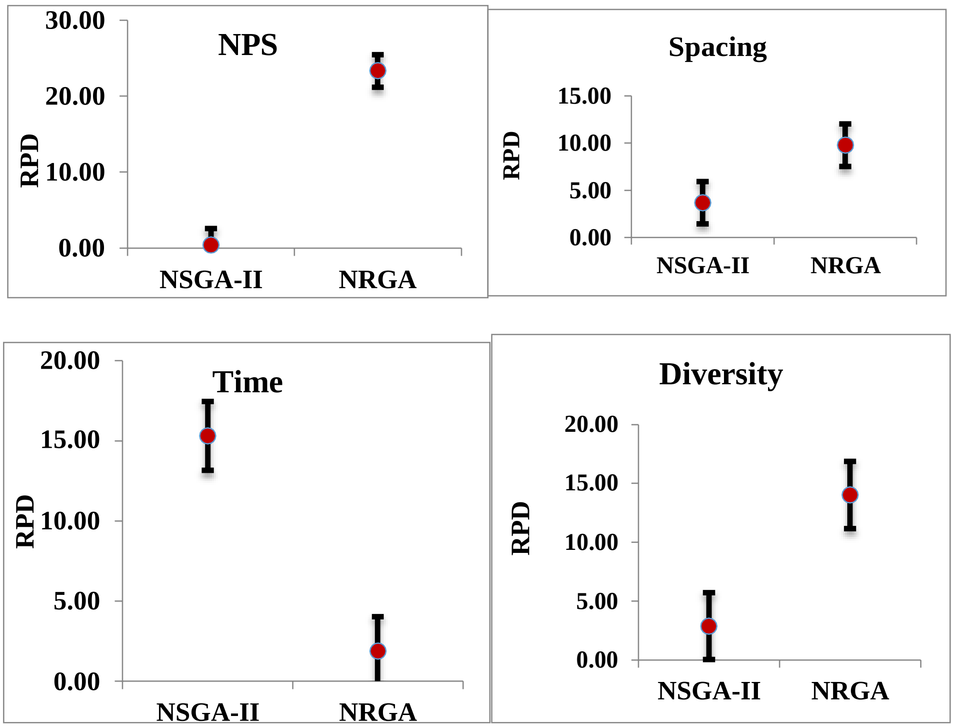

Figure 6. The results of Tukey tests for four metric criteria

6. Conclusions

In supply chain management and reverse logistics operations, the significance of network costs and responsiveness has grown dramatically in recent years. This paper presents a new mixed integer programming model for integrated forward and reverse logistics network with three objective functions due to the growing significance of customer service level as customer responsiveness and product quality as quality level in supply chain management and forward/reverse logistics activities. The primary goal is to reduce the overall cost of the supply chain network. The second goal aims to raise the bar for customer service across forward and reverse networks. The third goal seeks to reduce the overall amount of flaws in the raw materials purchased from suppliers, ultimately raising the degree of quality. The model application demonstrates that the proposed scenario lowers overall costs. Two meta-heuristic algorithms (NSGA-II and NRGA) are employed to solve the suggested model. In addition, several test issues are created and the performance of the two algorithms is assessed to determine which method performs better. The variety and convergence of algorithms were examined using four numerical performance indicators. Eventually, the results showed that NSGA-II and NRGA more effectively satisfy the condition. Future scholars can adopt the following strategies:

Think about the problem's random or fuzzy parameters.
• Evaluating several multi-objective meta-heuristic algorithms to solve the issue, such as MOPSO or MOSA.
• The creation of heuristic methods as opposed to the original segment's random data generation.
• Handling the supply of returned goods and the demand unpredictability in a multi-product integrated logistics network.

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