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Impact of Closed–Loop Supply Chains on Reducing Carbon Emission and Gaining Competitive Advantage: NSGA-II and MOPSO Solutions

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Abstract

The purpose of this paper is presenting a mathematical model of the closed-loop supply chain network design dynamic positioning facility, through a strategic review of Multi-period planning horizon in order to minimize the environmental impact and the gain the competitive advantage based on of Porter's view. A new multi-objective mixed integer programming model for locating facilities and simultaneous designing of forward and reverse network is developed in order to determine the strategic long-term comprehensive solutions that maximize the Net Present Value (NPV) of cash flow for the entire supply chain and to minimize emissions of greenhouse gases products suppliers. The proposed algorithm parameters Multiple Objective Particle Swarm Optimization (MOPSO) and non-dominated sorting genetic algorithm version 2 (NSGA-II) are adjusted using the Taguchi method. Numerical results show that the new model with the above-mentioned meta-heuristic algorithms can be used obtain quantitative aspects of strategic planning in terms of closed-loop supply chain.

Keywords: Competitive Advantage, Carbon Emission, Closed-Loop Supply Chain, Multi-Objective Mixed Integer Programming, Net Present Value (NPV)

1. Introduction

Logistics network design is one of the most strategic decisions in supply chain management; it is including decisions on the number of facilities, and determines the location and capacity of the facility that affects both the cost and the level of customer service.

Facility location problems from the 1960s find an important place in the literature of operation research. Generally the term of location refers to this modeling, formulating and solutions of problems that can define them in placing facilities in the space in the best way.

No doubt correct facility location has great effects on the economic benefits of the location is one of the interests of management science and operations research scientists, and signification progress has been made in this area.

1.1 Problem Statement

To create a reverse supply chain of traditional forward supply chain separately, not only increases the cost of infrastructure but also to reduce the profit of product improvement, supply chain integration with forward reverse, a closed-loop supply chain with the aim of closing the loop material flows is expanded to guarantee that products can be returned back effectively and efficiently to various facilities in the supply chain. Consequently greenhouse gas emissions and waste residues, as well as overhead costs are reduced and causing an increase in productivity[1]. Inaddition, Kavitha[2] quated Saman et al. say a Closed-Loop Supply Chain (CLSC) network that is investigated with multiple plants, collection centers, demand markets, products and a mixed-integer linear programming model which minimizes the total cost.

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Therefore, environmental issues focused on reducing wastes, hazardous materials, residues of consumer, industrial and commercial firms, as well as economic value of expanding the usable life of as well as the time use products manufactured goods are considered as two important objectives of the closed-loop supply chain. Indeed, from an economic standpoint, companies can use the benefit from the recovery and recycling of products directly, even in some products, after-sales repair services can provide satisfaction of more customers and thus companies gain indirectly more benefit.

Green supply chain in addition to the enjoyment of the benefits arising from the use of resources, energy, warehouses, pollution reducing, using environmentally friendly materials, reduce waste and efficiency benefits and production of green and recyclable productions. In addition to reducing the cost of environmental degradation uses the response strategy or in other words differentiation strategy. Simultaneous combinations of these two strategies are known as Porter's strategy[3], will accompany with competitive advantage in the industry.

After the conference relating to earth in Rio in 1992 in 154 countries, stabilization emissions (climate treaty) after the Kyoto Protocol in 1997[4], reducing carbon(CO_2) and income derived from it economic assessment and cost-effectiveness of initiatives with the Clean Development Mechanism (CDM) of the economy in the long term goal seemed very good for this reason.

However, the issue of environmental impact is considered more than the economic aspects, both objectives (economic and environmental) using efficient models, are available by applying the same infrastructure.

This paper seeks to provide a mathematical model for locating facilities with a capacity of commodity-loop supply chain network design-manufacturing plants closed ,to determine the optimal locations, distribution centers collection centers for production equipment as well as waste disposal with the aim of maximizing NPV of cash flow for the entire supply chain, with restrictions on carbon emissions in order to avoid environmental destruction due to the income from reducing of the production of per kg carbon and sale it in the form of protocol goals. And also increase the utility and acceptability among customers to provide competitive advantage.

In 1998 Marin and Pelgrin began the first researches on the reverse logistics network design and analysis of a problem with the placement of the plant. In this model, which is known as the problem of recursive plant placement, the objective is to minimize system costs that are made up of customers and suppliers and there is a flow of returned products from the customers' side. In this paper in addition to the exact solving techniques, an innovative method based on Lagrangian decomposition scheme is used to solve the model[5].

Jayaramn and colleagues in 1999 presented a mixed integer linear programming model for the purpose of cost minimization. In this article revived activities for returned products is taken into consideration. Inthismodelwhere the demandandsupplyisregardedto bedefinitive,several recyclable products are received in collection centers, are sent to revive centers to rebuild. And then the revived products are sent to the customers for re-use.Each revived facility, can reconstruct of all kinds of returned products. And for the maximum number of revival centers that can be deployed, the restriction is regarded.This is one of the few papers deals with design an elastic system in reverse logistics based on customer demand for revived products. The computational results show the performance of the model in determining the optimal number of facilities reconstruction.The impact of transportation costs of the input and output associated with revived facilities on the network design has been studied[6].

Krike and his colleagues in 1999 with regard to the processing costs of the returned products and inventory in the objective function, using a mixed integer linear programming model began to design periodical reverse logistics network for a manufacturer Copiers. This model made decision about reconstruction processes in two candidate places that the allocation to each of them is faced with management constraints[7].

In 2003 Jayaramn and his colleagues offered other research in the field of logistics network design for the reconstruction able products with the certain demand and supply. In this paper, recyclable product includes a wide range of products as products calls from clients for processing, Risk products that should be given priority destruction, as well as used products that should be disposed of or recycled. The model allows you to send goods directly to the customers of revived facility. And also up and down limit is regarded the number of the collection centers and revival facilities that can be deployed, up and down limit is regarded. To solve the model creative, innovative and improvement methods are proposed. And computational efficiency of the proposed method results in finding high quality solutions for large scale problems have been demonstrated[8].

One of the important characteristics of reverse logistics networks is the uncertainty in demand and the type and quality of the returned products. Listes and Dekker in 2005, taking into account this uncertainty, offered a stochastic mixed integer-programming model for stone recovery process with the goal of maximizing the benefit. In this paper first, the supply and demand for certain. In this paper, first the supply as definitively and demand as probabilistic, and both are considered to be probabilistic, and for the case as a probabilistic two-stage and three-stage optimization proposed, The model under different scenarios have been developed[9].

Min and his colleagues in 2006 in line with the management of the returned products at the right time a Mixed Integer Non Linear Programming (MINLP) model offered conclusive for the purpose of cost minimization, In this model, the distance between the centers customer and collection centers is regarded an upper limit, In addition, the products are sent to the collection centers over a period of several days integrated and then sent to revived centers. Thus, for each collection center duration of a period of collecting is a decision variable that should not exceed a specified range the existence of this decision variable making model is nonlinear. In this paper, to obtain near-optimal solutions for MINLP model proposed genetic algorithm is used. The computational results presented in this study, make a balance between the cost of maintenance and integration of duty on the one hand And the costs and the level of customer service[10] on the other hand, The research presented by Üster and colleagues in 2007, a multi-product semi-integrated network for producing parts in the automotive industry, aimed at minimization of fixed costs, transportation and processing has been studied where to logistics network is assumed to be direct, only the collection centers and recovery in reverse logistics is located but the forward and reverse flows are optimized simultaneously. The remarkable feature of this paper is to provide an exact solution based on the Benders decomposition method for this model[11].

Ko and Evans in 2007, have presented an advanced model of two-objective mixed integer programming and integration with distribution centers and collection centers rehabilitation centers for closed loop logistics network design of third-party logistics service providers and they have considered only the revived aspect from the various states of repair. In this paper, instead of the location, the revitalized capacity of the existing and potential centers is made. The objectives of this model include cost minimization and time minimization of services to the customer. To solve the proposed model, they have presented a mixed distributed search method[12].

Demirel and Gokcen in 2008 offered a numerical mathematical model for a restructuring that includes direct and reverse currents. In this model, in addition to disassembling and assembling and distribution facility locations, the optimum value of the current values of the products was also determined[13].

Aras and Asken offered a mixed numerical linear programming model in 2008, for locating the collection centers of used products of their customers. In this model, the customer decision to go to these centers to deliver used products depends on the proposed financial incentives and their distance to the nearest centers. And the remarkable point of this research is the ability of the model to determine the optimal amount of financial incentives for each type of product return And the remarkable point of this research of the ability of the model is to determine the optimal amount of financial incentives for returning any product in addition to the facility where the resulting profit. In this paper, to solve the proposed model is used an innovative method based on forbidden search method[14].

Pishvaee and his colleagues in 2009 provided a mixed numerical linear programming model aiming at minimize the transportation costs and fixed costs of opening facilities in a reverse logistics network. To solve the model they used of a simulated annealing[15].

Wang et al. in 2010, assumed a generalized closed-loop logistics model with a spanning-tree based genetic algorithm to solving large scale problems within a shorttime[16].

Salema et al. in 2010 developed a strategic and tactical model for the simultaneous design of forward and reverse supply chains[17].

Joochem in 2012 proposed in an article demonstrated designing the closed-loop supply chain with maximizing NPV, using MILP[18].

In this paper we are searching to propose a mathematical dynamic multi-commodity capacitated facility location in closed-loop supply chain model to maximize NPV of liquidity for the whole of supply chains. We are searching to show the importance of restrictions in posing on Carbon Emission in order to protect the environmental destructive effects. Incomes resulted from decreasing in producing of per kilos Carbon, and selling. them within the objects of

Tokyo Protocol, increasing the utility and acceptability among customers creates a competitive advantage.

Brief history and the relationship with the article are given in Table 1.

2. Model

2.1 Notation

Index Sets

L: set of location sites, indexed by $l \in L$.

$O \subset L$: set of selectable location sites, indexed by $o \in O$.

$E \subset O$: set of existing location sites, indexed by $e \in E$.

$O \subset N$: set of potential new location sites, indexed by $n \in N$.

$J \subset O$: set of plant sites for production anddisassembly-remanufacturing centers, indexed by $j \in J$.

$I \subset O$: set of intermediate sites for distribution and collection centers, indexed by $i \in I$.

$S \subset L$: set of locations of external suppliers, indexed by $s \in S$.

$K \subset L$: set of locations of customers, indexed by $k \in K$.

$U \subset L$: set of locations of external subcontractors for disassembly-remanufacturing process, indexed by $u \in U$.

C: set of center types for supply chain processes, indexed by $c \in C$.

$F \subset C$: set of center types for forward supply chain processes, indexed by $f \in F$.

$R \subset C$: set of center types for reverse supply chain processes, indexed by $r \in R$.

$A \subset C$: set of center types at plant sites, indexed by $a \in A$.

$B \subset C$: set of center types at intermediate sites, indexed by $b \in B$.

P: set of product types, indexed by $p \in P$.

$G \subset P$: set of final products, indexed by $g \in G$.

$M \subset P$: set of parts/components, indexed by $m \in M$.

T: set of periods in the planning horizon, indexed by $t \in T$.

Note that

$$E \cap N = \phi,\ J \cap I = \phi,\ E \cup N,\ J \cup I = E \cup N = J \cup I = O.$$

2.2 Parameters

Capacity of Location Sites

KO_o^{max}: maximum allowable capacity of selectable location site $o \in O$.

$Kf_{o,c}$: initial capacity of center $c \in C$ at selectable location site $o \in O$.

$KC_{o,c}^{max}$: maximum allowable capacity of center $c \in C$ at selectable location site $o \in O$.

$KC_{o,c}^{min}$: minimum allowable capacity of center $c \in C$ at selectable location site $o \in O$.

$KM_{o,c}$: fixed expanding and/or locating size for capacity of center $c \in C$ at selectable location site $o \in O$.

$KS_{s,m,\tau}^{max}$: maximum available capacity of external supplier $s \in S$ for part/component $m \in M$ in period $t \in T$.

$KU_{u,g,\tau}$: maximum available capacity of disassembly-remanufacturing subcontractor $u \in U$ for returned final product $g \in G$ in period $t \in T$.

Selling Prices

$SC_{o,k,g,t}$: variable price of selling one unit of final product $g \in G$ from selectable location site $o \in O$ to customer $k \in K$ in period $t \in T$.

Costs

$CB_{s,j,m,t}$: variable cost of purchasing one unit of part/component $m \in M$ from external supplier $s \in S$ by plant site $j \in J$ in period $t \in T$.

$CP_{j,a,g,t}$: variable cost of processing one unit of final product $g \in G$ by center $a \in A$ at plant site $j \in J$ in period $t \in T$.

$CS_{l,u,g,t}$: variable cost of subcontracting one unit of returned final product $g \in G$ from location site $l \in L$ by external subcontractor $u \in U$ in period $t \in T$.

$CT_{t,l',p,t}$: variable cost of shipping one unit of product $p \in P$ from location site $l \in L$ to location site $L' \in L$ in period $t \in T$.

$CF_{O,t}$: fixed cost of operating selectable location site $o \in O$ in period $t \in T$.

$CC_{e,\tau}$: fixed cost of closing existing location site $e \in E$ in period $t \in T$.

$CO_{n,t}$: fixed cost of opening new location site $n \in N$ in period $t \in T$.

$CFF_{o,c,t}$: fixed cost of operating center $c \in C$ at selectable location site $o \in O$ in period $t \in T$.

$CVE_{o,c,t}$: variable cost associated with expanding capacity of center $c \in C$ at selectable location site $o \in O$ in period $t \in T$.

$CVR_{e,n,c,t}$: variable cost associated with relocating capacity of center $c \in C$ from existing location site $e \in E$ to new location site $n \in N$ in period $t \in T$.

$CFC_{e,c,t}$: fixed cost of closing center $c \in C$ at existing location site $e \in E$ in period $t \in T$.

$CFO_{n,c,t}$: fixed cost of opening center $c \in C$ at new location site $n \in N$ in period $t \in T$.

Table 1. Classification of the closed loop supply chain model and comparing it with the model (research finding)

Article	Objective Function[1]	Period[2]	Commodity[2]	Echelon[2]	Capacity Constraints[3]	Relocation and/ or Expansion[4]	Directional Flow of Facilities[5]	Solution
Demirel and G□kçen, 2008	C	S	M	M	C	NO	UF	MILP
Feischmann et al., 2001	C	S	M	M	U	NO	BF	MILP
Jayaraman et al., 1999	C	S	M	M	C	NO	UF	MILP
Ko and Evan, 2007	C	M	M	M	C	CE	UF	Spanning tree based genetic algorithm
Krikke et al., 2003	M	S	M	M	U	NO	UF	MOMIP
Lee and Dong 2009	C	M	M	M	C	NO	HF	(SAA) method with aheuristicalgorithm
Lu and Bostel, 2007	C	S	S	M	U	NO	HF	m Lagrangian Heuristic
Marin and Pelegrin, 1998	C	S	S	S	U	NO	HF	Method Lagrangian
Sahyouni et al., 2007	C	S	S	M	U	NO	HF	decomposition
Salema et al., 2009	P	M	M	M	C	NO	UF	Lagrangian relaxation
Üster et al., 2007	C	S	M	M	U	NO	UF	MILP
Wang et al., 2010	C	S	M	M	C	NO	UF	
Joochim, 2012	NPV	M	M	M	C	CE,C R	HF	Benders decomposition Spanning tree based genetic algorithm MILP
The Proposed Model	M	M	M	M	C	CE,C R	HF	MOMIP Meta-Heuristic Algorithms (NSGAII,MOPSO)

[1]C: Cost, P: Profit, M: Multiple, NPV: Net Present Value
[2]S: Single, M: Multiple
[3]U: Uncapacitated, C: Capacitated
[4]CR: Capacity Relocation, CE: Capacity Expansion, NO: No Capacity Relocation and Expansion
[5]UF: Unidirectional Flow, BF: Bidirectional Flow, HF: Hybrid Uni/Bidirectional Flow

$CDP_{j,a,g,t}$: variable disposal cost per unit of returned final product $g \in G$ discarded from center $a \in A$ at plant site $j \in J$ in period $t \in T$.

IR: interest rate for the time value of money.

2.3 Decision Variables

$x_{j,a,g,t}$: amount of final product $g \in G$ processed by center $a \in A$ at the plant site $j \in J$ in period $t \in T$.

$y_{l,l',p,t}$: amount of product $p \in P$ shipped from location site $l \in L$ to location site $l' \in L$ in period $t \in T$.

$w_{o,c,t}$: number of fixed sizes for expanding center $c \in C$ at selectable location site $o \in O$ in period $t \in T$.

$v_{e,n,c,t}$: number of fixed sizes for relocating from existing location site $e \in E$ to new location site $n \in N$ for center $c \in C$ in period $t \in T$.

$exp_{o,c,t}$: total amount of the capacity expanded for center $c \in C$ at selectable location site $o \in O$ in period $t \in T$.

$mov_{o,o',c,t}$: total amount of the capacity relocated from selectable location site $o \in O$ to selectable location site $o' \in O$ for center $c \in C$ in period $t \in T$.

2.4 Model Formulation

Multi-objective *mixed integer programming* model (MOMIP) indicates the proposed complex mathematical relationships between different components. Therefore, before the description of the model, it was decided that a simple overview of the model is presented. In general, the following formula is given.

2.5 Objective Functions

We assumed two objective functions;

Maximizing NPV of flow in equation (1) the NPV here includesthe time value of money and profit means is the sum of all costs in $t \in T$ period (Total revenue - Total cost).

$$MAX\ NPV = \sum_{t \in T} \left(\frac{\overbrace{\sum_{o \in O} \sum_{k \in K} \sum_{g \in G} SC_{o,k,g,t}\, Y_{o,k,g,t}}^{Total\ \ Revenue} - \overbrace{TOC_t^{total}}^{Total\ \ Cost}}{(1+IR)^t} \right) \tag{1}$$

Minimizing the Carbon Emission for supplied products from supplier

$$MIN\ \ Z = \sum_{i=1}^{n} G_i S_i \tag{2}$$

In equation (2) n is the number of supplier, Gi, the extent of Carbon Emission for supplied products from ith supplier and S_i a number of purchased units from ith supplier.

2.5.1 Constraints

2.5.1.1 Product-related Carbon Emission

$$\sum_{i=1}^{n} G_i s_i \le C^{cap} \tag{3}$$

Total quantity of Carbon Emission of different products must be not exceeding a certain limitation and bought products from different supplier should have the least quantity of Carbon Emission. In the other words if G_i is the quantity of Carbon Emission, for supplier products from i th supplier and if C^{Cap} is the maximum quantity of Carbon Emission for different products. Supplier, who measured the quantity of their emission, is more preferable than other supplier strategically.

2.5.1.2 Forward Supply Chain

- Ensure enough parts/components $m \in M$. for manufacturing.
- Control the shipments between forward facilities to ensure enough final products $g \in G$.

2.5.1.3 Reverse Supply Chain

- Control the shipments of returned final products $g \in G$. between reverse facilities.
- Control the shipments of reusable parts/component $m \in M$ from disassembly-remanufacturing process.

2.5.1.4 Capacity, Expansion and Relocation

- Establish the capacity expansion condition.
- Limit the maximum capacity for forward and reverse supply chain processes.
- Limit respectively the capacity of external suppliers and disassembly-remanufacturing subcontractor.
- Limit respectively the size for relocating and expanding capacity.
- The capacity increase at any new location site $n \in N$.
- The capacity relocation and expansion atany existing location sit $e \in E$.
- The minimum capacity for forward and reverse supply chain processes.

2.5.1.5 Closing and Opening of Facilities

- Establish the conditions for closing and opening of facilities.

2.5.1.6 Non-Negativity and Integrity Constraints

- Constraints enforce the non-negativity condition on the decision variables. Lastly, the binary decision variable constraints.

3. Algorithms

3.1 Pareto Optimality Concept and Multi-Objective Problems

Pareto optimality is coined in the name of the Italian economist, Vilfredo Pareto, which was used as a measure of efficiency in multi-objective optimization problems. In the multi-objective problems rather than an objective function, a number of objective functions should be optimized simultaneously. In such circumstances, it usually will have more than one optimal solution that is called Pareto optimal answers. Pareto optimal concept is described in the form x ∗ = (x1, x2, x3, ..., xn) is a Pareto optimal. If any other member of the permissible x i = {1, 2, ..., K} we have (for a minimization problem):

$$\forall_{i\in I}(f(\overline{\mathrm{x}}) \leq f_i(\overline{\mathrm{x}}_i))$$

Where n is the number of decision variables in space and k is the number of objective functions. In other words, a Pareto optimal if there is no other vector x for improving the functions of at least one objective function does not worsen. Pareto optimal solutions are known as recessive incomplete answers.

3.2 Proposed Solution Methods

To solve the proposed model is presented the two meta-heuristic algorithm based on Pareto have used is described.

3.2.1 Multiple Objective Particle Swarm Optimization(MOPSO)

Particle Swarm optimization algorithm (PSO) as a search technique was introduced by Eberhart and Kennedy[19]. In developing this method the collective motion of particles is modeled. In some cases, the algorithm also known incorrectly as the algorithm birds or fish, This optimization technique is considered as one of the methods Swarm intelligence or intelligence group and it is based on the principle at each moment of each particle in the search space according to the place where it is located far And the whole place has been found Sets. Particle crowding optimization algorithm based on research conducted in many engineering problems, including the problem of parameter estimation, design, supply networks, the problem of choosing the optimal portfolio of shares, issue of the vehicle, the problem of production scheduling, etc. Clustering has a good performance. With respect to the performance of PSO algorithm to solve single objective, Sierra and Coello Coello[20] with changes in the structure of the algorithm, particle-crowding algorithm for Multiple Objective Particle Swarm Optimization (MOPSO) were introduced. The investigation showed that the performance of this algorithm is a multi-objective optimization problem.

This algorithm, like other mass algorithm, started to work with the general population. In fact, any member is a particle that makes a swarm. The swarm according to a swarm velocity of every particle in the decision move towards an optimum point. Thus, the motion vector at each iteration, each particle is influenced by the position of the particle is yet to come (Pbest) is the best part of it is already capable position (Gbase) The method for producing a swarm of objective and relevant in each iteration mined Gbest. To go to the next step, each swarm of Gbest moves itself to the next swarm. While Pbest specifically obtained for each swarm. Finally, after a certain number of repetitions of the last swarm, to give a final swarm points are presented as the solution swarm or Pareto. Pareto set of cholera have any superiority over each other to reduce the objective function, the objective function value increases vice versa.

3.2.2 The Non-Dominated Sorting Genetic Algorithm Version 2 (NSGA-II)

NSGA-II algorithm is the most widely used and most powerful of the existing algorithms for solving multi-objective optimization and its efficiency in solving various problems have been proven. Srinivas and Deb[21] NSGA introduced optimization method for solving multi-objective optimization problems. Remarkable points about this optimization method are as follows:

- Answer is no other answer certainly better than not having more points. Answers based on there is some answers better than them are ranked and sorted.
- Competence (fitness) for answers, according to their rank and overcome other answers are allocated.
- Fitness sharing the suitability of the method is used In order to be well-adjusted dispersion solution and answer to be distributed uniformly in the search space.

Due to the relatively high sensitivity performance and solution quality parameters of the algorithm NSGA fitness sharing and other parameters, the second version, called NSGA algorithm NSGA-II was introduced in 2000 by Deb[22] et al. Along with everything that NSGA-II is, it can be considered a model for the formation of multi-objective optimization algorithm. The algorithm and its unique way of dealing with multi-objective optimization problems is used over and over again by different people to create new multi-objective optimization algorithms. No doubt this algorithm is the most basic collection of evolutionary multi-objective optimization algorithm is that it can be called the second generation of these methods. The main features of the algorithm are as follows:

- The definition of Crowding Distance methods such features as an alternative to sharing fitness.
- The use of two-binary tournament selection operator.
- Improper storage and archiving solutions that have been resulted in the previous steps of the algorithm (elitism)

In the NSGA-II algorithm of each generation solutions, some of them using binary tournament selection are selected. In the binary method, two answers will be chosen at random from the population and then, a comparison is made between the two results and the answer which is better, will be selected finally. Criteria for selecting the algorithm NSGA-II in the first place is the rank of answer and in the second place is the summative distance relating to the answer. The lower the rank and whatever the answer is far more abundant, more desirable.

By repeating binary operator selection on the population of each generation, a generation of people is selected to participate in the intersection and mutation. On the part of the selected people, the act of intersection and on the other, the mutation operation is performed, and a population of children and mutations survivors is made. Then, this population is integrated with the main population. Members of the newly formed population first based on the rank and in ascending are ordered. Members of the population who have the same rank in terms of summative and distance are in decreasing order. However, members of the population, primarily in terms of rank, and secondly in terms of summative distance is sorted. Equal to the number of main members of population, some members are selected from the top of the list is sorted and the rest of the population is disposed. Selected members are forming the next generation. Moreover, the mentioned cycle in this sector, is repeating to realizing the ending situation.

Non-defeated answers obtained from solving multi-objective optimization, often known as the Pareto front. None of the solutions of the Pareto optimal are preferred over the other and depending on the circumstances, can be considered either as an optimal decision.

4. The Criteria for Assessing the Quality of the Answer

The criteria for evaluating the two proposed algorithm is introduced. Generally, since the convergence to the Pareto optimal solutions and providing a variety among a set of obtained answers are two separate and somewhat contradictory targets in multi-objective evolutionary algorithms. Absolute measure alone can decide on the performance of the algorithms, has been presented.

4.1 Analysis of Results

To analyze the results of the proposed model first we offer some explanation for the producing of test problems and then for adjusting the input parameters and we compare the analysis results.

4.1.1 Generate Test Problems

The capabilities of the proposed methodology through a case study of a fictitious network of closed-loop supply chain that includes several new and existing facilities have been created. During the planning horizon for potential new facilities may be closed and opened a set of selected locations. Also responsible for a number of clients and subcontractors are in fixed locations.

After considering being NP-hard the problem the model is implemented for 10 test problem and compare the solving methods. In table 2 either by using software algorithms R2012a (7.14.0.739) 64-bit Matlab with Windows 7 operating system have been implemented Model input parameters for the algorithms implemented in (Tables 3, 4 and 5) is stated. Then with the proposed algorithm for comparing solution, problems in different sizes are enforced and consider the best Indexes of multi-objective algorithms.

4.1.2 Adjusting Parameters

The results of the meta-heuristic algorithm is dependent on the values of the input parameters, it has been proposed

Table 2. Shows the number of different sample issues

Number Problem	Green Supplier	Production/ Disassembly-Remanufacturing Center	Disassembly-Remanufacturing Subcontractor	Distribution /Collection Center	Customer
1	2	3	5	3	5
2	5	10	10	5	10
3	5	10	15	10	15
4	10	15	20	15	20
5	15	30	25	30	40
6	20	40	30	40	60
7	25	50	30	50	80
8	30	60	35	60	100
9	35	70	40	65	110
10	40	80	40	70	130

Table 3. Distribution of the input parameters for sample issues

Parameter	Distribution Function	Parameter	Distribution Function
$DP_{k,g,t}$	U(30,60)	$Gr_{s,t}$	U(300,900)
$RC_{k,g,t}$	U(2,15)	$AM_{m,g}$	U(1,4)
$KO_0^{\max}$	U(200,400)	$RH_{m,g}$	U(1,4)
$KO_{o,c}$	U(300,500)	$FR_{g,t}$	U(60,85)
$KO_{o,c}^{\max}$	U(200,400)	$FC_{o,c}$	U(10,90)
$KO_{o,c}^{\min}$	U(200,400)	IR	0.5

Table 4. Factor levels in the candidate algorithm (NSGA-II)

Algorithm parameters	Lower	Normal	Upper
nPop	15	30	45
PCrossover(Pc)	0.5	0.7	0.9
PMutation(Pm)	0.2	0.3	0.4

to explain how to adjust our values. In addition, stop condition is considered to twenty repetitions.

4.1.3 Numerical Results and Comparison

It can be learned from the results, in all of the cases, that when a demand increases, total cost of supply chain system increase and when return rate increases, costs of disassembly-remanufacturing for the same demand decreases.

The reason is that we assume purchasing one unit of new part/component consequently buying, one unit of the reusable parts/components and improvement of one unit of the part/component of disassembly-remanufacturing in plant is more expensive.

Even if the costs of transportation exceeds than increasing of return rate of process costs, again it is more expensive than transportation costs. It is learned from the capacity increasing or/and replacing costs in across of planning horizon.

As it is expected, the by considering the quantity of returned rate for each period, the profit will be increased.

Results for both customary demand and the value of returned rate lead inn higher NPV, consequently a more profitable investment in long term and less rate of Carbon Emission.

Thus with proposed algorithms for comparison between solving procedures, the problem in different size is executed and the best quantity of multi object algorithm index is considered.

By considering the standard criteria, comparison of Pareto based multi objecting algorithms, the function of proposed algorithm is drawn based on respected criteria graphically and in box plot.

For more detailed comparison of the statistical analysis, we used t tests. For this purpose, the output of the P-Value Analysis of variance was obtained. Graphic chart of the two algorithm parameters for sample issues criteria and confidence intervals are drawn as the diagrams Box plot.

Regarding the amount of P-Value for indicators Diversity and Time and NPS and MID respectively

Table 5. Factor levels in the candidate algorithms (MOPSO)

Algorithm parameters		Lower	Normal	Upper
nPop		15	30	45
Velocity	Coefficient of inertia	[0.7045, 0.7269]		
	Nstalvzhy factor	[1.4735, 1.5203]		
	Coefficient of society	[1.4735, 1.5203]		
nRepository		40	50	60

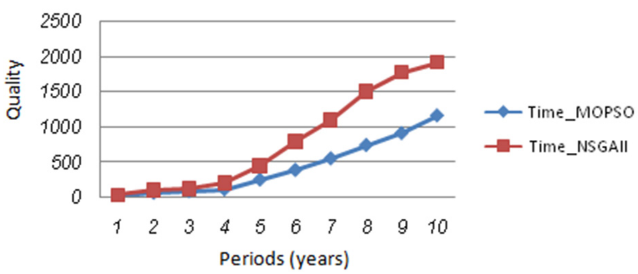

Figure 1. A comparison of algorithms, MOPSO algorithm based on the criterion of Spacing, Time and MID and enjoys a higher utility.

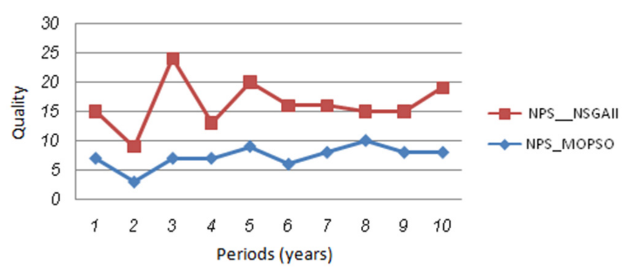

Figure 2. A comparison of algorithms, NSGA-II algorithm based on the criterion of NPS and Diversity enjoys higher utility.

equal to 0.595 and 0.088 and 0.888, and 0.383 is also consistent with the level of significance being considered (0.05 = α) assumes equal means is not rejected differences meaningful algorithm there are both algorithms can meet these criteria are compatible with each other.

However, the P-Value for Spacing index of 0.002 was considered significant difference with regard to the level of (0.05 = α) rejects the assumption of equality mean significant differences exist between the algorithms. Thus, according to the box plot (3) algorithm NSGA-II is better.

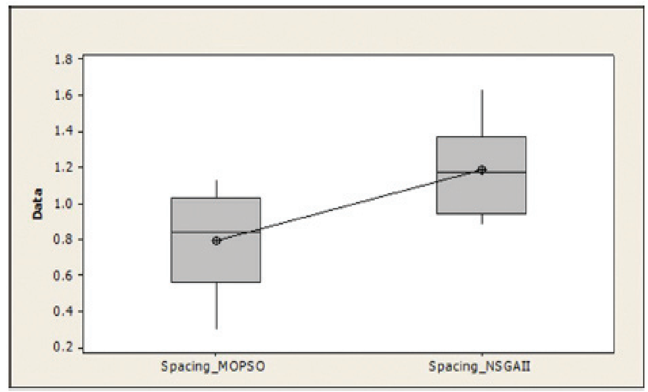

Figure 3. A Box plot comparison of Confidence Intervals of MOPSO and NSGA-II algorithms based on Spacing criterion.

5. Conclusions and Future Recommendations

We first developed general MILP model for the design of concurrent planning forward and reverse supply chain network that we formed multilevel structure of the supply chain network to forward and inverse relationship between companies and customers through distribution centers and collection then the model MOMIP be developed to minimize the impact of greenhouse gases.

As a main conclusion, we suggest that companies should create incentives for consumers to return their used products to improve its competitive advantage to become more environmental problems will be able to earn more profit Case studies show that the numerical exact configuration of the forward and reverse channels, each of which has a strong influence on performance.

Facilities should be close to areas of demand and supply, transportation is a major part of total costs, while the cost of processing facilities and/or operating costs are in constant need of focus.

Mutual eliminates cause to eliminate considerable costs, infrastructure facilities, equipment and human resources. Only separation of forward and reverse facility may be reduced the total cost in the case of transportation and/or (re) construction of a large part be useful. As it can be noticed from the results, increasing in the demand for products and returned products cause to replacement of capacity and increasing the facility development. We see that the maximum NPV target is suitable for long-term planning horizon.

That appeared about "Environment and Competitiveness" in the late 1980 and early 1990 on "(Porter, 1990; Porter, 1991; Estee, 1994), While traditional economic thought argues that the competitive position of the data (input) is based on the low cost to day often the competitive advantage is achieved by unexpected ways to lower the cost of production of goods or to identify ways to increase the value of a product - whether directly or indirectly derived Direct. Therefore, productivity increased by a factor of competitiveness that companies actually makes (Porter and van Lind a1995, 106).

What can be concluded from the results is that the presented models are a great idea in the quantitative aspects of strategic closed-loop supply chain planning.

The presented model can indicate that further improvement of the network is considered. This can lead to release of final demand and recall the issues are possible. About a real problem in scale - a large meta-heuristic method was developed and finally the so-called loop supply chain - package includes the design and to minimize environmental effects on economic performance improvement was achieved.

5.1 Future Research Guidance

The more research that can be done:

- Minimizing other environmental impacts (to prevent water pollution, toxic materials, etc).
- Locating centers of different industries waste
- Using Matlab software for the model time series
- Despite all the papers presented studies, there is no comprehensive model that all-important activities to meet the needs of long-term strategic planning. So this outstanding issue, the new models will be developed.

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