Genetic and simulated annealing algorithms for the allocation of customers to potential distribution centers in green supply chain network

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Abstract

In this paper, we study a supply chain network design problem with environmental concerns. There are customers with particular demands and potential places which are candidate to be distribution centers. Each of the potential DCs can ship to any of the customers. Three types of costs are considered; Environmental investment cost and opening cost, assumed for opening a potential DC plus shipping cost per unit from DC to the customers. The proposed model selects some potential places as distribution centers in order to supply demands of all the customers. Since the problem is considered as an NP-hard, in this paper we propose several meta-heuristics to solve the problem. Furthermore, we apply the Taguchi experimental design method to set the proper values of the algorithms in order to improve their performances. For the purpose of evaluating the performances of the proposed algorithms, various problem sizes are utilized and the computational results of the algorithms are compared with each other. The results show that our model can be applied as an effective tool for strategic planning of green supply chains.

Keywords:
Green supply chain, Genetic algorithm, simulated annealing algorithm, Taguchi experimental design.

Introduction

Over the last two decades, supply chain management (SCM) turned into an important subject in industry. It is defined as the management of the flow of goods and services and it plays a vital role in company's success and customer's satisfaction. SCM consists of different phases which starts with customer's order registration and usually ends to supplying customer's demand. This is representative of the fact that customers are part and parcel of a supply chain.

In this industrial world, the public became more aware of environmental issues. As a result, customers are more eager to know about how green the products they are purchasing are processed. To satisfy this concern of the customers, companies tried to improve their environmental performance. As a result, a new concept has emerged and that is Green Supply Chain Management (GSCM). The network is illustrated in Figure 1.

In addition to environmental concerns, distributing services are significantly and positively associated with customer's satisfaction. Considering the importance of transportation and distribution of products, many researchers work on developing models and methodologies to minimize distributing costs.

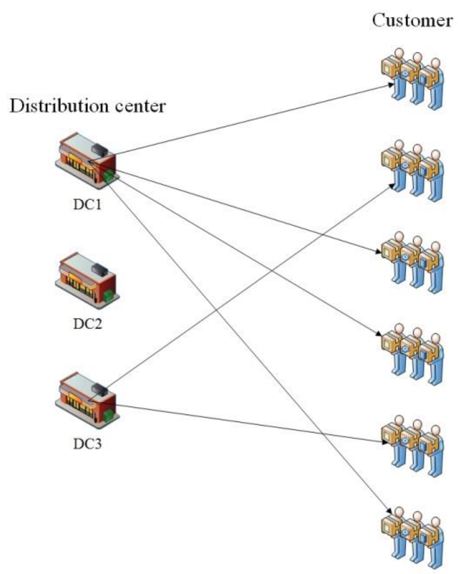

Figure 1 – Allocation of customers to potential DCs in green supply chain networks.

Literature review

The importance of the issue of supply chain, made many researchers work on developing new models which gives the least total cost. The first research on this issue was done by Geoffrion and Graves [1] who presented a two-stage distribution problem. Gengui *et al*. [2] worked on a location-allocation problem in which customers have aggregated demand. A model had been proposed to maintain the best balance of customer service and total cost of transportation. The model was based on naïve balanced star spanning forest formulation. As the model was NP-hard, it was solved by a genetic algorithm method. Anthony Ross *et al*. [3] evaluated the results achieved by SA and TS algorithms for the problem of locating cross-dock distribution centers in SCN. The evaluation of the model was done systematically to figure out the importance of each factor on the experimental design. Felix T.S. *et al*. [4] contributed a model to allocate customers to DCs with the objective of minimizing both the total cost and the imbalance of DCs. The model was solved by a multiple ant colony optimization (MACO) in order to keep the most economist equilibrium between distributing time and level of service for customers. Jawahar and Balaji [5] proposed a genetic algorithm for solving a two-stage distribution center problem in which fixed charge has been considered. The model of this problem was designed in a way that by increasing the amount of products transported from DC to customer, the continuous cost increases linearly. Borisovsky *et al*. [6] did researches on a supply management problem with lower-bounded demands (SMPLD). The results were taken by GA and they were experimentally tested. In this model, lower and upper bounds were considered for shipment sizes. Bilge Bilgen [7] considered an approach for the production allocation and distribution in SCN. As a real supply chain environment is not stable, a fuzzy model was proposed to reach the best balance between producing and distributing. Molla Alizadeh *et al*. [8] offered a mathematical model for a capacitated fixed-charge transportation problem. In their studies, DCs with finite capacity and customers with particular demand were supposed. In order to solve this model, AIA and GA algorithms were utilized on the basis of the spanning tree and Prufer number representation. Mir Saman Pishvaee *et al*. [9] proposed a robust optimization model in which the uncertainty of input data in a closed-loop SCN is considered. For solving this problem, a deterministic mixed-integer linear programming model was proposed and the answer was compared with that of a novel robust optimization model. Hajiaghaei keshteli [10] utilized GA and SA to solve a model that allocates customers to candidate places which are going to be selected as distribution centers. It was supposed that the customers have particular demand and each of the DCs have the capability of supplying the demand of each customer. Antony Arokia Durai *et al*. [11] considered a two-stage SC problem with two different scenarios. In the first one, the per-unit transportation cost and the fixed cost associated with a route has been considered. In the second one, the opening cost of each DC, and the per-unit transportation cost from the DC to customer has been considered. Both scenarios were solved by genetic algorithm and it contributed a better solution to this problem in comparison with former researches. Considering a fixed charge solid transportation problem (FCSTP), the researches of Molla alizadeh *et al*. [12] could be noticed. They did their research under a fuzzy environment supposing both direct and fixed costs to be fuzzy numbers and finally the model was solved by three metaheuristic algorithms. Pradip Kundu *et al*. [13] supposed having fuzzy demand, supply and conveyance capacity for a multi-objective multi-item solid transportation problem. Paravash Kumar *et al*. [14] did the same study supposing fuzzy demand, supply, conveyance capacity and also fuzzy transported quantities or decision variables.

In recent years, by emerging the new concept of green supply chain, a lot of researches have been done on this subject. The most relevant study to our work was done by Fan Wang *et al*. [15]. They proposed a multi objective optimization model that captures the trade-off between the total cost and the environment influence. Samir Elhedhli *et al*. [16] considered a supply chain network design problem that takes Co_2 emissions into account. Emission costs were considered alongside fixed and variable location and production costs. Nabil Absia *et al*. [17] introduced new environmental constraints, namely carbon emission constraints, in multi-sourcing lot-sizing problems. Bertrand Baud-Lavigne *et al*. [18] proposed a mathematical model for optimizing costs in the face of carbon emissions restrictions and for optimizing carbon emissions, given the need to limit costs in the current economic climate. Mohammad Mahdi Saffar *et al*. [19] introduced a bi-objective supply chain network design, which uses fuzzy programming to obtain the capability of resisting uncertain conditions. The design considers production, recovery, and distribution centers. The advantage of using the model includes the optimal facilities, locating them and assigning the optimal facilities to them. It also chooses the type and the number of technologies. Krishnendu Shaw *et al*. [20] contributed to the body of green supply chain literature through addressing uncertainties of suppliers' capacities, plants' capacities, warehouses' capacities and demand for sustainable supply chain network design problem. The study applied Benders decomposition algorithm to handle chance constrained sustainable supply chain network design problem. The proposed models were illustrated with suitable examples and results were carefully analyzed and discussed. Hao Yu *et al*. [21] proposed a novel idea for the design and planning of a general reverse logistics network with multi-objective mixed integer programming. The mathematical model not only took into account the minimization of system operating costs, but also considered the minimum amount of carbon emissions related to the transportation and processing of used products. Yi-Wen Chen *et al*. [22] studied an integrated closed loop supply chain network design problem with cost and environmental concerns in the solar energy industry from sustainability perspectives. A multi-objective closed-loop supply chain design (MCSCD) model has been proposed, in consideration of many practical characteristics including flow conservation at each production/recycling unit of forward/reverse logistics, capacity expansion, and recycled components. Kartina Puji Nurjannia *et al*. [23] proposed a new green supply chain design approach to deal with the trade-offs between environmental and financial issues in order to reduce negative impacts on the environment caused by the increasing levels of industrialization. Their approach incorporate a closed loop network to accommodate the reprocessing paradigm of disposal products and a multi-objective optimization mathematical model to minimize overall costs and carbon dioxide emissions when setting the supply chain.

In this study, two stages of supply chain network have been considered. In this specific kind of linear programming problem, there are potential places which are candidate to be opened as distribution centers (DC). They are selected in such a way that the demand of all customers could be supplied at minimum cost. The DCs have ample capacity however the demand of all the customers and the shipping cost from each distribution center to each customer are particularly defined. After modeling the problem, two known metaheuristics- genetic and simulated annealing- were proposed in order to solve the problem. Also we used a new representation to achieve the graph of transportation in algorithms and comparing the results. To the best of our knowledge, the simulated annealing algorithm is firstly applied in this research area. In addition, Taguchi experimental design has been used in order to set parameters of metaheuristic algorithms. Finally, for evaluating and comparing the performance of the proposed metaheuristic algorithms and the representation method in terms of solution quality and computation time, we used the test data from Hajiaghaei-Keshteli *et al*. [10].

Mathematical model and descriptions

In this paper, it is assumed that there is only one kind of product which could be sent from each of distribution centers to each of the customers. The demand of all the customers should be supplied but not from more than a single supplier. A DC is established only if it could supply each of the customer's demand. Otherwise it is not economic to be established. Another precondition which should be satisfied for opening a DC is that the amount of pollution it causes should not be more than the specified level. Only a single protection level should be defined for each DC, and the total amount of pollution caused in a DC should not be more than the specified amount.

m is representative of the number of DCs. n shows the number of customers. a_i is the amount of products that the DC_i have supplied and b_j shows the demand of customer j. w_i shows the level of Co_2 emission and e_{ij} is representative of the amount of pollution disposed on the way from distributor *i* to customer *j*. and z_i is the environmental protection level in distribution center *i*.

Three groups of costs are assumed:

f_i : The opening costs of distribution center *i*.

c_{ij} : The shipping cost of product from distribution center *i* to customer *j*.

g_i : The environmental investment costs for distribution center *i*

The model has been defined as below:

$$Min\, Z = \sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}.b_j.x_{ij} + \sum_{i=1}^{m} f_i(z_i).y_i + \sum_{i=1}^{m} g_i(z_i).y_i \quad (1)$$

s.t.

$$\sum_{i=1}^{m} x_{ij} = 1; \qquad \forall j = \{1,\dots,n\} \quad (2)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in \{1,\dots,m\} \quad \forall j \in \{1,\dots,n\} \quad (3)$$

$$y_i = 0 \quad if \sum_{j=1}^{n} x_{ij} = 0 \qquad \forall i \in \{1,\dots,m\} \quad (4)$$

$$y_i = 1 \quad if \sum_{j=1}^{n} x_{ij} > 0 \qquad \forall i \in \{1,\dots,m\} \quad (5)$$

$$z_i \le y_i.L \qquad \forall i \in \{1,\dots,m\} \quad (6)$$

$$z_i \in Z \quad and \quad z_i \in [0,L] \qquad \forall i \in \{1,\dots,m\} \quad (7)$$

$$\sum_{l=1}^{L} z_{il} \le 1; \qquad i = 1,2,\dots,m \quad (8)$$

$$z_{il} \in \{0,1\}; \qquad \forall i \in \{1,\dots,m\} \quad \forall l \in \{1,\dots,L\} \quad (9)$$

$$z_{il} = \begin{cases} 1 & if\ the\ environment\ protection\ level\ 'l'\ is\ selected \\ 0 & otherwise \end{cases} \quad (10)$$

$$w_i(z_i).\sum_{j=1}^{n} b_j.y_i + \sum_{j=1}^{n} e_{ij} b_j.x_{ij} \le \left(\frac{72}{2^{z_i-1}} \times a_i\right) + \left(\frac{\sum_{i=1}^{m}\sum_{j=1}^{n} e_{ij}}{m \times n} \times a_i\right); \quad \forall i \in \{1,\dots,m\} \quad z_i \in [0,L] \quad (11)$$

We explicitly consider an objective function. The objective function (1) measures the total cost. The first part is the total transportation cost, the second part is the opening costs and the third one is representative of the environmental protection investment. Constraint (2) shows that all demand of each customer should be supplied by a single distribution center. Constraint (3) states whether the distribution center (*i*) sends products to customer (*j*) or not. Constraint (4) ensures that if the customers had not been supplied by potential distribution centers, the centers would not have been opened. Constraint (5) ensures that if even a single customer is supplied by any of the potential distribution centers, that center should be established. Constraint (6) shows that decision makers can only choose one environmental level less than L for opening facility (i). Constraint (7) restricts that z_i are integers in interval [0, L]. Constraint (8) restricts that only one environmental level can be set for any opening facility. Constraints (9) defines the types of the variables. Constraint (10) states that the decision maker selects one and only one environmental protection level among L possible levels. Constraint (11) is that the amount of pollution that each DC causes should not be more than the specified level.

Proposed metaheuristics

To explain the proposed metaheuristics, at first we describe the random allocation encoding scheme. We employ this representation method into the developed algorithms; simulated annealing, and genetic algorithm.

Encoding scheme

The first step in solving the problem model is linking it with metaheuristic algorithm structure, i.e., making a communication bridge between the original problem and solution space in which evolution occurs. In practice, represent a method to feasible chromosomes to be selected. So choosing an appropriate representation method is one of the most important parts of designing an algorithm. To generate a set of initial solutions, random allocation representation has been used to achieve initial feasible solutions in this study. The modified decoding algorithm of the random allocation representation for the GSCM is depicted in Figure 2.

Random allocation representation
Input
    m: number of distribution centers;
    n: number of customers;
Step 1: Produce a string of number with n digit of number set of distribution centers. $P(T)$
Step 2: Produce a permutation string of numbers with n digit of number set in customers. $\overline{P}(T)$
Step 3: Allocation each gene on chromosome $P(T)$ into each gene on chromosome $\overline{P}(T)$, respectively.
Step 4: Check the protection level condition
    If the protection level condition is satisfied
        $P(T)$ and $\overline{P}(T)$ are feasible solution chromosomes.
    else
        while (not produce a feasible solution)
            repeat step 1, step 2 and step 3;
        end
    end
Output: A transportation tree.

Figure 2 – The proposed representation method to achieve a feasible solution.

Genetic algorithm

Genetic Algorithms (GA) arise in the 1970s by the work of Holland [24]. Nowadays, GA is considered to be one of the typical metaheuristic methods for tackling various optimization problems. GA employs a population of chromosomes each of them represents an encoded solution. A fitness value is allocated to each chromosome according to its performance in which the more desirable the chromosome, the higher the fitness value becomes. By using genetic operators, each successive incremental improvement in a chromosome becomes the basis for the next generation. The process continues by a set of genetic operators until some stopping criterion is met. Four fundamental steps are mostly used in GA: reproduction, selection mechanism, crossover and mutation.
The structure of the proposed GA is given in Figure 3.

Genetic Algorithm
Step 1: Initialize the problem and GA parameters
    Input: the data instance of the optimization problem and GA parameters;
Step 2: Get an initial solution(t), by random allocation representation.
Step 3: Evaluation $P(t)$
Step 4: While (not termination condition) do
    Crossover $P(t)$ to yield $O(t)$ by single point crossover & two point crossover.
    Mutation $P(t)$ to yield $O(t)$ by scramble, insertion and swap mutation.
    Evaluation $O(t)$.
Step 5: Select $P(t+1)$ from $P(t)$ and $O(t)$ by rank selection mechanism.
Step 6: Check the stop criterion
    while (not termination criterion)
        repeat step 4 and step 5;
    Output: minimum total cost;

Figure 3 - The proposed GA procedure for the GSCM.

Simulated annealing algorithm

The SA is an optimization technique that has been successfully used for solving a wide range of combinatorial optimization problems. The algorithm was first proposed by Kirkpatrick *et al.* [25] based on the physical annealing process of solids. First, the solid is heated up to a high temperature. At that temperature all the molecules of the material have high energies and randomly arrange themselves into a liquid state. Then the temperature decreases at a certain rate which will reduce the molecules' energies and their freedom to arrange them. Finally, the temperature goes down to such a level that all the molecules lose their freedom to arrange themselves then the material crystallizes. If the temperature decreases at a proper rate, the material can obtain a regular internal structure at the minimum energy state. However, if the temperature goes down too fast, the irregularities and defects will appear in the solid and the system will be at a local minimum energy state.

In analogy to the annealing process, the feasible solutions of the optimization problem are correspond to the states of the material, the objective function values computed at these solutions are represented by the energies of the states, the optimal solution to the problem can be viewed as the minimum energy state of the material and the suboptimal solutions correspond to the local minimum energy states. The structure of the proposed SA is given in Figure 4.

Simulated Annealing
Step 1: Initialize the problem and SA parameters
Input: the data instance of the optimization problem and SA parameters;
Step 2: Get an initial solution X_m , by random allocation representation.
Step 3: Set an initial temperature, $T > 0$
Step 4: While not frozen do the following:
Step 4.1: Do the following n times:
Step 4.1.1: Sample a neighbor X'_m from X_m, (i.e., Scramble, Insertion and Swap Mutation)
Step 4.1.2: Let *Delta* = *cost* (X'_m) – *cost* (X_m)
Step 4.1.3: If $Delta < 0$
then set $X_m = X'_m$
else set $X_m = X'_m$ with the probability of $exp(-Delta/T)$
Step 4.2: Set $T = T \times \alpha$, where α is the reduction factor.
Step 5: Return X_m
Step 6: Check the stop criterion
while (not termination criterion)
repeat step 4 and step 5;
Output: minimum total cost;

Figure 4 - The proposed SA procedure for the GSCM.

Experimental design

Taguchi [26] proposed a new method of conducting the design of experiments which are based on well-defined guidelines. This method uses a special set of arrays called orthogonal arrays. These standard arrays stipulate the way of conducting the minimal number of experiments which could give the full information of all the factors that affect the performance parameter. The crux of the orthogonal arrays method lies in choosing the level combinations of the input design variables for each experiment.

Data generation

In order to evaluate the performance of the algorithms for solving the problem, a plan is utilized to generate test data. Table 1 shows the experimental design. The data required for the problem include the number of DCs and customers. The values of parameters are used from [10]. Seven different problem sizes are considered for experimental study which presents different levels of difficulty for alternative solution approaches. The problem size is determined by the number of DCs and customers. Within each problem size, four problem types (A–D) are employed. For a given problem size, problem types differ from each other by the range of opening cost, which increases upon progressing from problem type A through problem type D. The variable costs range over the discrete values from 3 to 8. The problem sizes, types, DCs, customers, opening costs and environmental investment cost ranges are shown in Table 1.

Table 1 - Test problems characteristics.

Problem size	Total supply	Problem type	Range of variable costs		Range of opening cost		Range of Environmental investment cost	
			Lower limit	Upper limit	Lower limit	Upper limit	Lower limit	Upper limit
10×10	10000	A	3	8	50	200	0.3×50	0.3×200
10×20	15000	B	3	8	100	400	0.3×100	0.3×400
15×15	15000	C	3	8	200	800	0.3×200	0.3×800
10×30	15000	D	3	8	400	1600	0.3×400	0.3×1600
50×50	50000							
30×100	30000							
50×200	50000							

Parameter setting

As the effectiveness of metaheuristic algorithms depends on the correct choice of the parameters, here, we study the behavior of the different parameters of the proposed algorithms. Twenty-eight test problems, with different sizes, are solved to evaluate the performance of the presented algorithm. The experiments on the SA were based on the L_9 and the GA was based on the L_{18} orthogonal array. Due to stochastic nature of metaheuristics, ten replications were performed for each trial to achieve the most reliable results. Because the scale of objective functions in each instance is different, they could not be used directly. To solve this problem, the relative percentage deviation (RPD) is used for each instance. The RPD is obtained by the following formula:

$$\mathrm{RPD} = \frac{\mathrm{Alg}_{\mathrm{sol}} - \mathrm{Min}_{\mathrm{sol}}}{\mathrm{Min}_{\mathrm{sol}}} \times 100$$

Where Alg_{sol} and Min_{sol} are the obtained objective value for each replication of trial in a given instance and the best obtained solution respectively. After converting the objective values to RPDs, the mean RPD is calculated for each trial. To do according to Taguchi parameter design instructions, these mean RPDs, are transformed to S/N ratios. The S/N ratios of trials are averaged in each level and the value is shown in the related figures.

The control factors of SA are initial temperature (T_0), reduction ratio of temperature (α), and type of mutation. These factors and their levels are illustrated in Table 2.

Table 2 - Factors and their levels in SA algorithm.

Factors	SA symbols	SA Levels
Initial temperature	A	A (1) – 4000 A (2) – 4500 A (3) – 5000
Alpha	B	B (1) – 0.93 B (2) – 0.95 B (3) – 0.97
Type of mutation	C	C (1) – Swap C (2) – Scramble C (3) – Insertion

The Table 3 shows an L9 orthogonal array. There are totally 9 experiments to be conducted and each experiment is based on the combination of level values as shown in the table. For example, the third experiment is conducted by keeping the independent design variable 1 at level 1, variable 2 at level 3, and variable 3 at level 3.

Table 3 - The modified orthogonal array L_9.

Trial	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Figures 5 and 6, shows the best levels for SA parameters as 2, 2, and 2, respectively, according to their alphabetical order.

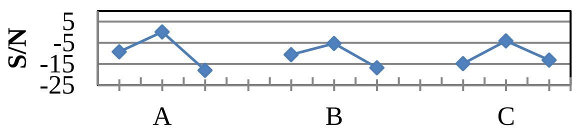

Figure 5 - Mean S/N ratio plot for each level of the factors in SA.

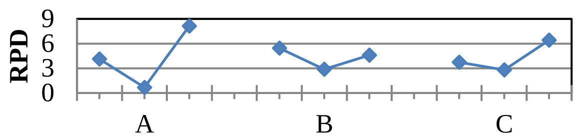

Figure 6 - Mean RPD plot for each level of the factors in SA

There are two basic parameters of GA, crossover probability and mutation probability. Crossover probability says how often crossover will be performed. Crossover is made in hope that new chromosomes will have good parts of old chromosomes and maybe the new chromosomes will be better. However it is good to leave a part of the population survive and go to the next generation.

Mutation probability says how often parts of chromosome will be mutated. If there is no mutation, offspring is taken after crossover (or copied) without any change. Mutation is made to prevent falling GA into local extreme, but it should not occur very often, because then GA will in fact change to random search.

There are also some other parameters of GA, Such as population size, type of crossover and type of mutation. These factors and their levels are illustrated in Table 4.

Table 4 - Factors and their levels in GA algorithm.

Factors	GA symbols	GA Levels
Type of crossover	A	A (1) – one-point crossover A (2) – two-point crossover
Type of mutation	B	B (1) – Swap B (2) – Scramble B (3) – Insertion
Population size	C	C (1) – 20 C (2) – 30 C (3) – 40
Crossover percentage	D	D (1) – 60% D (2) – 70% D (3) – 80%
Mutation probability	E	E (1) – 0.05 E (2) – 0.1 E (3) – 0.15

The Table 5 shows an L_{18} orthogonal array. There are totally 18 experiments to be conducted and each experiment is based on the combination of level values as shown in the table. For example, the third experiment is conducted by keeping the independent design variable 1 at level 1, variable 2 at level 1, variable 3 at level 3, variable 4 at level 3, and variable 5 at level 3.

Table 5 - The modified orthogonal array L_{18}.

Trial	A	B	C	D	E
1	1	1	1	1	1
2	1	1	2	2	2
3	1	1	3	3	3
4	1	2	1	1	2
5	1	2	2	2	3
6	1	2	3	3	1
7	1	3	1	2	1
8	1	3	2	3	2
9	1	3	3	1	3
10	2	1	1	3	3

11	2	1	2	1	1
12	2	1	3	2	2
13	2	2	1	2	3
14	2	2	2	3	1
15	2	2	3	1	2
16	2	3	1	3	2
17	2	3	2	1	3
18	2	3	3	2	1

Besides, Figures 7 and 8 shows the best levels for GA parameters as 2, 2, 2, 2 and 2 respectively, according to their alphabetical order.

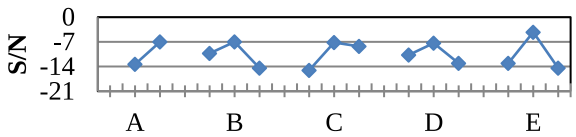

Figure 7 - Mean S/N ratio plot for each level of the factors in GA.

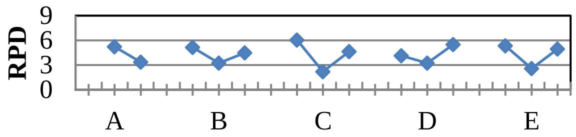

Figure 8 - Mean RPD plot for each level of the factors in GA

Experimental results

In order to be fair, searching time is set identical for both algorithms which is equal to 5×n×m milliseconds. This criterion is sensitive to both problem sizes, n and m. using this stopping criterion, searching time increases according to the rise of either number of DCs or number of customers. Also due to the random nature of metaheuristic algorithm to achieve reliable results, 30 repetitions are considered for each of the samples. Then using these repetitions, the best cost, average cost and worst cost are specified and the average cost is used to compare the results in terms of response quality. We use RPD measure to compare the algorithms. In order to verify the statistical validity of the results, we have performed an analysis of variance (ANOVA) to accurately analyze the results. The results demonstrate that there is a clear statistically significant difference between performances of the algorithms. The means plot and LSD intervals at the 95% confidence level for two algorithms are shown in Figure 9.

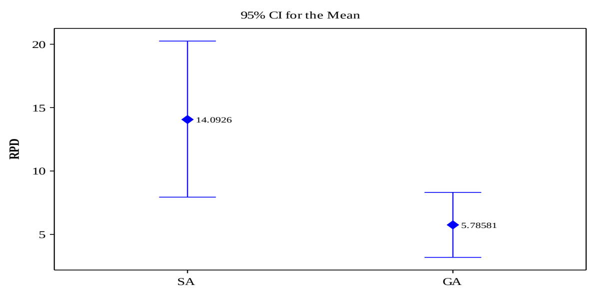

Figure 9 - Means plot and LSD intervals for the algorithms

In order to evaluate the robustness of the algorithms in different situations, we analyzed the effects of the problem size on the performance of both algorithms. Figure 10 shows the interaction between the quality of the algorithms and the size of problems. As it is obvious, we can conclude that genetic algorithm has better performance than Simulated Annealing algorithm.

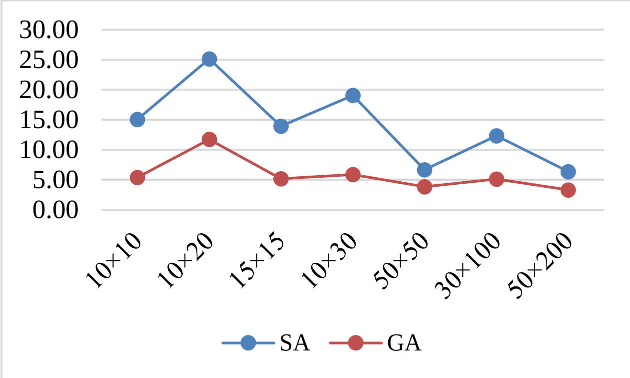

Figure 10 - Means plot for the interaction between each algorithm and problem size.

Conclusion and future works

This paper considers two stages of green supply chain network; distribution centers (DCs) and customers. The distinguishing feature of our model is its consideration of environmental elements which include environmental level of facility and environmental influence in transportation process. This model will have an important application in the regional or global supply chain network design with green consideration. The proposed model minimizes the total cost with selecting some potential places as distribution centers in order to supply demands of all the customers. Finally, sensitivity analysis of the test problem is conducted and we observe that improving the capacity of the network and increasing the supply to the facilities can decrease environmental emission of the whole network and total cost. On the other hand, considering the environmental emission of supply chain network is more effective and necessary at a higher demand level.

In order to solve the given problem, two algorithms (GA and SA) are presented. However, the effectiveness of most metaheuristic algorithms significantly depends on the correct choice of parameters. We developed two crossover and three mutation operators for the problem from the GA and SA literature. To adjust the parameters and operators of the proposed algorithms, the Taguchi parameter design method was employed. The robustness of the algorithms may be improved by fine-tuning the parameters and operators, relating the population size, reproduction percentage, mutation probability, crossover and mutation types in GA, and initial temperature, alpha (reduction ratio of temperature), mutation types in SA.

To propose research directions for future works, we recommend utilizing recent and strong metaheuristics and the other representation methods in this research area.

References

[1] D.J. Thomas, p.M. Griffin, Coordinated supply chain management, European Journal of Operational Research, 1996, 94, 1-15.

[2] Gengui Zhou, Hokey Min, Mitsuo Gen, The balanced allocation of customers to multiple distribution centers in the supply chain network: A genetic algorithm approach, 2002, 43, 251-261.

[3] Anthony Ross, Vaidyanathan Jayaraman, An evaluation of heuristics for the location of cross-docks distribution centers in supply chain network design, Computer and Industrial engineering, 2008,55,64-79.

[4] Felix T.S.chan, Niraj Kumar, Effective allocation of customers to distribution centers: A multiple ant colony optimization approach, 2009, 25, 1-12.

[5] Jawahar N,Balaji AN, A genetic algorithm for the two-stage supply chain distribution problem associated with a fixed charge,2009, 194,496-537.

[6] P. Borisovsky, A. Dolgui, A. Eremeev, Genetic algorithms for a supply management problem: MIP-recombination vs greedy decoder, European Journal of Operational Research, 2009, 195, 770-779.

[7] Bilge Bilgen, Application of fuzzy mathematical programming approach to the production allocation and distribution supply chain network problem, Expert Systems with Applications, 2010, 37, 4488-4495.

[8] S. Molla-Alizadeh-Zavardehi, M. Hajiaghaei-Keshteli, R. Tavakkoli-Moghaddam, Solving a capacitated fixed-charge transportation problem by artificial immune and genetic algorithms with a prufer number representation, Expert System with Applications, 2011, 38, 10462-10474.

[9] Mir Saman Pishvaee, Masoud Rabbani, Seyed Ali Torabi, Arobust optimization approach to closed-loop supply chain network design under uncertainty, Applied Mathematical modelling, 2011,35,637-649

[10] Hajiaghaei Keshteli Mostafa, The allocation of customers to potential distribution centers in supply chain network: GA and AIA approaches, Applied Soft Computing, 2011, 11, 2069-2078.

[11] K.Antony, Arokia Duraj Raj, Chandrasekharan Rajendran, A genetic algorithm for solving the fixed-charge transportation model: Two stage problem, Computer and Operation Research, 2012, 39, 2016-2032.

[12] MollaAlizadeh Zevardehi,S., Genetic and differential evolution algorithms for the allocation of customers to potential distribution centers in a fuzzy environment, Springer London, 2014,70,1939-1954

[13] Pradip Kundu, Samarit Kar, Manoranjan Maiti, Multi-objective multi-item solid transportation problem in fuzzy environment, Applied mathematical modelling, 2012, 37, 2028-2038

[14] Praash Kumar, Giri Manas Kumar, Maiti Manoranjan Maiti, Fully fuzzy fixed charge multi-item solid transportation problem, Applied soft computing, 2014

[15] Fan Wang, Xiaofan Lai, Ning Shi, A multi-objective optimization for green supply chain network design, Decision Support Systems, 2011, 262–269

[16] Samir Elhedhli, Ryan Merrick, Green supply chain network design to reduce carbon emissions, Transportation Research Part D, 2012, 370–379

[17] Nabil Absia, Stéphane Dauzere-Peresa, Safia Kedad-Sidhoumb, Bernard Penzc, Christophe Rapined, Lot sizing with carbon emission constraints, European Journal of Operational Research, 2013, 55-61

[18] Bertrand Baud-Lavigne, Bruno Agardb, Bernard Penza, Environmental constraints in joint product and supply chain design optimization, Computers & Industrial Engineering, 2014,16-22

[19] Mohammad Mahdi Saffar, Hamed Shakouri G., Jafar Razmi, A new multi objective optimization model for designing a green supply chain network under uncertainty, International Journal of Industrial Engineering Computations, 2015,15-32

[20] Krishnendu Shaw, Mohd Irfan, Ravi Shankar, Surendra S. Yadav, Low carbon chance constrained supply chain network design problem, Computers and Industrial Engineering, 2016,483-497

[21] Hao Yu, Wei Deng Solvang, A general reverse logistics network design model for product reuse and recycling with environmental considerations, The International Journal of Advanced Manufacturing Technology, 2016, 2693-2711

[22] Yi-Wen Chen , Li-Chih Wang , Allen Wang , Tzu-Li Chen, A particle swarm approach for optimizing a multi-stage closed loop supply chain for the solar cell industry, Robotics and Computer-Integrated Manufacturing, 2017, 111-123

[23] Kartina Puji Nurjannia, Maria S. Carvalho, Lino Costa, Green supply chain design: A mathematical modeling approach based on a multi-objective optimization model, International Journal of Production Economics, 2017,421-432

[24] Holland, John H. Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. U Michigan Press, 1975.

[25] Kirkpatrick, Scott, C. Daniel Gelatt, and Mario P. Vecchi. "Optimization by simulated annealing." science 220, no. 4598 (1983): 671-680.

[26] Taguchi, Genichi. Introduction to quality engineering: designing quality into products and processes. 1986.