Research Letter

Reinforcing sustainability in close-loop supply chain model

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Abstract

In this paper, a methodology for reinforcing sustainability in closed-loop supply chain (CLSC) model is proposed. For the methodology, economic, environmental and social factors are simultaneously considered in the CLSC model. The minimization of total cost, the minimization of total amount of CO_2 emission, and the maximization of total social influence are used for economic, environmental, and social factors, respectively. The CLSC model is represented as a mathematical formulation. Since the three factors are considered as each objective in the mathematical formulation, the CLSC model can be a multi-objective optimization problem. A hybrid genetic algorithm (HGA) approach, one of meta-heuristics approaches, is implemented for solving the CLSC model. In numerical experiment, some scales of the CLSC model are presented and the performance of the HGA approach is compared with those of some conventional approaches. The experimental results prove that the HGA approach outperforms the competing approaches.

Keywords

sustainability, closed-loop supply chain, hybrid genetic algorithm, multi-objective optimization problem, meta-heuristics approaches

1. Introduction

Close-loop supply chain (CLSC) model is generally considered as a multi-stage network model with various facilities at each stage of forward logistics (FL) and reverse logistics (RL). Among the major trends in the CLSC model, a methodology for reinforcing sustainability becomes popular in conventional literatures [Devika et al., 2014; Özceylan et al., 2017]. According to this methodology, economic, environmental, and social factors are usually considered for effectively reinforcing sustainability in the CLSC model.

Economic factor usually considers the maximization of total profit or the minimization of total cost resulting from the operation process of the CLSC model [Wang and Hsu, 2010; Chen et al., 2015]. Wang and Hsu [2010] suggested a CLSC model with the minimization of the total cost which consists of total production cost, total transportation cost, and total fixed cost. On the other hand, the CLSC model suggested by Chen et al. [2015] maximized the total profit which consists of total sale revenue and total costs (= total processing cost + the total transportation cost + the total fixed cost).

Environmental factor usually takes into account the minimization of the total amount or cost of CO_2 emitted from various stages of the CLSC model [Paksoyet et al., 2011; Talaei et al., 2016]. Paksoyet et al. [2011] suggested a CLSC model to minimize the total cost of CO_2 emitted from the transportation of materials or products at each stage of the FL and RL. Talaei et al. [2016] showed a simple CLSC model for minimizing the total amount of CO_2 emitted from the production and transportation of products at each stage of the FL and RL.

Social factor usually considers various social influences such as the number of job opportunities created by the introduction of new technology, the number of lost days caused by work's damage, and the number of unemployment [Devika et al., 2014; Özceylan et al., 2017]. Devika et al. [2014] and Özceylan et al. [2017]) treated various social influences (i.e., the number of newly created job opportunities, and work's damage caused by the establishment and operation processes of facilities at each stage of the FL and RL) in their CLSC models.

As mentioned above, although many conventional literatures considered various economic, environmental, and social factors, few papers taken into account three factors simultaneously in the CLSC model [Devika et al., 2014; Özceylan et al., 2017]. In the CLSC model by Devika et al. [2014], the minimization of the total cost, the minimization of the total environmental cost, and the maximization of social influences were considered as economic, environmental, and social factors, respectively. Imperialist competitive algorithm (ICA) approach, one of metaheuristic approaches, was implemented for solving the CLSC model. However, the search speed of the ICA approach became slower than those of the conventional competing approaches according that the problem scales of the CLSC model are increased. Özceylan et al. [2017] also considered all three factors in their CLSC model simultaneously. However, their CLSC model was a single-objective optimization problem, not a multi-objective optimization problem. Therefore, various measures of performance such as $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(j)$ [Ishibuchi and Murata, 1998] were not be taken into consideration.

To cope with these kinds of weakness caused by conventional literatures which considers the CLSC mode for reinforcing sustainability, we propose a CLSC model in this paper. The proposed CLSC model has economic, environmental, and social factors simultaneously and is represented by a multi-objective optimization problem.

In Section 2, a conceptual structure of the proposed CLSC model is presented. Section 3 shows a mathematical formulation for representing the proposed CLSC model. A hybrid genetic algorithm (HGA) approach, one of metaheuristic approaches, is implemented to solve the proposed CLSC model in Section 4. In numerical experiments of Section 5, the performance of the HGA approach is compared with those of some conventional approaches using various measures of performance. Finally, some conclusions and a future study direction for improving the proposed CLSC model and HGA approach are suggested in Section 6.

2. Proposed CLSC model

A conceptual flow of the proposed CLSC model is displayed in Figure 1. Products are produced at manufacturer (MF) and then are sent to distribution center (DC). The DC sends the products to first customer (FC) via retailer (RT). Some (α_1%) of the used products from the FC are sent to recovery center (RC) for recovery process and the others (α_2% = 1 – α_1%) to disposal center (DP) for waste disposal process. At the RC, after checking and recovering the function and quality of the used products, they are classified into the recycled parts of β_1% and the recovered products of β_2%. The recycled parts are sent to the MF and then used for producing products. The recovered products are sent to second customer (SC) to be resold. For sustainability, economic, environmental and social factors are considered at each facility and transportation processes.

3. Mathematical formulation

Some assumptions should be considered for effectively presenting the proposed CLSC model and they have usually been considered in many network models such as the proposed CLSC model [Chuluunsukh et al., 2018; Yun et al., 2020].

Index set, parameters, and decision variables are defined as follows:

- Index set
  - m: index of MF, $m \in M$
  - d: index of DC, $d \in D$
  - r: index of RT, $r \in R$
  - c: index of FC, $c \in C$
  - p: index of DP, $p \in P$
  - e: index of RC, $e \in E$
  - s: index of SC, $s \in S$
- Parameter
  - i_m: fixed cost at m
  - i_d: fixed cost at d
  - i_r: fixed cost at r
  - i_p: fixed cost at p
  - i_e: fixed cost at e
  - h_m: unit handling cost at m
  - h_d: unit handling cost at d
  - h_r: unit handling cost at r
  - h_p: unit handling cost at p
  - h_e: unit handling cost at e
  - t_{md}: unit transportation cost from m to d
  - t_{dr}: unit transportation cost from d to r
  - t_{rc}: unit transportation cost from r to c
  - t_{cp}: unit transportation cost from c to p
  - t_{cp}: unit transportation cost from c to e
  - t_{em}: unit transportation cost from e to m
  - t_{es}: unit transportation cost from e to s
  - d_{md}: distance between m and d
  - d_{dr}: distance between d and r
  - d_{rc}: distance between r and c
  - d_{cp}: distance between c and p
  - d_{ce}: distance between c and e
  - d_{em}: distance between e and m
  - d_{es}: distance between e and s
  - q_{md}: quantity transported from m to d
  - q_{dr}: quantity transported from d to r
  - q_{rc}: quantity transported from r to c
  - q_{cp}: quantity transported from c to p
  - q_{ce}: quantity transported from c to e
  - q_{em}: quantity transported from e to m
  - q_{es}: quantity transported from e to s
  - c_m: capacity at m
  - c_d: capacity at d
  - c_r: capacity at r
  - c_c: capacity at c
  - c_p: capacity at p
  - c_e: capacity at e
  - c_s: capacity at s
  - ca: capacity shipped in a vehicle
  - cv: CO_2 amount emitted from vehicle per kilometer
  - cm_m: unit CO_2 amount emitted from manufacturing process at m
  - cj_m: number of the job opportunity created by using new technology at m
  - cw: weight for the job opportunity created
  - un_m: number of the unemployment caused by using new

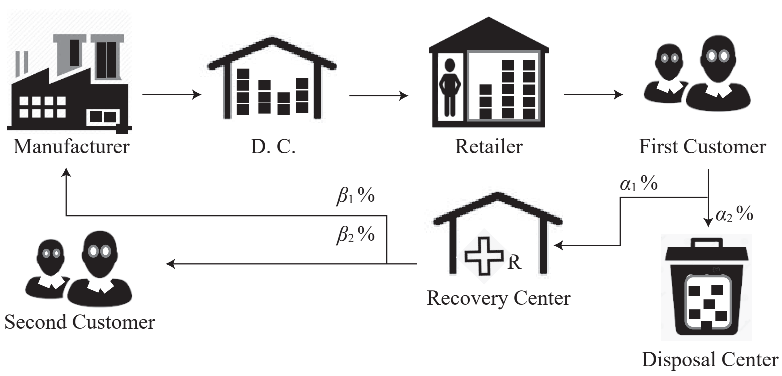

Figure 1: Conceptual flow of the proposed CLSC model

technology at m

uw: weight for the unemployment caused

- Decision variables

x_m: takes the value of 1, if m is opened and 0 otherwise

x_d: takes the value of 1, if d is opened and 0 otherwise

x_r: takes the value of 1, if r is opened and 0 otherwise

x_p: takes the value of 1, if p is opened and 0 otherwise

x_e: takes the value of 1, if e is opened and 0 otherwise

n_m: takes the value of 1, if new technology is used at m and 0 otherwise

For economic factor, the minimization of the total cost is used as first objective $F_1(x)$.

$$\begin{aligned} min.\ F_1(x) = {} & \textstyle\sum_m i_m x_m + \sum_d i_d x_d + \sum_r i_r x_r + \sum_p i_p x_p + \\ & \textstyle\sum_e i_e x_e + \sum_m h_m c_m x_m + \sum_d i_d c_d x_d + \sum_r i_r c_r x_r + \\ & \textstyle\sum_p i_p c_p x_p + \sum_e i_e c_e x_e + \sum_m \sum_d t_{md} c_m x_m x_d + \\ & \textstyle\sum_d \sum_r t_{dr} c_d x_d x_r + \sum_r \sum_c t_{rc} c_r x_r + \sum_c \sum_p t_{cp} c_c \alpha_2\% x_e + \\ & \textstyle\sum_c \sum_e t_{ce} c_c \alpha 1\% x_e + \sum_e \sum_m t_{em} c_e \beta_1\% x_e x_m + \\ & \textstyle\sum_e \sum_s t_{es} c_e \beta_2\% x_e \end{aligned} \quad (1)$$

In Equation (1), the sum of the total fixed costs, total handling costs and total transportation costs at each stage is used for minimizing the total cost. For environmental factor, the minimization of the total amount of CO_2 emission is used as second objective function $F_2(x)$.

$$\begin{aligned} \text{min. } F_2(x) = {} & \textstyle\sum_m \sum_d d_{md} x_m x_d (c_m / ca)\, cv + \\ & \textstyle\sum_d \sum_r d_{dr} x_d x_r (c_d / ca)\, cv + \sum_r \sum_c d_{rc} x_r (c_r / ca)\, cv + \\ & \textstyle\sum_c \sum_p d_{cp} x_p ((c_c\, \alpha_2\%) / ca)\, cv + \sum_c \sum_e d_{ce} x_e ((c_c\, a_1\%) / ca) \\ & \textstyle cv + \sum_e \sum_m d_{em} x_e x_m ((c_e \beta_1\%) / ca)\, cv + \sum_e \sum_s d_{es} x_e \\ & ((c_e \beta_2\%) / ca)\, cv \end{aligned} \quad (2)$$

In Equation (2), the total amount of CO_2 emitted during transportation process between each stage is minimized. For social factor, the maximization of social influences is used as third objective function $F_3(x)$.

$$max.\ F_3(x) = (cw \textstyle\sum_m cj_m x_m n_m) - (uw \sum_m un_m x_m n_m) \quad (3)$$

In Equation (3), the number of the job opportunity created by using new technology and the number of the unemployment caused by using new technology at m are taken into consideration.

For optimizing the above-mentioned three objectives, the following constraints are considered.

$$\textstyle\sum_m \sum_d q_{md} x_m x_d - \sum_d c_d x_d \le 0 \quad (4)$$

$$\textstyle\sum_d \sum_r q_{dr} x_d x_r - \sum_r c_r x_r \le 0 \quad (5)$$

$$\textstyle\sum_r \sum_c q_{rc} x_r - \sum_c c_c \le 0 \quad (6)$$

$$\textstyle\sum_c \sum_p q_{cp} x_p - \sum_p c_p \le 0 \quad (7)$$

$$\textstyle\sum_c \sum_e q_{ce} x_e - \sum_e c_e \le 0 \quad (8)$$

$$\textstyle\sum_e \sum_m q_{em} x_e x_{\text{m}} - \sum_m c_m \le 0 \quad (9)$$

$$\textstyle\sum_e \sum_s q_{es} x_e - \sum_s c_s \le 0 \quad (10)$$

$$\textstyle\sum_m x_m = 1 \quad (11)$$

$$\textstyle\sum_d x_d = 1 \quad (12)$$

$$\textstyle\sum_r x_r = 1 \quad (13)$$

$$\textstyle\sum_p x_p = 1 \quad (14)$$

$$\textstyle\sum_e x_e = 1 \quad (15)$$

$$x_m, x_d, x_r, x_p, x_e = \{0, 1\},\text{” “}\forall m \in M, \forall d \in D, \forall r \in R, \forall p \in P, \forall e \in E \quad (16)$$

$$c_m, c_d, c_r, c_c, c_p, c_e, c_s \ge 0,\text{” “}\forall m \in M, \forall d \in D, \forall r \in R, \forall c \in C, \forall p \in P, \forall e \in E, \forall s \in S \quad (17)$$

Equations (4) to (10) indicate the limitation of transportation amount between each stage. Equations (11) to (15) means that only one facility at each stage should be opened. In equation (16) each decision variable should have 0 or 1. Equation (17) shows the non-negativity of each parameter.

4. HGA approach

Since most complicated multi-stage network problems including the proposed CLSC model have known to be NP-complete [Gen and Cheng 2000; Savaskan et al., 2004; Gen et al., 2018], meta-heuristics approaches such as genetic algorithm (GA), Tabu search (TS), and particle swarm optimization (PSO) have adapted to solve them effectively. However, many situations exist that conventional single-based meta-heuristics approaches do not be particularly well adapted. Therefore, to overcome this weakness, various hybrid approaches combined with existing single-based meta-heuristics approaches have been proposed [Chuluunsukh et al., 2018; Gen et al., 2018]. Chuluunsukh et al. [2018] suggested a hybrid approach using GA and Cuckoo search (CS) to solve a CLSC model. Their hybrid approach is not only to consider global search using the GA, but also to take into account local search using CS. The hybrid approach suggested by Gen et al. [2018] combines GA for global search with iterative hill climbing for local search.

In this paper, we also suggest a hybrid approach for effectively solving the CLSC model. The suggested hybrid approach is called as the HGA approach which combines GA with revised CS. Main difference between the hybrid approach by Chuluunsukh et al. [2018] and HGA approach is that the former uses conventional CS scheme, but the latter revised CS scheme. With the conventional CS scheme, only one solution is randomly chosen among all solutions resulting from GA search

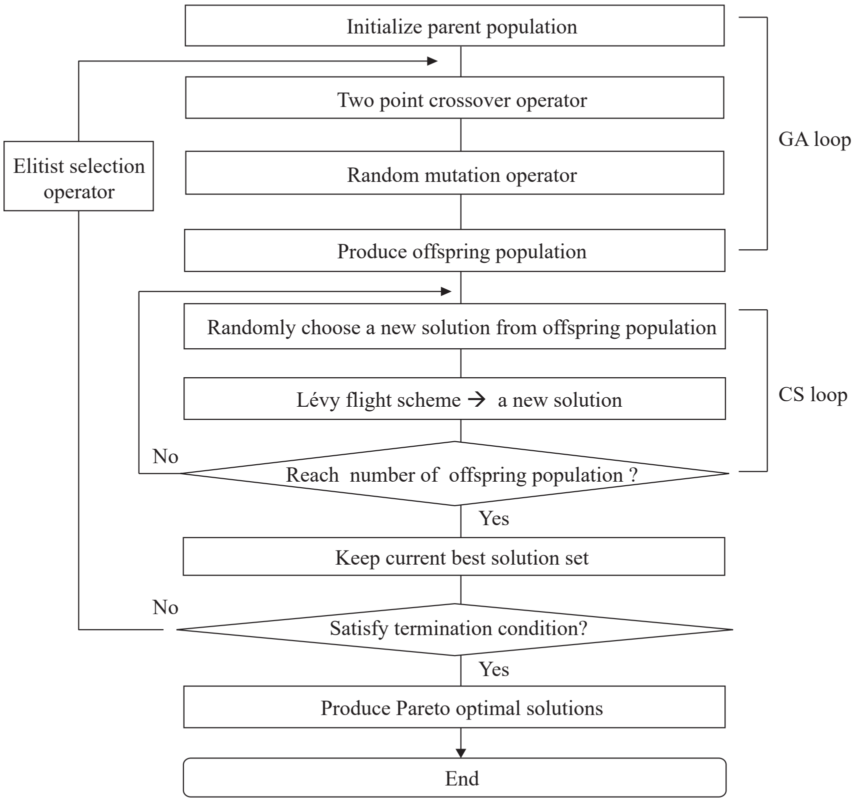

Figure 2: Implementation procedure of the HGA approach

loop and Levy flight scheme [Kanagaraj et al., 2013] is then adapted to improve the solution. However, with the revised CS scheme, Levy flight scheme is applied to all solutions resulting from GA search loop. Therefore, HGA approach with revised CS scheme can achieve more possibility to locate global optimal solution than the hybrid approach by Chuluunsukh et al. [2018] with conventional CS scheme. The detailed implementation procedure of the HGA approach is shown in Figure 2.

5. Numerical experiments

Two scales of the CLSC model are considered in numerical experiments. They has various facilities at each stage of the FL and RL as follows: 15 MFs, 15 DCs, 15 DCs, 15 RTs, 15 RCs and 1 FC, 1 SC, 1 DP for scale 1, and 30 MFs, 30 DCs, 30 DCs, 30 RTs, 30 RCs and 1 FC, 1 SC, 1 DP for scale 2 are considered. Various data such as fixed cost, unit handling cost, distance, quantity, and capacity presented in Section 3 mathematical formulation for establishing and operating the facilities are randomly generated using Microsoft Excel, since there exists no real data for implementing two scales of the CLSC model in real world situation.

The performances of GA approach [Gen and Cheng, 2000] and con-HGA approach [Kanagaraj et al., 2013] are used to compare that of the HGA approach.

Each approach was programmed by MATLAB version 2014b and ran under a same computation environment (IBM compatible PC 1.3 Ghz processor-Intel core I5-1600 CPU, 4 GB RAM, and OS-X EI). The parameter settings for the GA, con-HGA and HGA approaches are as following: total number of generations is 1,000, population size 20, crossover rate 0.5, and mutation rate 0.3. Number of host nest (n) is 10, $\alpha = 1$, $p_a = 0.25$ for the CS. These parameter setting values were obtained after the fine tuning procedures of each approach. Total 20 independent runs were carried out to eliminate the randomness of the search process of each approach. Various measures as shown in Table 1 are used for comparing the performances of the GA, con-HGA and HGA approaches.

Table 1: Performance measures

Measure	Description
$\lvert S_j \rvert$	Number of Pareto optimal solutions which coincide with reference solution set (S*) [Ishibushi et al., 2003]
$R_{NDS}(S_j)$	Rates of Pareto optimal solutions within the S* [Ishibushi et al., 2003]
$DI_R(S_j)$	Average distance between Pareto optimal solutions and the S* [Ishibushi et al., 2003]
CPU time	Average CPU time over 10 runs (Sec.)

For providing a convenience for performance comparison of each approach, three objectives in Section 3 mathematical formulation are divided into the following several types [Gen et al., 2018].

- Problem 1: min. $F_1(x)$ and min. $F_2(x)$
- Problem 2: min. $F_1(x)$ and max. $F_3(x)$
- Problem 3: min. $F_2(x)$ and max. $F_3(x)$

Tables 2 and 3 show the computation results of each ap-

Table 2: Computation results of GA, con-HGA and HGA approach using scale 1

	Scale 1								
	Problem 1			Problem 2			Problem 3		
Measure	GA	con-HGA	HGA	GA	con-HGA	HGA	GA	con-HGA	HGA
$\lvert S_j \rvert$	2	3	3	0	0	4	2	0	3
$R_{NDS}(S_j)$	0.250	0.375	0.375	0.000	0.000	1.000	0.400	0.000	0.6000
$DI_R(S_j)$	23,597	30,065	7,046	155	96	0	49,521	45,679	30,442
CPU time(s)	22.7	23.7	24.9	22.7	23.7	24.9	22.7	23.7	24.9

Table 3: Computation results of GA, con-HGA and HGA approach using scale 2

	Scale 2								
	Problem 1			Problem 2			Problem 3		
Measure	GA	con-HGA	HGA	GA	con-HGA	HGA	GA	con-HGA	HGA
$\lvert S_j \rvert$	0	2	3	2	0	3	0	1	3
$R_{NDS}(S_j)$	0.000	0.400	0.600	0.400	0.000	0.600	0.000	0.250	0.750
$DI_R(S_j)$	81,855	22,422	0	488	162	0	75,537	25,808	21,860
CPU time(s)	23.4	24.8	25.0	23.4	24.8	25.0	23.4	24.8	25.0

proach. For Problem 1 of Table 2, in terms of the $|S_j|$, we can find that three Pareto optimal solutions resulting from the con-HGA and HGA approaches coincide with reference solution set (S*), but two ones from the GA approaches coincide with the S*. This result also affects that of the $R_{NDS}(S_j)$, that is, the rates of Pareto optimal solutions within the S* at the con-HGA and HGA approaches is slightly higher than that at the GA approach. However, in terms of the $DI_R(S_j)$, average distance between Pareto optimal solutions of the HGA approach and those of the S* is significantly shorter than those of the GA and con-HGA approaches. In terms of the CPU time, there is no significant differences among all the approaches. By the result analysis of Problem 1, we can know that the performances of the con-HGA and HGA approach are superior to those of the GA approach in terms of the $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$.

For Problem 2 of Table 2, four Pareto optimal solutions obtained by the HGA approach are located in the S*, whereas any ones by the GA and con-HGA approaches do not located in the S* in terms of the $|S_j|$. This result also affect that of the $R_{NDS}(S_j)$, that is, the performance of the HGA approach is significantly superior to those of the GA and con-HGA approaches. In terms of the $DI_R(S_j)$, the HGA approach outperforms the GA and con-HGA approaches. However, in terms of the CPU time, no significant difference exists in all approaches. Similar results are also shown in Problem 3. The HGA approach shows to be better performances in terms of the $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$, except for the CPU times.

For Problem 1 of Table 3, the performance of the HGA approach is slightly better than that of the con-HGA approach, and the GA approach shows the worst performance in terms of the $|S_j|$ and $R_{NDS}(S_j)$.

Especially, in terms of the $DI_R(S_j)$, the average distance by the HGA approach is 0, which indicates that all Pareto optimal solutions by the HGA approach are located in the S*. Similar results are also shown in the Problem 2, that is, the performances of the HGA approaches are superior to those of the GA and con-HGA approaches in terms of the $|S_j|$, $R_{NDS}(S_j)$ and $DI_R(S_j)$. For the problem 3, it can be shown that the performance of the HGA approach is more efficient in terms of the $|S_j|$, $R_{NDS}(S_j)$ and $DI_R(S_j)$ than those of the GA and con-HGA approaches.

Figures 3, 4 and 5 show the convergence behaviours of Pareto optimal solutions in each approach in Scale 2. In Figure 3, the HGA approach has more Pareto optimal solutions within the S* than the con-HGA approach. However, none of Pareto optimal solution by the GA approach is located in the S*. These results coincide with those of the Problem 1 in Table 3 in terms of the $|S_j|$.

Similar situations are also shown in Figures 4 and 5. More Pareto optimal solutions by the HGA approach are located in the S* than those by the GA and con-HGA approaches. Using the analysed results of Tables 2 and 3 and Figures 3, 4 and 5, the following conclusion can be reached.

- The HGA approach proposed in this paper shows to be significantly better performances in terms of the $|S_j|$, $R_{NDS}(S_j)$

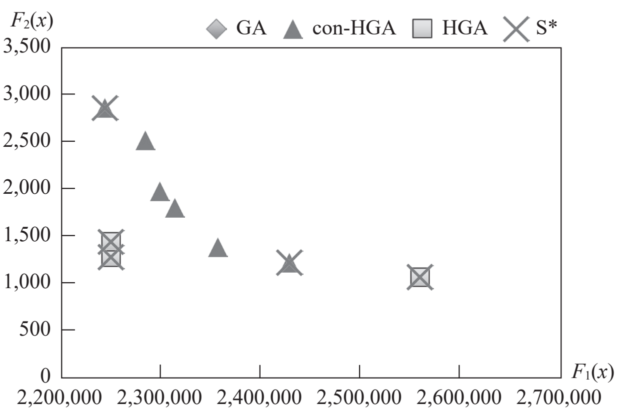

Figure 3: Pareto optimal solutions when compared with the S* in the Problem 1 of Scale 2

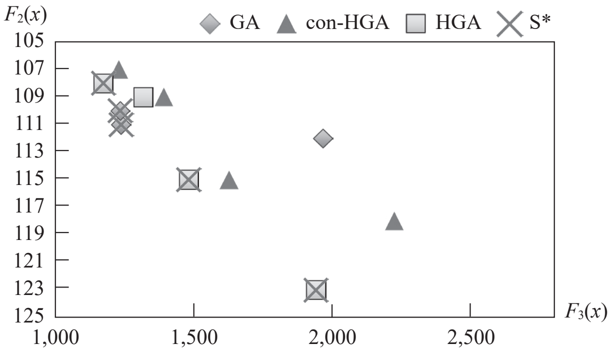

Figure 4: Pareto optimal solutions when compared with the S^* in the Problem 2 of Scale 2

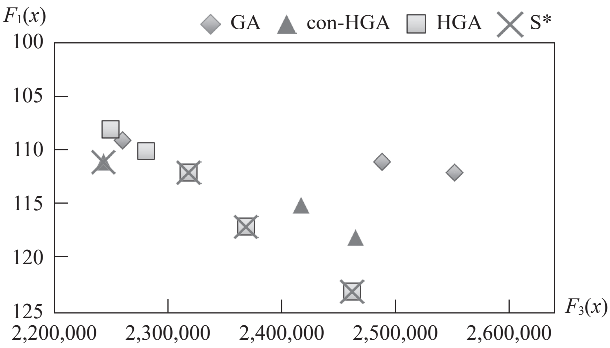

Figure 5: Pareto optimal solutions when compared with the S^* in the Problem 3 of Scale 2.

and $DI_R(S_j)$ than the con-HGA and GA approaches. This implies that the former is more efficient than the latter in the viewpoint of the multi-objective optimization.

6. Conclusion

In this paper, the CLSC model for reinforcing sustainability has been designed. For designing the CLSC model, manufacturers, DC, retailer and first customer in the FL and disposal center, recovery center and second customer in the RL have been considered. In mathematical formulation, economic, environmental and social factors for reinforcing sustainability in the CLSC model have been assigned as each objective function. For economic factor, the total cost resulting from the establishment and operation of the facilities at each stage of the CLSC model has been minimized. For environmental and social factors, the total amount of CO_2 emission and the total social influences have been minimized and maximized, respectively.

The HGA approach with GA and revised CS scheme have been implemented to solve the CLSC model. Two scales of the CLSC model have been presented and the performance of the HGA approach has been compared with those of the two conventional approaches (GA and con-HGA approaches). Experimental results using various measures of performance have shown that the HGA approach outperforms the GA and con-HGA approaches. For our future research direction, larger-sized CLSC models using data obtained from real world environment will be considered. Also, more various HGA approaches using recent developed metaheuristics will be compared with the HGA approach proposed in this paper..

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