Original Article

Reinforcing sustainability in supply chain model

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Abstract

In this paper, a methodology for reinforcing sustainability in supply chain (SC) model is proposed. For the sustainability, economic, environmental and social issues are considered in the SC model which consists of various facilities at each stage. Each issue considers i) the minimization of total cost, ii) the minimization of total amount of CO_2 emission and iii) the maximization of total social influence. The SC model with reinforced sustainability is represented as a mathematical formulation and implemented using a hybrid approach. In numerical experiment, two scales of the SC model are presented and the performance of the proposed hybrid approach is compared with those of the some conventional approaches. The experimental results show that the proposed hybrid approach is more efficient than the competing approaches.

Keywords

sustainability, supply chain, hybrid genetic algorithm, economic, environmental and social issues

1. Introduction

Generally speaking, supply chain (SC) model consist of suppliers, manufacturers, distribution centers (DCs), retailers and customers for the production and distribution of raw materials or products. There exist many studies for optimizing the SC model [Gen and Cheng 2000; Chiang and Monahan, 2005; Chen et al., 2017; Gen et al., 2017; Chuluunsukh et al., 2018]. Most of the studies have focused on (i) the minimization of total cost which is the sum of the total fixed cost, total handling cost and total transportation cost, or (ii) the maximization of total profit which is the sum of the total revenue, resulting from the operation process of the SC model.

Recently, with the increased concerns on environmental and social issues, many companies have focused on constructing their SC networks more efficiently so that they have environmental and social–oriented SC models [Mota et al., 2015; Arampantzi and Minis, 2017; Özceylan et al., 2017; Varsei and Polyakovskiy, 2017]. For environmental issues, the minimization of total amount or cost of CO_2 emission which results from the transportation of raw materials or products between each stages of the SC model has been usually considered [Özceylan et al., 2017; Varsei and Polyakovskiy, 2017]. For social issues, the maximization of total social influence such as the increase of the new employment by new technology, the lost day by work damages has been taken into account [Mota et al., 2015; Arampantzi and Minis, 2017]. However, a few studies have considered the economic, environmental and social issues in the SC model simultaneously.

Therefore, in this study, we suggest a SC model with economic, environmental and social issues simultaneously. Since the three issues are used as each objective, the SC model has three conflicting objectives. Therefore, there is a trade-off among the objectives, which makes it very difficult to reach a single optimal solution that optimizes all objectives simultaneously. This trade-off often lead to a set of optimal solutions at the end of optimization process called Pareto optimal solution [Ishibushi et al., 2003]. For each Pareto optimal solution, it is impossible to improve any objective without deteriorating at least another objective. To obtain the Pareto optimal solutions, we apply a hybrid genetic algorithm (pro-HGA) approach, one of meta-heuristics. The pro-HGA approach combines a conventional genetic algorithm (GA) with other heuristics and can overcome the weakness of the GA approach (i.e., premature convergence to a local optimal solution, the absence of local search scheme).

In Section 2, the SC model with economic, environmental and social issues is presented. A mathematical formulation for representing the SC model is suggested in Section 3. The pro-HGA approach is implemented to solve the SC model in Section 4. In Section 5, the performance of the pro-HGA approach are compared with those of some conventional approaches using the SC models with two scales. A conclusion is summarized and a future study direction for improving the SC model and the pro-HGA approach is suggested in Section 6.

2. Proposed SC model

Figure 1 shows a conceptual flow of the SC model. Manufacturer produces products and sends them to DC with α_1 % by normal delivery (NRD) and to customer with α_2 % by direct shipment (DRS). Similar situation is also shown at DC, that is, DC sends the products to retailer with β_1 % by the NRD and to customer with β_2 % by direct delivery (DRD). Retailer sends the products to customer by the NRD. For sustainability, economic, environmental and social issues are considered at each facility and transportation processes.

3. Mathematical formulation

First, some assumptions are considered for implementing the SC model suggested in Section 2 [Chuluunsukh et al., 2018]. Index set, parameters, and decision variables are defined as follows:

- Index Set
  m: manufacturer index, $m \in M$
  d: DC index, $d \in D$

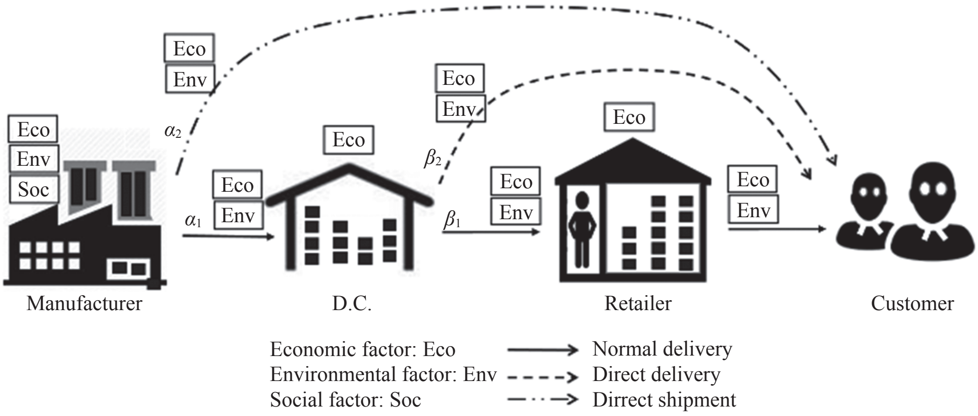

Figure 1: Conceptual flow of the SC model

r: retailer index, $r \in R$

c: customer index, $c \in C$

- Parameter

a_m: fixed cost at m

a_d: fixed cost at d

a_r: fixed cost at r

b_m: unit handling cost at m

b_d: unit handling cost at d

b_r: unit handling cost at r

c_{md}: unit transportation cost from m to d

c_{mc}: unit transportation cost from m to c

c_{dr}: unit transportation cost from d to r

c_{dc}: unit transportation cost from d to c

c_{rc}: unit transportation cost from r to c

d_{md}: distance between m and d

d_{mc}: distance between m and c

d_{dr}: distance between d and r

d_{dc}: distance between d and c

d_{rc}: distance between r and c

e_{md}: quantity transported from m to d

e_{mc}: quantity transported from m to c

e_{dr}: quantity transported from d to r

e_{dc}: quantity transported from d to c

e_{rc}: quantity transported from r to c

ca_m: capacity at m

ca_d: capacity at d

ca_r: capacity at r

ca_c: capacity at c

ca_v: capacity shipped in a vehicle

co_v: CO_2 amount emitted from vehicle per kilometer

co_m: unit CO_2 amount emitted from manufacturing process at m

j_w: weight for the created job opportunity

j_m: number of the created job opportunity at m using technology t

u_w: weight for unemployment

u_m: number of unemployment at m

- 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

t_m: takes the value of 1, if t is used at m and 0 otherwise

First objective $F_1(x)$, as an economic issue, is to minimize the total cost as follows:

$$min.\ F_1(x) = \sum_m a_m x_m + \sum_d a_d x_d + \sum_r a_r x_r + \sum_m b_m ca_m x_m + \sum_d b_d ca_d x_d + \sum_r b_r ca_r x_r + \sum_m \sum_d c_{md}\, ca_m\, \alpha_1 x_m x_d + \sum_m \sum_c c_{mc}\, ca_m\, \alpha_2 x_m + \sum_d \sum_r c_{dr}\, ca_d\, \beta_1 x_d x_r + \sum_d \sum_c c_{dc}\, ca_d\, \beta_2 \mathrm{x}_d + \sum_r \sum c\, c_{rc}\, ca_r x_r \tag{1}$$

Equation (1) shows the minimization of the total cost which consists of the sum of the fixed costs, handling costs and transportation costs at each stage. Second objective function $F_2(x)$, as an environmental issue, is to minimize the total amount of CO_2 emission as follows:

$$min.\ F_2(x) = (\sum_m \sum_d d_{md} x_m x_d)((ca_m \alpha_1)/ca_v)\, co_v + (\sum_m\sum_c d_{mc} x_m)((ca_m \alpha_2)/ca_v)\, co_v + (\sum_d \sum_r d_{dr} x_d x_r) + ((ca_d \beta_1)/ca_v)\, co_v + (\sum_d \sum_c d_{dc} x_d)((ca_d \beta_2)/ca_v)\, co_v + (\sum_r \sum_c d_{rc} x_r)(ca_r/ca_v)\, co_v + \sum_m ca_m x_m co_m \tag{2}$$

Equation (2) stands for the minimization of the total amount of CO_2 emitted during transportation process between each stage and that emitted during production process at manufacturers. Third objective function $F_3(x)$, as a social issue, is to maximize the social influence as follows:

$$max.\ F_3(x) = (j_w \sum_m j_m x_m t_m) - (u_w \sum_m u_m x_m t_m) \tag{3}$$

Equation (3) means the maximization of the social influence which is composed of the created job opportunity and unemployment at manufacturer m. The following constraints should be taken into consideration for optimizing three objective functions mentioned above.

subject to

$$\sum_m \sum_d e_{md}\, \alpha_1\, x_m\, x_d - \sum_d ca_d\, x_d \leq 0 \quad (4)$$

$$\sum_m \sum_c e_{mc}\, \alpha_2\, x_m - \sum_c ca_c \leq 0 \quad (5)$$

$$\sum_d \sum_r e_{dr}\, \beta_1\, x_d\, x_r - \sum_r ca_r\, x_r \leq 0 \quad (6)$$

$$\sum_d \sum_c e_{dc}\, \beta_2\, x_m - \sum_c ca_c \leq 0 \quad (7)$$

$$\sum_r \sum_c e_{rc}\, x_r - \sum_c ca_c \leq 0 \quad (8)$$

$$\sum_m x_m = 1 \quad (9)$$

$$\sum_d x_d = 1 \quad (10)$$

$$\sum_r x_r = 1 \quad (11)$$

$$\mathrm{x}_m = \{0,1\},\ \forall M \quad (12)$$

$$\mathrm{x}_d = \{0,1\},\ \forall D \quad (13)$$

$$\mathrm{x}_r = \{0,1\},\ \forall R \quad (14)$$

$$ca_m, ca_d, ca_r, ca_c \geq 0,\ \forall m \in M,\ \forall d \in D,\ \forall r \in R\ \forall c \in C \quad (15)$$

Equations (4) to (8) show that the limitation of transportation amount between each stage. Equations (9) to (11) means that only one facility should be opened and the others closed at each stage. Equations (12) to (14) indicates the constraint of the decision variables with 0 or 1. The non-negativity of each parameter is shown in equation (15).

4. pro-HGA approach

Many approaches have contributed to find global optimal solution in the SC model [Gen and Cheng 2000; Chen et al., 2017; Chuluunsukh et al., 2018]. Of them, the HGA approaches which combine GA with other local search techniques have successfully adapted to the SC model [Yun et al., 2012; Chuluunsukh et al., 2018]. These HGA approaches have some advantages such as the efficiency to find global optimum and the quick search speed, when compared with the GA approaches.

In this paper, we also develop the pro-HGA approach to solve the SC model efficiently. The pro-HGA approach uses a conventional GA [Gen and Cheng, 2000] for global search, the Cuckoo search (CS) [Kanagaraj et al., 2013] for local search, and fuzzy logic controller (FLC) [Gen and Yun, 2006] for the adaptive scheme of the GA parameters. The performance of the pro-HGA approach is compared with those of some conventional approaches in Section 5. The detailed implementation procedure of the pro-HGA approach is as follows:

- Step 1: initialization
  Various parameters are initialized.
- Step 2: GA procedure
  A new offspring is produced using crossover and mutation operators.
- Step 3: CS procedure
  Step 3.1 Generate a new solution x_{new} from x_i using Lévy flight scheme.
  Step 3.2 Select a solution x_{ram} from offspring randomly.
  Step 3.2 Compare the fitness values of x_{new} and x_{ram}. Insert x_{new} into offspring, if the fitness value of the x_{new} outperforms that of the x_{ram}.
  Step 3.3 A fraction of the worst solutions is abandoned and then randomly regenerate new solutions x_{ng} as many as the fraction. Insert x_{ng} into offspring,
- Step 4: Solution improvement
  Store the best solution after comparing the solution by GA procedure with that by CS procedure.
- Step 5: FLC procedure
  Apply FLC scheme to regulate the GA parameters (crossover and mutation operators) automatically.
- Step 6: Termination condition
  Repeat Step 2 to Step 5 until a pre-determined termination condition is satisfied.

5. Numerical experiment

In numerical experiment, two scales of the SC model are considered. Since there is no exact SC model which can be applied to a real world situation, the SC model in the numerical experiment is considered under virtual environment. For the two scales, the detailed information of the facilities considered at each stage is as follows: 40 suppliers, manufacturers, DC, retailers and 1 customer for the scale 1, and 60 suppliers, manufacturers, DC, retailers and 1 customer for the scale 2 are considered, respectively.

Two conventional approaches [GA by Gen and Cheng, 2000; HGA with GA and CS by Kanagaraj et al., 2013] are used for comparing the performance of the pro-HGA approach. All the approaches were programmed by MATLAB version 2014b and ran under a same computation environment (IBM compatible PC 1.3 Ghz processor-Intel core I5-1600 CPU, 4GB RAM, and OS-X EI). The parameter settings for the GA, HGA and pro-HGA approaches are as following: total number of generations is 1,000, population size 10, crossover rate 0.8, and mutation rate 0.6. The parameter setting values were obtained after the fine tuning procedures of each approach. Number of host nest (n) is 10, $\alpha = 1$, $p_a = 0.25$ for the CS. Total 10 independent runs were carried out to eliminate the randomness of the search process of each approach. The performances of all the approaches are compared by the various measures as shown in Table 1.

For the convenience of the computation analysis among each approach, the mathematical formulation in Section 3 are divided into the following three sub-problems.

- 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*. $F_3(x)$

Table 1: Performance measures

Measure	Brief description
$\|S_j\|$	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	CPU time averaged over 10 runs (Sec.)

Using the two scales, the computation results of all approaches are shown in Tables 2 and 3. In Table 2, the performance of the HGA approach is the same as that of the pro-HGA approach, and both are more efficient in terms of the $|S_j|$ than the GA approach for the problem 1. These results of the $|S_j|$ also affect those of the $R_{NDS}(S_j)$, that is, the Pareto optimal solutions within the S* have the same rate in the HGA and pro-HGA approaches. However, in terms of the $DI_R(S_j)$, we can see that the Pareto optimal solutions using the pro-HGA approach are all located in the S*, which indicates that the pro-HGA approach is more efficient than the GA and HGA approaches. In terms of the CPU time, there is no significant differences among all the approaches.

For the problem 2 of Table 2, the performances of the GA approach are more efficient in terms of the $|S_j|$ and $R_{NDS}(S_j)$ than those of the HGA and pro-HGA approaches. However, in terms of the DIR(Sj), the pro-HGA approach outperforms the others. For the problem 3 of Table 2, the performances of the GA approach are the same with the problem 2 in terms of the $|S_j|$ and $R_{NDS}(S_j)$. In terms of the $DI_R(S_j)$ and CPU time, the GA approach shows to be slightly better results than the others.

For the problem 1 of Table 3, the performances of the GA and pro-HGA approaches are superior to that of the HGA approach in terms of the $|S_j|$ and $R_{NDS}(S_j)$. Especially, in terms of the $DI_R(S_j)$, the average distance using the pro-HGA approach is 0, which means that all Pareto optimal solutions by the pro-HGA approach are located in the S*. Similar results are also shown in the problem 2, that is, the performances of the GA and pro-HGA approaches are superior to that of the HGA approach in terms of the $|S_j|$ and $R_{NDS}(S_j)$. The pro-HGA approach is more efficient in terms of the $DI_R(S_j)$ than the GA and HGA approaches. For the problem 3, all the approaches have the same results in terms of the $|S_j|$ and $R_{NDS}(S_j)$. However, in terms of the $DI_R(S_j)$, the GA approach outperforms the others. In terms of the CPU time, all the approaches have almost same results in the problems 1, 2, and 3. Figures 2, 3 and 4 show the convergence behaviours of Pareto optimal solutions in each problem.

In Figure 2, four Pareto optimal solutions in the HGA and pro-HGA approaches are located in the S*, but no Pareto opti-

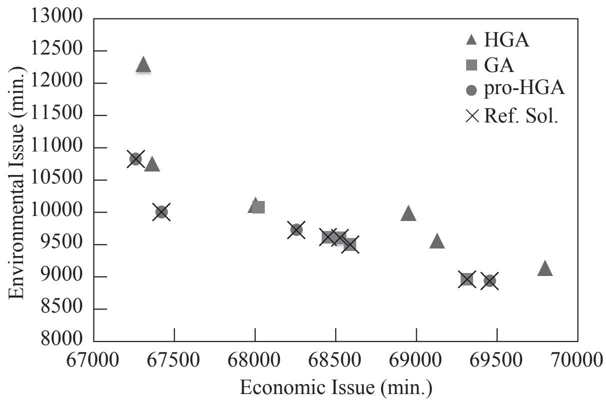

Figure 2: Pareto optimal solutions when compared with S* in the problem 1 of the scale 2

Table 2: Computation results of each problems in Scale 1

	Scale 1								
	Problem 1			Problem 2			Problem 3		
Measure	GA	HGA	pro-HGA	GA	HGA	pro-HGA	GA	HGA	pro-HGA
$\|S_j\|$	1	2	2	3	1	2	3	1	2
$R_{NDS}(S_j)$	0.20	0.40	0.40	0.50	0.17	0.33	0.50	0.17	0.33
$DI_R(S_j)$	620	277	589	1367	649	0	439	694	534
CPU time	5.1	5.2	6.3	5.1	5.2	6.3	5.1	5.2	6.3

Table 3: Computation results of each problems in Scale 2

	Scale 2								
	Problem 1			Problem 2			Problem 3		
Measure	GA	HGA	pro-HGA	GA	HGA	pro-HGA	GA	HGA	pro-HGA
$\|S_j\|$	4	0	4	3	0	3	1	1	1
$R_{NDS}(S_j)$	0.50	0.00	0.50	0.50	0.00	0.50	0.33	0.33	0.33
$DI_R(S_j)$	584	468	0	402	2,397	338	7	123	499
CPU time	5.3	5.4	6.8	5.3	5.4	6.8	5.3	5.4	6.8

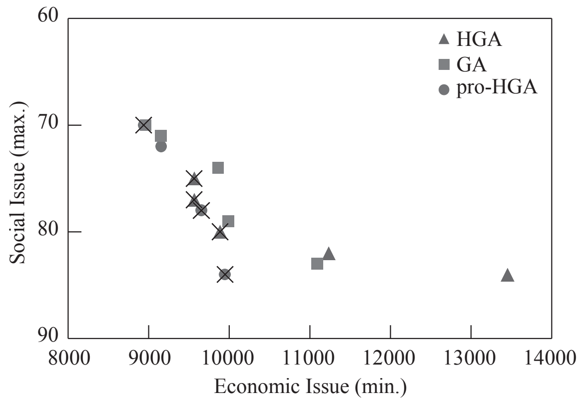

Figure 3: Pareto optimal solutions when compared with S^* in the problem 2 of the scale 2

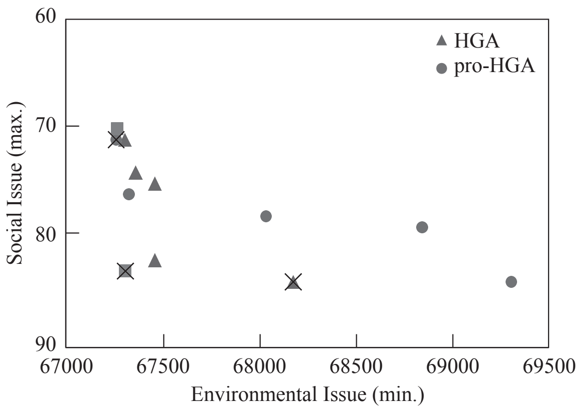

Figure 4: Pareto optimal solutions when compared with S^* in the problem 3 of the scale 2

mal solutions in the GA approach is located in it. This means that the HGA and pro-HGA approach are significantly efficient rather than the GA approach. These results coincide with those of the problem 1 in Table 2 in terms of the $|S_j|$.

Similar situation is also shown in Figure 3. In Figure 4, each one Pareto optimal solution in the GA, HGA and pro-HGA approaches is located in the S^*. Using the analysed results of Tables 2 and 3 and Figures 2, 3 and 4, the following conclusions can be reached.

- The pro-HGA approach proposed in this paper shows to be slightly better performances in terms of the $|S_j|$, $R_{NDS}(S_j)$ and $DI_R(S_j)$ than the GA and HGA approaches, which proves that the former is more efficient than the latter in the view of the multi-objective optimization concept.
- The search speed of the pro-HGA approach is slightly slower than those of the GA and HGA approaches in terms of the CPU time. Therefore, any effort is required for reducing the running time of the pro-HGA approach.

6. Conclusion

In this paper, we have suggested a SC model for reinforcing sustainability. The SC model has a simple network using manufacturers, DCs, retailers and customers in forward logistics. For the sustainability, economic, environmental and social issues have been considered in the SC model. The minimization of total cost as an economic issue, the minimization of total amount of CO_2 emission as an environmental issue, and the maximization of total social influence as a social issue have been taken into consideration.

The SC model has been represented as a mathematical formulation and implemented using the pro-HGA approach. In numerical experiments, the performances of the pro-HGA approach have been compared with those of the conventional GA and HGA approaches using two scales of the SC model. Experimental results have shown that the pro-HGA approach outperforms the GA and HGA approaches. However, two scales of the SC model presented in numerical experiments is relatively small sizes, thus larger-scaled SC models will be tested. Also, more various HGA approaches using AI-related techniques such as Tabu search, heuristic greedy search, etc., will be considered for comparing the performance of the pro-HGA approach.

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