

# Environmentally-friendly supply chain network with various transportation types

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## Abstract

*The objective of this paper is to design an environmentally-friendly supply chain (efSC) network by efficiently regulating CO<sub>2</sub> emission amount resulting from transportation process of materials or products. For designing the efSC network, a mathematical formulation considering various transportation types (i.e., normal delivery, direct delivery and direct shipment) is suggested and implemented using hybrid genetic algorithm (pro-HGA) approach. In numerical experiment, the performance of the pro-HGA approach is compared with those of other conventional approaches, and the efficiency of the efSC network is also compared with that of the SC network not regulating CO<sub>2</sub> emission amount under various measures. Finally, it is proved that the performance of the pro-HGA approach is superior to those of the others and the efSC network outperforms the conventional SC network.*

## Keywords

*environmentally-friendly supply chain, transportation type, normal delivery, direct delivery and shipment, hybrid genetic algorithm*

## 1. Introduction

In general, supply chain (SC) network considers various facilities at each stage. For example, suppliers, manufacturers, distribution centers (DCs), retailers and customers are usually taken into consideration for the production and transportation of materials or products. Recently, with the increased concerns on environmental problems, many companies have focused on constructing their SC networks efficiently. Especially, among the environmental problems, the CO<sub>2</sub> emission amount resulting from the transportation of materials or products between various stages of the SC network has been continuously increasing, which stimulates many researchers to develop more efficient SC network in order to decrease it. One of the solutions for decreasing the CO<sub>2</sub> emission amount is to increase the efficiency of transportation in the SC network. The efficiency can be calculated by applying various transportation types to the SC network. Three types of transportation are generally considered in the SC network: normal delivery (NMD), direct delivery (DRD) and direct shipment (DRS). The NMD is to transport materials or products from a stage to another adjoining to this one. For example, some materials can be transported from suppliers to manufacturers in a series of the SC network (suppliers → manufacturers → DCs → retailers → customers), which can be called as the NMD. Some products can be directly delivered from DCs to customers not via retailers, this kind of transportation type is called as the DRD. Some products can be also directly shipped from manufacturers to retailers or customers not via DCs and this can be called as the DRS.

The efficiency of the SC network under three types of transportation mentioned above has been considered in many conventional literatures [Chiang et al., 2003; Chiang and Mo-

nahan, 2005; Hua et al., 2010; Chen et al., 2017; Özceylan et al., 2017]. Chiang et al. [2003] analysed a dual-channel SC network using direct marketing. They used the DRS by transporting a product to retailer or customer directly and showed that the profit and efficiency of the SC network can be increased by using the DRS efficiently and strategically. Similar to Ching et al. [2003], Chiang and Monahan [2005] suggested a two-echelon dual-channel SC network for efficient inventory management. In this study, they focused three scenarios for transportation: i) first scenario is to consider a situation that products are transported from manufacturer to customer through retailer by the NMD alone, ii) in second scenario, two types of transportation are considered simultaneously, that is, products are transported from manufacturer to customer through retailer by the NMD and are also directly shipped from manufacturer to customer by the DRS and iii) in the final scenario, products are directly shipped from manufacturer to customer by the DRS alone. The experimental result showed that the performance of the second scenario using both the NMD and DRS is superior to those of the first and third scenarios using the NMD or DRS alone.

Hua et al. [2010] suggested a dual-channel SC network for determining product price and lead time. They used the NMD, DRD and DRS in the SC network to analyse how does these types of transportation have influence on product price and lead time. The experimental result using various scenarios showed that the duplicated use of the NMD, DRD and DRS in the SC network is more efficient in controlling product price and lead time than the single use of them. Chen et al. [2017] proposed a SC network with two types of transportation. The first type is to consider the NMD in the SC network and in the second one, the NMD, DRD and DRS are taken into account in it. The performances of the SC network with two types were compared with each other and proved that the SC network with the NMD, DRD and DRS are more efficient than that with the NMD alone. Özceylan et al. [2017] proposed a SC network for automotive industry in Turkey. In the proposed SC network,

the NMD was only used for transporting automotive and automotive-related components from supplier to user cluster via manufacturer and DC. To consider an environmental problem in transporting them, they proposed a mathematical formulation considering CO<sub>2</sub> emission amount.

By analysing the previous studies mentioned above, we can reach the following two key points:

- Except for Özceylan et al. [2017], they did not consider any kind of environmental problems such as CO<sub>2</sub> emission amount, though various transportation types was considered in their SC networks.
- Except for Chen et al. [2017], they considered relatively simple and small-sized SC network, though most of the SC networks are complicated and large-sized networks.
- They did not analysed the performances of their SC networks using various measures such as best solution, average solution, average search speed and average number of iteration.

Therefore, in this paper, we develop an improved SC (iSC) network. The iSC network i) uses CO<sub>2</sub> emission amount as a constraint for considering environmental problem, ii) considers complicated and large-sized networks, and iii) compares the performance of our approach with those of the other conventional approaches using various measures. For the approach to analyse its performance, we develop a hybrid genetic algorithm (pro-HGA) approach which combines a genetic algorithm (GA) approach with cuckoo search (CS) approach. Therefore, the performance of the pro-HGA approach is compared with those of the other conventional approaches.

In Section 2, the SC network with the NMD, DRD and DRS is presented. A mathematical formulation for representing the SC network which considers CO<sub>2</sub> emission amount is suggested in Section 3. The pro-HGA approach is implemented to solve the SC network in Section 4. In Section 5, the numerical experiments using complicated and large-sized SC networks are done for proving the efficiency of the pro-HGA approach using various measures. Finally, some conclusions are summarized in Section 6.

## 2. Proposed iSC network

In this section, we propose the structure of the iSC network with the NMD, DRD and DRS altogether. Its flow is as fol-

low. Supplier prepares parts and sends them to manufacturer. Manufacturer produces products using the parts and send them to retailer via DC. Finally, retailer sends the products to customer. This flow is proceeded using the NMD. The DRD is occurred at DC, that is, DC directly sends products to customer not via retailer. Some products can be also directly sent from manufacturer to customer not via DC and retailer and this flow is the DRS. The conceptual flow of the iSC network is shown in Figure 1.

## 3. Mathematical formulation

First, some assumptions are considered for implementing the iSC network presented in Section 2.

- Single type of product is only considered.
- The numbers of facilities considered at each stage of supplier, manufacturer, DC, retailer and customer are fixed and already known.
- Only one facility is opened at each stage of supplier, manufacturer, and DC. However, all facilities at retailer and customer are always opened.
- The fixed costs for operating the facilities considered at each stage of supplier, manufacturer, DC, and retailer are different and already known.
- The unit handling costs of the facilities considered at each stage of supplier, manufacturer, DC and retailer are different and already known.
- The unit transportation costs of the facilities among supplier, manufacturer, DC, retailer and customer are different and already known.
- The proposed iSC network is considered under steady-state situation.

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

- Index Set
  - $s$ : index of supplier,  $s \in S$
  - $m$ : index of manufacturer,  $m \in M$
  - $d$ : index of DC,  $d \in D$
  - $r$ : index of retailer,  $r \in R$
  - $c$ : index of customer,  $c \in C$
- Parameter
  - $FCS_s$ : fixed cost at supplier  $s$

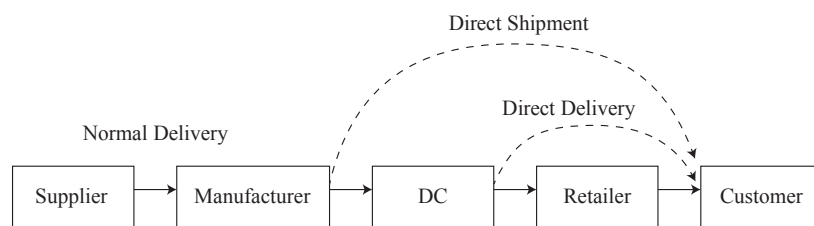


Figure 1: Conceptual flow of the iSC network with the NMD, DRD and DRS

$FCM_m$ : fixed cost at manufacturer  $m$

$FCD_d$ : fixed cost at DC  $d$

$FCD_r$ : fixed cost at retailer  $r$

$HCS_s$ : unit handling cost at supplier  $s$

$HCM_m$ : unit handling cost at manufacturer  $m$

$HCD_d$ : unit handling cost at DC  $d$

$HCR_r$ : unit handling cost at retailer  $r$

$TSM_{sm}$ : unit transportation cost from supplier  $s$  to manufacturer  $m$

$TMD_{md}$ : unit transportation cost from manufacturer  $m$  to DC  $d$

$TMC_{mc}$ : unit transportation cost from manufacturer  $m$  to customer  $c$  by the DRS

$TDR_{dr}$ : unit transportation cost from DC  $d$  to retailer  $r$

$TDC_{dc}$ : unit transportation cost from DC  $d$  to customer  $c$  by the DRD

$TRC_{rc}$ : unit transportation cost from retailer  $r$  to customer  $s$

$CO2_{MAX}$ : allowable maximum amount of CO<sub>2</sub> emission

$CO2_A$ : amount of CO<sub>2</sub> emission per material or product when transporting them

$CO2_C$ : cost of CO<sub>2</sub> emission per material or product when transporting them

$CM_m$ : capacity of manufacturer  $m$

$CD_d$ : capacity of DC  $d$

$CR_r$ : capacity of retailer  $r$

$CC_c$ : capacity of customer  $c$

• Decision Variable

$qsm_{sm}$ : amount of materials transported from supplier  $s$  to manufacturer  $m$

$qmd_{md}$ : amount of products transported from manufacturer  $m$  to DC  $d$

$qmc_{mc}$ : amount of products transported from manufacturer  $m$  to customer  $c$  by the DRS

$qdr_{dr}$ : amount of products transported from DC  $d$  to retailer  $r$

$qdc_{dc}$ : amount of products transported from DC  $d$  to customer  $c$  by the DRD

$qrc_{rc}$ : amount of products transported from retailer  $r$  to customer  $c$

$xs_s$ : takes the value of 1 if supplier  $s$  is opened and 0 otherwise

$xm_m$ : takes the value of 1 if manufacturer  $m$  is opened and 0 otherwise

$xd_d$ : takes the value of 1 if DC  $d$  is opened and 0 otherwise

Under considering the above assumptions, a mathematical formulation for the iSC network is developed. Objective function is to minimize total cost ( $TC$ ) under satisfying various constraints. The  $TC$  is consisted of total fixed cost ( $TFC$ ), total handling cost ( $THC$ ) and total transportation cost ( $TTC$ ).

$$\text{Minimize } TC = TFC + THC + TTC \quad (1)$$

$$TFC = \sum_s FCS_s \cdot xs_s + \sum_m FCM_m \cdot xm_m + \sum_d FCD_d \cdot xd_d$$

$$+ \sum_r FCR_r \quad (2)$$

$$THC = \sum_s HCS_s \cdot CS_s \cdot xs_s + \sum_m HCM_m \cdot CM_m \cdot xm_m + \sum_d HCD_d \cdot CD_d \cdot xd_d + \sum_r HCR_r \cdot CR_r \quad (3)$$

$$TTC = CO2_C (\sum_s \sum_m TSM_{sm} \cdot qsm_{sm} \cdot xs_s \cdot xm_m + \sum_m \sum_d TMD_{md} \cdot qmd_{md} \cdot xm_m \cdot xd_d + \sum_m \sum_c TMC_{mc} \cdot qmc_{mc} \cdot xm_m + \sum_d \sum_r TDR_{dr} \cdot qdr_{dr} \cdot xd_d + \sum_d \sum_c TDC_{dc} \cdot qdc_{dc} \cdot xd_d + \sum_r \sum_c TRC_{rc} \cdot qrc_{rc}) \quad (4)$$

Subject to

$$\sum_s \sum_m qsm_{sm} \cdot xs_s \cdot xm_m - \sum_m CM_m \cdot xm_m \leq 0 \quad (5)$$

$$\sum_m \sum_d qmd_{md} \cdot xm_m \cdot xd_d - \sum_d CD_d \cdot xd_d \leq 0 \quad (6)$$

$$\sum_d \sum_r qdr_{dr} \cdot xd_d - \sum_r CR_r \leq 0 \quad (7)$$

$$\sum_m \sum_c qmc_{mc} \cdot xm_m + \sum_d \sum_c qdc_{dc} \cdot xd_d + \sum_r \sum_c qrc_{rc} - \sum_c CC_c \leq 0 \quad (8)$$

$$CO2_A ((\sum_s \sum_m qsm_{sm} \cdot xs_s \cdot xm_m) + (\sum_m \sum_d qmd_{md} \cdot xm_m \cdot xd_d) + (\sum_m \sum_c qmc_{mc} \cdot xm_m) + (\sum_d \sum_r qdr_{dr} \cdot xd_d \cdot xr_r) + (\sum_d \sum_c qdc_{dc} \cdot xd_d) + (\sum_r \sum_c qrc_{rc} \cdot xr_r)) \leq CO2_{MAX} \quad (9)$$

$$\sum_s xs_s = 1 \quad (10)$$

$$\sum_m xm_m = 1 \quad (11)$$

$$\sum_d xd_d = 1 \quad (12)$$

$$xs_s = \{0, 1\}, \forall S \quad (13)$$

$$xm_m = \{0, 1\}, \forall M \quad (14)$$

$$xd_d = \{0, 1\}, \forall D \quad (15)$$

$$cs_s, cm_m, cd_d, cr_r, cc_c \geq 0, \forall s \in S, \forall m \in M, \forall d \in D, \forall r \in D, \forall c \in C \quad (16)$$

Equations (1) shows the objective function of the  $TC$ . Equations (2) through (4) show the  $TFC$ ,  $THC$ ,  $TTC$ , respectively. Especially, in Equation (4), the cost of CO<sub>2</sub> emission per material or product when transporting them is considered. Equations (5) though (8) mean that the sum of amount of materials or products transported from current stage to the next stage is less than or equal to the capacity of the next stage. Equation (9) represents that total amount of CO<sub>2</sub> emission when transporting materials or products is less than or equal to the allowable maximum amount of CO<sub>2</sub> emission. Equations (10) though (12) show that only one facility should be opened at each stage. Equations (13) to (15) represent that each decision variable should take a value of 0 or 1. Equation (16) refers to non-negativity.

#### 4. pro-HGA approach

Since most of the complicated network problems including the iSC network have NP-complete nature [Savaskan et al., 2004; Gen and Cheng, 2000], GA approach, one of the meta-heuristics, has been adapted to find optimal solution in many literatures [Min et al., 2006; Yun et al.; 2012; 2013]. However, there are many situations that the conventional GA approach does not well perform particularly. First, GA approach sometimes gets stuck at local optimal solutions instead of finding global optimal solution. Secondly, when GA approach converges to a feasible region including global optimal solution, finding the global optimal solution within the region using GA approach become difficult or impossible because of the lack of local search ability in it. Therefore, to cope with the weaknesses of GA search mentioned above, various HGA approaches using GA approach and other conventional approaches have been developed by many researchers [Gen and Cheng, 2000; Yun, 2006; Yun et al., 2013; Gen et al., 2017; Chuluunsukh et al., 2018].

In this paper, we also develop the pro-HGA approach to efficiently solve the iSC network. The pro-HGA approach which combines a conventional GA approach with a CS approach is an improved version of the conventional HGA approach by Kanagaraj et al. [2013]. Kanagaraj et al. [2013] proposed a HGA approach using GA and CS approaches for solving reliability optimization problems. The main search process is as follows: First, GA approach is applied to produce new population using GA operators (crossover, mutation and selection). Secondly, CS approach is adapted to produce more respective solutions using the new population produced by GA approach. The key point of this approach is to locate global optimal solution more quickly using Lévy flight scheme of CS approach. However, the Lévy flight scheme is applied to only one solution among all the solutions of the new population produced by GA approach and its use is done by only one time in each iteration. Also, if the fitness value of the solution produced by Lévy flight scheme is inferior to that of the solution randomly selected in the new population produced by GA approach, the improvement of the solution produced by Lévy flight scheme can become impossible.

To improve the weakness of the HGA approach by Kanagaraj et al. [2013] mentioned above, the continuous production of the respective solutions and the improvement of the solution should be required during GA and CS search processes. For achieving this strategy, we modify the Lévy flight scheme of CS approach, that is, all the solutions of the new population produced by GA approach are adapted to Lévy flight scheme in each generation. The detailed implementation procedure of the pro-HGA approach is shown in Figure 2.

#### 5. Numerical experiment

In numerical experiment, five scales of the iSC network are considered. The detailed information of the facilities consid-

**procedure:** pro-HGA approach

```

begin
   $x_{best} = 0$ 
   $t \leftarrow 0$ ; //  $t$ : generation number
  initialize population  $P(t)$  from  $n$  host nest  $x_i$  ( $i = 1, 2, \dots, n$ );
  while (not stop condition)
    create  $O(t)$  from  $P(t)$  by crossover and mutation routines;
    evaluate  $O(t)$  and store the best solution  $x_{Gbest}$ ;
    for each solution  $x_i$  of  $O(t)$  do
      generate a new solution  $x_{Levy}$  from the  $x_i$  by applying Lévy flight
      scheme;
      randomly choose a solution  $x_i$  among  $O(t)$ ;
      if ( $F(x_{Levy}) > F(x_i)$ ) then
         $C(t) \leftarrow x_{Levy}$  //  $C(t)$ : population of CS
      end
    end
    a fraction ( $p_a$ ) of worst solutions is abandoned;
    randomly regenerate new solutions  $x_{fra}$  as many as the fraction;
     $C(t) \leftarrow x_{fra}$ 
    evaluate  $C(t)$  and store the best solution  $x_{Cbest}$ ;
    if ( $F(x_{Gbest}) > F(x_{Cbest})$ ) then
       $x_{best} \leftarrow x_{Gbest}$ 
    else
       $x_{best} \leftarrow x_{Cbest}$ 
    end
    produce new  $P(t)$  using  $O(t)$  and  $C(t)$  by selection routine;
     $t \leftarrow t+1$ ;
  end
output: the best solution  $x_{best}$ ;
end

```

Figure 2: Detailed implementation procedure of the pro-HGA approach

Table 1: Five scales of the iSC network

Scale	Supp-ler	Manuf-acturer	DC	Reta-iler	Cust-omer
1	3	2	3	2	5
2	6	4	6	4	10
3	12	8	12	8	15
4	24	12	24	12	20
5	36	15	36	15	30

ered at each stage is shown in Table 1.

For example, in scale 1 of Table 1, three suppliers and DCs, two manufactures and retailers and five customers are considered. For comparing the performance of the pro-HGA approach, some conventional approaches are also used and their detailed information are summarized in Table 2.

All the approaches, except for LINGO, are programmed by

Table 2: Each approach for comparison

Approach	Description
GA	GA by Gen and Cheng [2000]
HGA1	HGA with GA and CS by Kanagaraj [2013]
HGA2	HGA with GA and TS by Xinyu and Liang [2016]
pro-HGA	Proposed HGA with GA and CS
LINGO	Optimization solver by Lindo [2015]

Table 3: Measures of performances

Measure	Description
Best Solution (BS)	Best solution in all trials
Average Solution (AS)	Values averaged over all trials
Average Iteration (AI)	Number of iterations averaged over all trials
Average Time (AT)	CPU time averaged over all trials
Percentage Different (P/D)	Performance difference between a approach and LINGO in terms of the BS

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, HGA1, HGA2 and pro-HGA approaches are as following: total numbers of generations is 2,000, population size 30, crossover rate 0.5, and mutation rate 0.2. These initial parameter values were obtained by fine tuning procedure of each approach. Number of host nest ( $n$ ) is 20,  $\alpha = 1$ ,  $p_a = 0.25$  for the search of CS approach used in the HGA1 and pro-HGA approaches [Kanagaraj et al., 2013].  $CO_{2A} = 1.15$  for  $CO_2$  emission used in Equation (9). Total 30 independent trials were carried out to eliminate the randomness of the

search process of each approach. The performances of all the approaches are compared using various measures as shown in Table 3.

Using the five scales in Table 1, the computation results of all approaches are shown in Tables 4, 5 and 6. In Scale 1, all the approaches including the pro-HGA approach locate the optimal solution in terms of the BS and AS. Also, all of them find the optimal solution at the first generation in terms of the AI. However, in terms of the AT, except the LINGO, the GA and HGA1 approaches are the quickest and the HGA2 approach is the slowest. Similar to Scale 1, in Scale 2, all the approaches locate the optimal solution in terms of the BS and AS. However, in

Table 4: Computation results using Scales 1 and 2

	Scale 1					Scale 2				
	GA	HGA1	HGA2	pro-HGA	LINGO	GA	HGA1	HGA2	pro-HGA	LINGO
BS	77,523	77,523	77,523	77,523	77,523	87,933	87,933	87,933	87,933	87,932
AS	77,523	77,523	77,523	77,523	–	87,933	87,933	87,933	87,933	–
AI	1	1	1	1	–	17	21	11	5	–
AT	3.53	3.57	181.34	7.92	0.21	3.82	3.93	293.17	4.18	0.20
P/D	0 %	0 %	0 %	0 %	–	0 %	0 %	0 %	0 %	–

Table 5: Computation results using Scales 3 and 4

	Scale 3					Scale 4				
	GA	HGA1	HGA2	pro-HGA	LINGO	GA	HGA1	HGA2	pro-HGA	LINGO
BS	98,752	98,285	98,376	98,285	102,725	109,475	109,278	109,278	109,089	113,061
AS	100,101	99,983	100,038	100,050	–	109,743	109,719	109,887	109,817	–
AI	21	25	16	3	–	17	13	57	23	–
AT	3.94	3.97	455.77	8.59	0.20	4.03	4.23	588.10	8.06	0.28
P/D	–3.87 %	–4.32 %	–4.23 %	–4.32 %	–	–3.17 %	–3.35 %	–3.35 %	–3.51 %	–

Table 6: Computation results using Scale 5

	Scale 5				
	GA	HGA1	HGA2	pro-HGA	LINGO
BS	136,086	136,045	136,045	135,829	181,752
AS	136,435	136,430	136,422	135,893	–
AI	29	7	137	127	–
AT	4.07	4.28	760.1	8.43	0.36
P/D	–25.13 %	–25.15 %	–25.15 %	–25.27 %	–

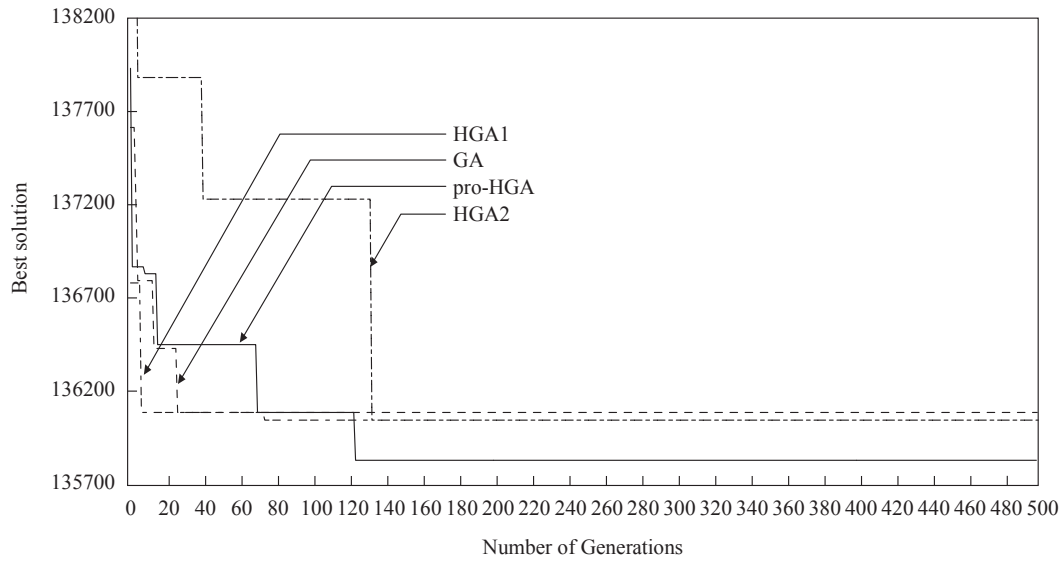


Figure 3: Convergence behaviours of each approach in scale 5

terms of the AI, the performance of the pro-HGA approach is superior to those the GA, HGA1 and HGA2 approaches. In terms of the AT, the GA, HGA1 and pro-HGA approaches show similar performances and they outperform the HGA2 approach.

In Scale 3 of Table 5, the HGA1 and pro-HGA approaches have the same performance, and their performances are slightly better than those of the GA and HGA2 approaches in terms of the BS. In terms of the P/D, the performances of the HGA1 and pro-HGA approaches are 0.09 % and 4.5 % advantageous than those of the HGA1 and GA approaches, respectively. In terms of the AI, the pro-HGA approach has significantly better performance than the others. However, in terms of the AS, the GA and HGA1 approaches show to be better performances than the pro-HGA approach. In Scale 4, the pro-HGA approach shows to be slightly better performances than the others in terms of BS and AS. In terms of the P/D, the differences of the GA, HGA1, HGA2, and pro-HGA approaches are respectively -3.17 %, -3.35 %, -3.35 %, and -3.51 %, when compared with the performance of the LINGO, which shows that the pro-HGA approach outperforms the others. In terms of the AI and AT, it can be seen that the performances of the GA and HGA1 are slightly superior to that of the pro-HGA approach and significantly better than that of the HGA2 ap-

proach.

In Scale 5 of the Table 6, the pro-HGA approach shows to be better performances in terms of the BS, AS, and P/D than the GA, HGA1 and HGA2 approaches. In terms of the AI, the HGA1 approach is the quickest and the HGA2 approach is the slowest. The average search time to optimal solution shows that the GA and HGA1 approaches are about two times quicker than the pro-HGA approach, and the HGA2 approach is the slowest.

For more various comparison, Figure 3 shows the convergence behaviours of the GA, HGA1, HGA2, and pro-HGA approaches until the generation number is reached to 500 in Scale 5.

In Figure 3, the GA and HGA1 approaches are quickly converged until about 30 generations, and the HGA2 approach shows a quick convergence behaviours until about 140 generations. However, after the generations, the GA, HGA1 and HGA2 approaches do not shows any convergence behaviours at all. The pro-HGA approach shows a quick convergence behaviours until about 125 generations and after that, its performance is better than the GA, HGA1 and HGA2 approaches.

Using the analysed results of Tables 4, 5 and 6 and the Figure 3, the following conclusions can be reached.

Table 7: Performances according to the changes of CO<sub>2</sub> emission amount

	1.00	1.05	1.10	1.15	1.20	1.25	1.30
<i>TTC</i>	86,360	90,678	94,996	99,314	103,632	107,950	112,267
<i>THC</i>	48,440	48,440	48,440	48,440	48,440	48,440	48,440
<i>TFC</i>	6,917	6,917	6,917	6,917	6,917	6,917	6,917
<i>TC</i>	141,717	146,035	150,353	154,671	158,989	163,307	167,624
Difference*	0.0 %	3.0 %	6.1 %	9.1 %	12.2 %	15.2 %	18.3 %

Note: \* Difference = each *TC* / (*TC* in CO<sub>2</sub> emission amount = 1.00)



- The pro-HGA approach proposed in this paper shows to be better performance in terms of the BS than the GA, HGA1 and HGA2 approaches, which indicates that the search scheme used in the pro-HGA approach is more efficient than those used in the others, though the former does not show any other strongpoints in terms of the AS and AI rather than the latter.
- The search speed of the pro-HGA approach is about two times slower than those of the GA, HGA1 and HGA2 approaches in terms of the AT. This means that the pro-HGA approach requires more computation times to find optimal solution than the others.

Table 7 shows the performances on the changes of CO<sub>2</sub> emission amount when its ratio is increased from 1.00 to 1.30 by 5%. The results of the *THC* and *TFC* are not changed, but the *TTC* is changed over all the ratios, since the amount of CO<sub>2</sub> emission have directly influence on the *TTC*. The 'Difference' shows that *TC* is increased by about 3% whenever the CO<sub>2</sub> emission amount is increased by 5%. This result indicates that, if we want to decrease the CO<sub>2</sub> emission amount for constructing environmentally-friendly supply chain network, the total cost of operating the network should be also increased.

## 6. Conclusion

In this paper, we have designed an environmentally-friendly supply chain network, called the iSC network. The structure of the iSC network is consisted of suppliers, manufacturers, DCs, retailers and customers at each stage. A mathematical formulation has been suggested for representing the iSC network, and it has been implemented using the pro-HGA approach with GA and CS approaches. In numerical experiments, five scales of the iSC network have been presented for comparing the performances of the pro-HGA with other competing approaches using various measures. Experimental results have shown that the pro-HGA approach outperforms the others.

The main objective of this paper is to consider CO<sub>2</sub> emission amount as a constraint for constructing environmentally-friendly supply chain network, since most of the conventional studies mentioned in Section 1 have not been considered it. Also we have confirmed the increase and decrease of *TC* according to the changes of CO<sub>2</sub> emission amount, which means that we can design more environmentally-friendly supply chain network if the increase of *TC* is permitted.

However, larger-scaled iSC networks will be tested and more various HGA approaches using particle swarm optimization (PSO), Tabu search, etc., will be considered for comparing the performance of the pro-HGA approach. This will be left to our future study.

## Acknowledgements

This work is supported by the National Research Founda-

tion of Korea Grant funded by Korean Government (NRF-2017R1A2B1010064).

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(Received April 13, 2018; accepted May 2, 2018)