Hybrid Genetic Algorithm for Optimizing the Closed-Loop Supply Chain Model with Direct Shipment and Delivery

Young Su Yun* · Anudari Chuluunsukh · Xing Chen
Department of Business Administration, Chosun University, Gwangju 61452, Korea
(Received 20 February 2018 : revised 1 May 2018 : accepted 8 May 2018)

Recently, product purchases online or in a mobile environment have been rapidly increasing with the development of IT-based technology. When the product purchase environment changes, the structure of the closed-loop supply chain (CLSC) model should also be changed by applying various transportation types, such as normal delivery (NDL) direct shipment (DSP) and direct delivery (DDL). Therefore, in this study, a CLSC model considering NDL, DSP and DDL is proposed. The CLSC model is represented in a mathematical formulation and is implemented using a hybrid genetic algorithm (HGA) approach that combines the genetic algorithm approach with the Tabu search approach. In a numerical experiment, five scales of the CLSC model are presented to compare the performance of the proposed HGA approach with those of some conventional approaches under various performance measures. Experimental results show that the proposed HGA approach outperforms the other competing conventional approaches.

PACS numbers: 89.20.Ff
Keywords: Closed loop supply chain, Hybrid genetic algorithm, Tabu search, Direct shipment, Direct delivery

I. INTRODUCTION

Recently, business environment has becoming increasingly difficult and complicate due to intensified competition, shorter product life cycle, the change of customer preference, and the environment regulation of government. These difficulties and complications have also influenced on the design of closed-loop supply chain (CLSC) model. Surana et al. [1] suggested that most of supply chain models including the CLSC should be treated as a complex adaptive system, and various methodologies for solving them are based on the fields of nonlinear dynamics, statistical physics and information theory. Therefore, in this paper, we propose a hybrid genetic algorithm (P-HGA) approach for efficiently designing a difficult and complicate CLSC model with direct shipment and delivery.

Generally, the CLSC model composes of forward logistics (FL) and reverse logistics (RL). In the FL, raw materials are transported to manufacturers from suppliers and manufacturers produce products. The products are delivered to customers ultimately through distribution center and retailer. In the RL, the products returned from customers are classified as recoverable products, recoverable modules, and unrecoverable modules at collection center. They are respectively transported to recovery center, module manufacturer and waste disposal center for reuse, recycling and waste disposal.

Recently, product purchase under online or mobile environment has been rapidly increasing along with the development of IT-based technology. Therefore, considering the change of the product purchase environment, the conventional CLSC model should be improved by applying various transportation types such as normal delivery (NDL) direct shipment (DSP) and direct delivery (DDL). The process of the NDL in the CLSC model starts from supplier. Raw materials are transported from supplier to manufacturer, the products produced at manufacturer are transported to retailer through distribution center, and then finally delivered to customer. The process of the DSP refers to the situation that the products produced at manufacturer are directly shipped to

*E-mail: ysyun@chosun.ac.kr

This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (http://creativecommons.org/licenses/by-nc/3.0) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.
retailer or customer not via DC. The DDL means the situation that the products at DC are directly delivered to customer not via retailer. There are many literatures considering the NDL, DSP and DDL.

Chiang et al. [2] analyzed a dual-channel supply chain design problem strategically. The products produced at manufacturer are directly shipped to customer through retailer by the DSP. In this study, they suggested that retailers should use the DSP efficiently and strategically. Chiang and Monahan [3] suggested a two-echelon dual-channel supply chain design problem. In this study, they focused three scenarios for transportation process: i) first scenario is to consider a situation that products are shipped to customer from manufacturer through retailer by the NDL, ii) in second scenario, products are directly shipped to customer from manufacturer by the DSP, and iii) in the final scenario, products are shipped to customer from manufacturer by both the NDL and DSP. The experimental result using the three scenarios showed that using both the NDL and DSP is more efficient than using the NDL or DSP alone. Hua et al. [4] focused on product price and lead time in a dual-channel supply chain design problem. They analyzed how the scenarios differ in terms of product price and lead time using the NDL, DSP and DDL. The experimental result showed that a relative use of the NDL, DSP and DDL is effective in controlling product price and lead time.

By analyzing the previous studies mentioned above, they all considered the NDL, DSP and DDL for transporting products in the FL, whereas, they did not consider the NDL, DSP and DDL in the RL or CLSC model. Therefore, in this paper, we develop an improved CLSC model with the NDL, DSP and DDL altogether. Since most of complicated network models like the CLSC model have been known as NP-complete problem [5,6], meta-heuristics such as genetic algorithm (GA) approach have been applied to solve them efficiently. However, GA approach sometimes fails to achieve global optimal solution because of its premature convergence property or the lack of local search scheme. To cope with these weaknesses, we propose the P-HGA approach that combines GA approach and Tabu search (TS) approach in order to solve the CLSC model with the NDL, DSP and DDL altogether.

In Sec. II, the CLSC model with the NDL, DSP and DDL is introduced. A mathematical formulation for effectively representing the CLSC model is suggested in Sec. III. The P-HGA approach is implemented to solve the CLSC model in Sec. IV. In Sec. V, the numerical experiments using several scales of the CLSC model is done for proving the efficiency of the P-HGA approach. Finally, some conclusions are summarized in Sec. VI.

II. PROPOSED CLSC MODEL

In this section, we design the structure of the CLSC model with the NDL, DSP and DDL altogether. First, for the FL, part supplier (PS), module manufacturer (MM), product manufacturer (PM), distribution center (DC) and retailer/customer (R/C) are considered. The parts and products are transported by the NDL in the route (PS → MM → PM → DC → R/C), but some products are directly shipped to R/C from the PM by the DSP. Secondly, for the RL, collection center (CC), recovery center (RC), redistribution center (RD), secondary market (SM), waste disposal center (WDC) are taken into consideration. The returned product from R/C are collected at the CC and they are classified into reusable products, recoverable products, recoverable modules, and unrecoverable modules.

The reusable products are directly delivered to the RD by the DDL. The recoverable products are recovered at the RC and transported to the SM through the RD by the NDL. The recoverable models are transported to the MM by the NDL so that they are reused for producing product. The unrecoverable modules are transported to the WDC for waste disposal by the NDL. The recovered products at the RC are directly shipped to the SM by the DSP. The conceptual network flow of the CLSC model is shown in Fig. 1.

III. MATHEMATICAL FORMULATION

Before presenting the mathematical formulation, some assumptions for representing the CLSC model are considered as follows.

- The production of single product is only considered.
• The numbers of facility at each stage are already known. Among them, only one facility of the PSs, MMs, PMs, DCs, CCs, RCs, and RDs should be opened at each stage, whereas, all facilities of the R/Cs, SMs, and WDCs are always opened.

• Fixed costs for operating the facilities opened at each stage are different and already known.

• Unit handling costs of the facilities opened at each stage are already known and are identical at the same stage.

• Unit transportation costs between each facility of each stage are already known and are different.

• All of the returned products from R/C are collected at the CC.

• The quality of the recovered products at the RC and that of the recoverable modules from the CC are identical with those of new products and modules.

The index sets, parameters and decision variables are set as follows:

**Index Set**
- $t$: index of the PS, $t \in T$
- $a$: index of area of the PS, $a \in A$
- $m$: index of the MM, $m \in M$
- $p$: index of the PM, $p \in P$
- $e$: index of the DC, $e \in E$
- $r$: index of the R/C, $r \in R$
- $c$: index of the CC, $c \in C$
- $v$: index of the RC, $v \in V$
- $d$: index of the RD, $d \in D$
- $s$: index of the SM, $s \in S$
- $z$: index of the WDC, $z \in Z$

**Parameters**
- $FCS_{ta}$: fixed cost at the PS $t$ of area $a$
- $FCM_{m}$: fixed cost at the MM $m$
- $FCP_{p}$: fixed cost at the PM $p$
- $FCD_{e}$: fixed cost at the DC $e$
- $FCC_{c}$: fixed cost at the CC $c$
- $FCR_{v}$: fixed cost at the RC $v$
- $FCI_{d}$: fixed cost at the RD $d$
- $HCS_{ta}$: unit handling cost at the PS $t$ of area $a$
- $HCM_{m}$: unit handling cost at the MM $m$
- $HCP_{p}$: unit handling cost at the PM $p$
$HCD_e$: unit handling cost at the DC $e$

$HCC_c$: unit handling cost at the CC $c$

$HCR_v$: unit handling cost at the RC $v$

$HCL_d$: unit handling cost at the RD $d$

$TCSM_{tam}$: unit transportation cost from the PS $t$ of area $a$ to the MM $m$

$TCSP_{top}$: unit transportation cost from the PS $t$ of area $a$ to the PM $p$

$TCMP_{mp}$: unit transportation cost from the MM $m$ to the PM $p$

$TCPD_{pe}$: unit transportation cost from the PM $p$ to the DC $e$

$TCPR_{pr}$: unit transportation cost from the PM $p$ to R/C $r$

$TCDR_{cr}$: unit transportation cost from the DC $e$ to R/C $r$

$TCCR_{rc}$: unit transportation cost from the R/C $r$ to the CC $c$

$TCCM_{cm}$: unit transportation cost from the CC $c$ to the MM $m$

$TCCR_{cr}$: unit transportation cost from the CC $c$ to the RC $v$

$TCCI_{cd}$: unit transportation cost from the CC $c$ to the RD $d$

$TCCW_{cz}$: unit transportation cost from the CC $c$ to the WDC $z$

$TCRR_{rd}$: unit transportation cost from the RC $v$ to the RD $d$

$TCRS_{vs}$: unit transportation cost from the RC $v$ to the SM $s$

$TCRS_{ds}$: unit transportation cost from the RD $d$ to the SM $s$

**Decision variables**

$s_{ta}$: handling capacity at the PS $t$ of area $a$

$m_{ma}$: handling capacity at the MM $m$

$p_{pa}$: handling capacity at the PM $p$

$e_{ce}$: handling capacity at the DC $e$

$r_{re}$: handling capacity at the R/C $r$

$c_{ce}$: handling capacity at the CC $c$

$v_{ve}$: handling capacity at the RC $v$

$d_{de}$: handling capacity at the RD $d$

$s_{sa}$: handling capacity at the SM $s$

$z_{ze}$: handling capacity at the WDC $z$

$x_{sta} = \begin{cases} 
1, & \text{if the PS } t \text{ of area } a \text{ is opened} \\
0, & \text{otherwise}
\end{cases}$

$x_{op} = \begin{cases} 
1, & \text{if the PM } p \text{ is opened} \\
0, & \text{otherwise}
\end{cases}$

$x_{de} = \begin{cases} 
1, & \text{if the DC } e \text{ is opened} \\
0, & \text{otherwise}
\end{cases}$

$x_{cc} = \begin{cases} 
1, & \text{if the CC } c \text{ is opened} \\
0, & \text{otherwise}
\end{cases}$

$x_{rv} = \begin{cases} 
1, & \text{if the RC } v \text{ is opened} \\
0, & \text{otherwise}
\end{cases}$

$x_{rd} = \begin{cases} 
1, & \text{if the RD } d \text{ is opened} \\
0, & \text{otherwise}
\end{cases}$

The objective function for the CLSC model is to minimize the total cost ($TC$) which consists of total fixed cost ($TF$), total handling cost ($TH$) and total transportation cost ($TT$) under satisfying various constraints, which can be expressed as Eq. 1 through (32).

$$\text{Minimize } TC = TT + TF + TT$$

$$TT = \sum_a \sum_t \sum_m (TCSM_{tam} \cdot s_{ta} \cdot x_{sta} \cdot x_{om_m}) + \sum_a \sum_p \sum_p (TCS_{top} \cdot s_{ta} \cdot x_{op} \cdot x_{op}) + \sum_m \sum_p (TCMP_{mp} \cdot m_{ma} \cdot x_{om_m} \cdot x_{op}) + \sum_p \sum_p (TCPD_{pe} \cdot p_{pa} \cdot x_{op} \cdot x_{op}) + \sum_p \sum_p (TCPR_{pr} \cdot p_{pa} \cdot x_{op} \cdot x_{op}) + \sum_p \sum_p (TCDR_{cr} \cdot d_{de} \cdot x_{de} \cdot x_{de}) + \sum_p \sum_p (TCCR_{rc} \cdot d_{de} \cdot x_{de} \cdot x_{de}) + \sum_{x_{om_m}} (TCCI_{cd} \cdot c_{ce} \cdot x_{cc} \cdot x_{cc}) + \sum_{x_{om_m}} (TCCW_{cz} \cdot c_{ce} \cdot x_{cc} \cdot x_{cc}) + \sum_{x_{om_m}} (TCRR_{rd} \cdot r_{re} \cdot x_{re} \cdot x_{re}) + \sum_{x_{om_m}} (TCRS_{vs} \cdot r_{re} \cdot x_{re} \cdot x_{re}) + \sum_{x_{om_m}} (TCRS_{ds} \cdot d_{de} \cdot x_{de} \cdot x_{de}) \quad (1)$$

$$F = \sum_a \sum_t (FCS_{sta} \cdot s_{ta} \cdot x_{sta}) + \sum_m (FCM_{cm} \cdot x_{om_m}) + \sum_p (FCP_{pa} \cdot x_{op}) + \sum_e (FCD_{ce} \cdot x_{de}) + \sum_s (FCR_{ve} \cdot x_{re}) + \sum_d (FDI_d \cdot x_{de}) \quad (2)$$

$$H = HCS_{sst} \sum_a (s_{ta} \cdot x_{sta}) + HC_{M_{cm}} \sum_m (m_{ma} \cdot x_{om_m}) + HCP_{pa} \sum_p (p_{pa} \cdot x_{op}) + HCD_{ce} \sum_e (e_{ce} \cdot x_{de}) + HCC_{ve} \sum_s (e_{ce} \cdot x_{re}) + HCR_{ve} \sum_d (e_{ce} \cdot x_{re}) \quad (3)$$

$$H = HCS_{sst} \sum_a (s_{ta} \cdot x_{sta}) + HC_{M_{cm}} \sum_m (m_{ma} \cdot x_{om_m}) + HCP_{pa} \sum_p (p_{pa} \cdot x_{op}) + HCD_{ce} \sum_e (e_{ce} \cdot x_{de}) + HCC_{ve} \sum_s (e_{ce} \cdot x_{re}) + HCR_{ve} \sum_d (e_{ce} \cdot x_{re}) \quad (4)$$
Subject to

\[ \Sigma_{ta}xos_{ta} = 1, \quad \forall t \in T \]  

(5)

\[ \Sigma_{m}xom_{m} = 1 \]  

(6)

\[ \Sigma_{p}xop_{p} = 1 \]  

(7)

\[ \Sigma_{c}xoc_{c} = 1 \]  

(8)

\[ \Sigma_{v}xor_{v} = 1 \]  

(9)

\[ \Sigma_{d}xod_{d} = 1 \]  

(10)

\[ \Sigma_{at}(hs_{at} \cdot xos_{at}) - \Sigma_{m}(hm_{m} \cdot pxo) = 0, \forall t \in T \]  

(11)

\[ \Sigma_{at}(hs_{at} \cdot xos_{at}) - \Sigma_{p}(hp_{p} \cdot xop_{p}) = 0 \]  

(12)

\[ \Sigma_{m}(hm_{m} \cdot xom_{m}) - \Sigma_{p}(hp_{p} \cdot xop_{p}) = 0 \]  

(13)

\[ a_{1}\%\Sigma_{p}(hp_{p} \cdot xop_{p}) - \Sigma_{c}(hd_{c} \cdot xod_{c}) = 0 \]  

(14)

\[ a_{2}\%\Sigma_{p}(hp_{p} \cdot xop_{p}) - \Sigma_{v}hr_{v} = 0 \]  

(15)

\[ a_{3}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) - \Sigma_{c}(hd_{c} \cdot xod_{c}) = 0 \]  

(16)

\[ a_{4}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) = \Sigma_{c}hr_{c} \leq 0 \]  

(17)

\[ a_{5}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) = \Sigma_{c}hr_{c} \geq 0 \]  

(18)

\[ a_{6}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) - \Sigma_{c}hs_{c} \geq 0 \]  

(19)

\[ a_{7}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) - \Sigma_{c}hs_{c} \leq 0 \]  

(20)

\[ a_{8}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) = \Sigma_{c}hs_{c} \leq 0 \]  

(21)

\[ a_{9}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) = \Sigma_{c}hs_{c} \geq 0 \]  

(22)

\[ a_{10}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) = \Sigma_{c}hs_{c} \leq 0 \]  

(23)

\[ a_{11}\%\Sigma_{c}(hc_{c} \cdot xoc_{c}) = \Sigma_{c}hs_{c} \geq 0 \]  

(24)

\[ xos_{ta} = \{0, 1\}, \quad t \in T, a \in A \]  

(25)

\[ xom_{m} = \{0, 1\}, \quad \forall m \in M \]  

(26)

\[ xop_{p} = \{0, 1\}, \quad \forall p \in P \]  

(27)

\[ xod_{d} = \{0, 1\}, \quad \forall d \in D \]  

(28)

\[ xoc_{c} = \{0, 1\}, \quad \forall c \in C \]  

(29)

\[ xor_{v} = \{0, 1\}, \quad \forall v \in V \]  

(30)

\[ xod_{d} = \{0, 1\}, \quad \forall d \in D \]  

(31)

\[ xos_{ta}, xom_{m}, xop_{p}, xod_{d}, xoc_{c}, xor_{v}, xod_{d} \geq 0, \quad \forall t \in T, a \in A, m \in M, p \in P, c \in C, e \in E, c \in C, v \in V, \]  

\[ d \in D, s \in S, z \in Z \]  

(32)

Eq. (1) is the objective function composed of the TT, TH, and TF using Eq. (2) through (4). Eq. (5) through (11) mean that only one facility should be opened at each stage. Eq. (12) though (18) show that the amount received from previous stage is the same as the treatment capacity at current stage. Eq. (19) though (24) imply that the handling capacity at current stage is the same or greater than that at the next stage. Eq. (25) to (31) show that each decision variable should take value 0 or 1. Eq. (32) means Non-negativity.

IV. PROPOSED P-HGA APPROACH

Since the proposed P-HGA approach combines a GA approach for global search with a TS approach for local search, we first examined some conventional HGAs using GA and TS approaches [7–9]. Xinyu and Liang [7] suggested the HGA approach combining GA and TS for flexible job shop scheduling problem. Its implementation procedure is as follows. First step is to randomly generate an initial population and search the current solution using the population. In second step, if the current solution is not the optimal solution, then create a new population (offspring) using GA approach. In third step, neighborhood group is produced using all individuals of the offspring and the most excellent individual within the neighborhood group is stored in Tabu list. This procedure is repeated until the Tabu list is filled. Finally, the best solution is located within the Tabu list. However, this HGA approach has some weaknesses. First, the search speed is relatively slow; since the neighborhood search procedure is applied to all individuals. Secondly, global search ability using the GA approach is reduced, due to the use of Tabu list using the initial population for producing offspring of the next generation.

Similar study was also performed by Zhang et al. [8]. Their search process is as follows. First, an initial population is randomly generated. Secondly, a TS procedure is applied to all individuals of the initial population until Tabu list is filled. Thirdly, all the individuals in the Tabu list are used as parent population of GA and GA operators is adapted to produce offspring population. Finally, these procedures are repeated until a pre-determined stop condition is satisfied and find the optimal solution. However, this study has a weakness as follows: the search speed becomes very slower since neighborhood search is adapted to all individuals of population. Also, the completion of TS List using initial population may make the search of the optimal solution using GA very difficult, when considering the large-scaled search space such as the CLSC model. In
general, for effectively constructing the HGA approach using GA and TS approaches, GA approach is firstly adapted and then TS approach is applied to the population using GA approach.

Kurahashi and Terano [9] proposed a HGA approach using GA and TS for the problem of multi-model and multi-objective function optimization. First, initial population is randomly generated. Secondly, a neighborhood search scheme is adapted to one of the individuals of the initial population and the new individual is stored into a long-term list or short-term list. This process is repeated until the long-term list and short-term list are filled. Thirdly, a parent population for GA approach is generated using the individuals in the long-term list and a short-term list. Finally, GA operators is performed and best solution is find. Similar to Xinyu and Liang [7], this HGA approach has a difficulty in finding global optimal solution when it is applied to the problem with large-scaled search space search such as the CLSC model.

The previous studies mentioned above have been applied to solving various optimization problems by designing HGA approaches which combine GA with TS approaches. However the conventional HGA approaches has the following limitations. First, their search schemes are time-consuming, since the neighborhood search for TS approach is adapted to all individuals in population. Secondly, GA search ability to find global optimal solution is deteriorated, due to the generation of Tabu list using initial population.

To cope with the limitations of the previous studies, we propose a new HGA approach (P-HGA) using GA and TS approaches for optimizing the CLSC model. The scheme of the P-HGA approach is as follows. First, the size of the Tabu list is defined and an arbitrary solution $M$ ($M$ is the big solution) inserted to the Tabu list. Secondly, an initial population for GA is generated randomly and it is used as the parent population of GA. Thirdly, GA operators (two-point crossover, random mutation operator, and elitist selection in enlarged sampling space) is adapted to the parent population and produce an offspring. Fourthly, the best individual from the offspring is selected and neighborhood search for TS is applied. If the fitness value of the best individual is greater than that of the $M$, then the best individual is stored in the Tabu list, and this process is repeated until the Tabu list is filled. Fifthly, a new parent population using the offspring and Tabu list is produced for the next generation.

All the procedure is repeated until a pre-defined stop condition is satisfied and finally optimal solution is located. The detailed implementation procedure for the P-HGA approach is as follows.

**Procedure: P-HGA Approach**

**Input:** problem data, GA parameters, TS parameters Set, Tabu list

**Output:** best solution

**Begin**

$best\_S \leftarrow 0$ // $best\_S$: Initial solution

$k \leftarrow 1$ // $k$: generation number

generate initial population $P(k)/P(k)$: parent population

while (not stop condition)

create $O(k)$ from $P(k)$ by crossover operators; // $O(k)$: offspring

create $O(k)$ from $P(k)$ by mutation operators; evaluate $O(k)$;

[Tabu List] $\leftarrow M$ // $M$: big solution

while [Tabu list] is full

randomly select an individual $Vb$ from $O(k)$;

generate a group using neighborhood structure from $Vb$;

select a best individual $Vb\_best$ from the group;

if $M$ in [Tabu list] $< Vb\_best$ then

[Tabu list] $\leftarrow Vb\_best$

end

end

produce $P(k + 1)$ from [Tabu list] and $O(k)$ by selection scheme;

$k \leftarrow k + 1$

store current best solution $S$ from $P(k + 1)$;

if $best\_S < S$ then

$best\_S \leftarrow S$

end

end

output $best\_S$

**end**
Table 1. Five Scales for the CLSC Model.

<table>
<thead>
<tr>
<th>Scale</th>
<th>PS 1</th>
<th>PS 2</th>
<th>PS 3</th>
<th>PS 4</th>
<th>MM</th>
<th>PM</th>
<th>DC</th>
<th>R/C</th>
<th>CC</th>
<th>RC</th>
<th>RD</th>
<th>SM</th>
<th>WDC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>10</td>
<td>5</td>
<td>3</td>
<td>3</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>8</td>
<td>10</td>
<td>8</td>
<td>15</td>
<td>10</td>
<td>8</td>
<td>8</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>12</td>
<td>15</td>
<td>12</td>
<td>20</td>
<td>15</td>
<td>12</td>
<td>12</td>
<td>15</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>15</td>
<td>20</td>
<td>15</td>
<td>25</td>
<td>20</td>
<td>15</td>
<td>15</td>
<td>20</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>18</td>
<td>25</td>
<td>18</td>
<td>30</td>
<td>25</td>
<td>18</td>
<td>18</td>
<td>30</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 2. Each approach for comparison.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS</td>
<td>TS by Glover et al. [10]</td>
</tr>
<tr>
<td>GA</td>
<td>GA by Gen and Cheng [6]</td>
</tr>
<tr>
<td>HGA1</td>
<td>HGA with GA and TS by Xinyu and Liang [7]</td>
</tr>
<tr>
<td>HGA2</td>
<td>HGA with GA and TS by Zhang et al. [8]</td>
</tr>
<tr>
<td>P-HGA</td>
<td>Proposed HGA with GA and TS in this paper</td>
</tr>
<tr>
<td>LINGO</td>
<td>Optimization solver by Lindo [11]</td>
</tr>
</tbody>
</table>

V. NUMERICAL EXPERIMENT

In numerical experiment, five scales of the CLSC model are considered. The detailed information of the facilities considered at each stage is shown in Table 1. For example, in scale 1, five PSs, PMs and CCs and three MMs, DCs, RCs and RDs are considered and one of them at each stage will be opened and the others are closed. However, all facilities of R/C, SMs, and WDCs are always opened. For comparing the performance of the P-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 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 P-HGA approaches are as following: total numbers of generations is 1,000, population size 20, crossover rate 0.3, and mutation rate 0.2. Total 30 independent runs were carried out to eliminate the randomness in the search process of each approach. The performances of all the approaches are compared using various measures of performance as shown in Table 3.

Using the five scales in Table 1, the computation results of all approaches are shown in Tables 4 and 5.

Table 3. Measures of performances.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Solution</td>
<td>Best solution in all trials.</td>
</tr>
<tr>
<td>Average Solution</td>
<td>Averaged solution through all trails.</td>
</tr>
<tr>
<td>Average Iteration</td>
<td>Averaged number of iteration through all trails.</td>
</tr>
<tr>
<td>Average Time</td>
<td>Averaged CPU time through all trails.</td>
</tr>
<tr>
<td>Percentage Different</td>
<td>The difference of best solution of TS, GA, HGA1, HGA2, P-HGA when compared with that of LIN.</td>
</tr>
</tbody>
</table>

It has been already known that the result of best solution is the most important measure when comparing various approaches. In Scale 1, among the single approaches (TS and GA), the best solution of the GA approach is superior to that of the TS approach, and among the hybrid approaches (HGA1, HGA2 and P-HGA), that of the P-HGA approach is shown to be more efficient than those of the HGA1 and HGA2 approaches. Also in terms of the percentage difference, the performance of the P-HGA approach is 0.9% and 0.5% advantageous than those of the LINGO and HGA1 approach, respectively. In terms of the average solution, the P-HGA approach is shows to be a slightly better performance than the TS, GA, HGA1, and HGA2 approaches. However, the P-HGA approach shows a worse performance in term of average iteration and average time than the others. In the scale 2, based on LINGO, the P-HGA approach outperforms the TS, GA, HGA1 and HGA2 approaches in terms of best solution and average solution. In term of average time, the search speed of the TS approach is quicker than the GA approach, and the P-HGA approach has the best search speed when compare with the HGA1 and HGA2 approaches.
The HGA1 and HGA2 approaches including P-HGA approach shows various and quick convergence behaviors at initial generations and after about 150 generations, the HGA1 and HGA2 approaches do not shows any convergence behaviors. However, the P-HGA approach shows a better convergence behavior after about 900 generations.

VI. CONCLUSION

Most of the CLSC models used in the previous studies only considered the NDL for transporting and delivering products (or parts) through the FL and RL. Recently, a rapid increase of product purchase under on-line or mobile environment has prompted researchers to consider the DDL and DSP in the CLSC model. Therefore, in this paper, we have proposed new type of the CLSC model considering NDL, DDL and DSP altogether.

The proposed CLSC model considers various facilities such as part supplier, module manufacturer, distribution center, retailer, collection center and so on at each stage of the FL and RL. To represent the proposed CLSC model, a mathematical formulation has been suggested and it has been implemented using the P-HGA approach.
which combines GA and TS approaches. The P-HGA approach is an improved approach to overcome the weaknesses of the conventional HGA approaches with GA and TS approaches. In numerical experiments, five scales of the CLSC model have been presented to compare the performance of the P-HGA approach with those of the conventional approaches (GA, TS, HGA1 and HGA2). Various analyses have been done using various measures of performance and the analysis results have showed that i) the CLSC model with the NDL, DDL and DSP altogether outperforms that with the NDL alone and ii) the P-HGA approach shows to be better performances than the conventional GA, TS, HGA1 and HGA2 approaches. However, the scales of the CLSC model used in numerical experiment are relatively small-sized ones, thus larger-scaled network problems will be used to compare the performances of the CLSC models with the NDL, DDL and DSP and more various HGA approaches using particle swarm optimization and Cuckoo search etc. will be considered to compare the performance of the P-HGA approach. This will be left to our future study.

**ACKNOWLEDGEMENTS**

This study was supported by research fund from Chosun University, 2017.

**REFERENCES**