

Article

MDP

Sustainable Closed-Loop Supply Chain Design Problem: A Hybrid Genetic Algorithm Approach

YoungSu Yun^{1,*}, Anudari Chuluunsukh¹ and Mitsuo Gen²

- ¹ Department of Business Administration, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju 61452, Korea; anudr11@naver.com
- ² Fuzzy Logic Systems Institute, Tokyo University of Science, 1-3 Kagurazaka Shinjiku-ku, Tokyo 162-8601, Japan; gen@flsi.or
- * Correspondence: ysyun@chosun.ac.kr

Received: 4 November 2019; Accepted: 2 January 2020; Published: 4 January 2020



Abstract: In this paper, we propose a solution to the sustainable closed-loop supply chain (SCLSC) design problem. Three factors (economic, environmental, and social) are considered for the problem and the three following requirements are addressed while satisfying associated constraint conditions: (i) minimizing the total cost; (ii) minimizing the total amount of CO₂ emission during production and transportation of products; (iii) maximizing the social influence. Further, to ensure the efficient distribution of products through the SCLSC network, three types of distribution channels (normal delivery, direct delivery, and direct shipment) are considered, enabling a reformulation of the problem as a multi-objective optimization problem that can be solved using Pareto optimal solutions. A mathematical formulation is proposed for the problem, and it is solved using a hybrid genetic algorithm (pro-HGA) approach. The performance of the pro-HGA approach is compared with those of other conventional approaches at varying scales, and the performances of the SCLSC design problems with and without three types of distribution channels are also compared. Finally, we prove that the pro-HGA approach outperforms its competitors, and that the SCLSC design problem with three types of distribution channels is more efficient than that with a single distribution channel.

Keywords: sustainable closed-loop supply chain; multi-objective optimization; Pareto optimal solution; hybrid genetic algorithm; economic; environmental; social factors

1. Introduction

In general, closed-loop supply chain (CLSC) design problems are multi-stage networks endowed with various facilities of forward logistics (FL) and reverse logistics (RL) at each stage. In FL, finished products are provided to customers via manufacturers, distribution centers (DCs), and retailers. On the other hand, in RL, some of the products returned by customers are recovered after performing classification and recovery processes at the collection center and the recovery center, respectively, and the rest are disposed at the disposal center.

Among the major trends in CLSC design problems, the principle of sustainable development has become popular in conventional literatures [1–23]. According to this principle, economic, environmental, and social factors are usually considered for effectively constructing a sustainable CLSC (SCLSC) design problem.

The economic factors considered include the maximization of the total profit or the minimization of the total cost resulting from construction and operation processes of the CLSC design problem [4–8,16,17,20,22]. Wang and Hsu [5] developed a CLSC design problem to minimize the total cost, which is the aggregate of the total production cost, the total transportation cost, and the total fixed cost. In the CLSC design problem, the supplier, the manufacturer, the DC, and the customer are

considered in FL and the dismantler is considered in RL. Following Wang and Hsu [5]. The CLSC design problem by Devika et al. [1] also seeks to minimize the total cost which is the aggregate of the total manufacturing cost, the total transportation cost, the total handling cost, the total purchasing cost, the total opening cost, and the total sale revenue. On the other hand, the CLSC design problem by Chen et al. [6] seeks to maximize the total profit, which is the aggregate of the total revenue (=the total sale revenue of new product) and the total cost (=total processing cost + the total transportation cost + the total fixed cost).

The environmental factors usually considered include the minimization of the total amount or the cost of CO_2 or carbon emitted during the production and transportation of materials and products at each stage of the CLSC design problem [3,9,10,18,19,21]. The CLSC design problem by Paksoyet et al. [9] seeks to minimize the total cost of CO_2 emissions during the transportation of materials or products at each stage by raw material suppliers, plants, DCs, warehouses, and customers in FL and collection centers, repairing centers, dismantlers, decomposition centers, and final disposals in RL. Talaei et al. [10] showed a simple CLSC design problem to minimize the total amount of CO_2 emissions during the establishment of facilities, production and transportation of products, and disposal of waste products at each stage by the manufacturers and markets in FL and disposal centers, collection centers, and inspection centers in RL. Following Talaei et al. [10], Özceylan et al. [3] also showed a CLSC design problem for the automotive industry in Turkey. They minimized the total amount of CO_2 emissions during the transportation of finished products and returned products at each stage. The CLSC design problem by Fahimnia et al. [19] seeks to minimize total cost of carbon emitted during the production and transportation of products at each stage. The CLSC design problem by Fahimnia et al. [19] seeks to minimize total cost of carbon emitted during the production and transportation of products at each stage by manufacturers, warehouses, and end-users in FL and collection centers, recycling centers and disposal centers in RL.

The relevant social factors usually considered are metrics like the number of job opportunities created by introducing new technology, the number of lost days due to damage to work, and general unemployment [1–3,23]. Devika et al. [1] constructed a CLSC design problem to optimize various social influences (e.g., the number of newly created job opportunities, their job types, and damage to work caused either during the establishment of facilities or during the manufacture and handling of products). Özceylan et al. [3] also considered some social influences (e.g., the number of new job opportunities by introducing new technology and the number of lost days due to damage to work) in their CLSC design problem.

As mentioned above, economic, environmental, and social factors have been individually considered in various studies. However, few papers have considered all three factors simultaneously for the SCLSC design problem [1,3,11].

The SCLSC design problem presented by Devika et al. [1] represents a multi-objective optimization problem by considering the three factors to be objective functions. For the economic factor, the problem focused on the minimization of the total cost (=the sum of the costs of manufacture, transportation, handling, purchase and opening – the sum of sale revenues). For the environmental and social factors, the metrics considered were the minimization of the total cost (=the sum of environmental damages the sum of environmental advantages) and the maximization of the total number (=the sum of the number of the new job opportunity – the sum of the number of lost days due to damage to work), respectively. To solve the multi-objective optimization problem, a meta-heuristic approach using an imperialist competitive algorithm and a variable neighborhood search was used. By performing numerical experiments based on various problem scales, it was proven that the meta-heuristic approach outperforms certain conventional hybrid approaches. However, the search speed of the meta-heuristic approach became slower than those of the conventional hybrid approaches as the problem scales were increased. On the other hand, the SCLSC design problem by Özceylan et al. [3] was represented by a single-objective optimization problem, by using the economic factor as the only objective function, and the remaining two factors (environmental and social factors) as constraints. The maximization of total profit (=the sum of total revenues – the sum of total costs) served as the economic factor. The total

amount of CO_2 emissions as well as the number of job opportunities created and the number of lost days due to damage to work were considered as the environmental and social factors, respectively.

One of the motivations behind the constructions of CLSC design problems is to distribute materials and products efficiently via the CLSC network. Consideration of various distribution channels reinforces the efficiency of production and distribution in a CLSC design problem. In general, three types of distribution channels (normal delivery: NRD, direct delivery: DRD, and direct shipment: DRS) are considered in such a problem [6]. The NRD is generally recognized to be the most basic distribution channel and is used to send materials or products from one stage to an adjoining one. For example, products are sent from the manufacturer to the DC via the NRD in a CLSC design problem that consists of a supplier, a manufacturer, a DC, a retailer, a customer, a collection center and a recovery center. The distribution channel in which a certain quantity of the products can be sent from DC to the customer directly, without routing it through the retailer, is called a DRD. The channel that allows direct shipment from the manufacturer to the customer, without any involvement of the DC and the retailer is called a DRS.

CLSC design problems with the three types of distribution channels mentioned above have been considered in conventional literature [4,8,13–15]. The CLSC design problem by Cardoso et al. [14] consists of a plant, a warehouse, a retailer and a market. Certain products manufactured at the plant are sent to market through the warehouse and the retailer via the NRD, and some others are sent from the plant to the market, without being routed through the warehouse or the retailer, via DRS. The rest of the products at the warehouse are sent to the market via the DRD, without involving the retailer. The CLSC design problem by Son et al. [8] consists of an external supplier, a pre-manufacturing processor, a parts manufacturer, an end-product manufacturer, and a customer in FL, and a collector, a recycler, and a disposal unit in RL. Certain materials and products are sent from one stage to the next via the NRD, some others are sent from the external supplier to the parts manufacturer via the DRD without involving the pre-manufacturing processors. Varsei and Polyakovskiy [15] designed a CLSC design problem for the wine industry in Australia. The CLSC design problem consisted of a supplier, a winery, a bottling plant, a DC and a demand point at each stage. Certain raw materials (e.g., grapes and bottles) and wine products were sent from one stage to the next via the NRD. Some others were sent from the supplier to the bottling plant via the DRD, without routing the mtorugh the winery.

As mentioned above, existing works have considered various distribution channels in their CLSC design problems. Unfortunately, most of them, except for Soleimani and Kannan [13], do not use the three distribution channels simultaneously.

Table 1 presents a brief review of conventional works in the literature on SCLSC design problems with regard to three factors of sustainability (economic, environmental, and social factors) and three distribution channels (NRD, DRD, and DRS).

As is evident from Table 1, although there are several works that have considered either all three factors for sustainability or all three types of distributions channels, no work has considered both sets simultaneously.

In this paper, we propose a SCLSC design problem considering all three factors for sustainability and all three types of distribution channels simultaneously. The conceptual structure of the SCLSC design problem is described in Section 2.1 As the three factors for sustainability are used as three separate objective functions, the proposed SCLSC design problem is a multi-objective optimization problem and it can be represented by the mathematical formulation discussed in Section 2.2 To effectively solve the multi-objective optimization problem, a hybrid genetic algorithm (pro-HGA) approach is proposed in Section 2.3 that combines the genetic algorithm (GA) with a cuckoo search (CS). Via the numerical experiments presented in Section 3, the SCLSC design problem is explored on five different scales. The performance of the pro-HGA approach is compared with those of other conventional approaches, and the performances of the SCLSC design problems with and without three types of distribution channel are also compared. Finally, some conclusions are summarized and directions for future study are mentioned in Section 4.

	Three Factors for Sustainability			Three Types	of Distributi	on Channels
-	Eco.	Env.	Soc.	NRD	DRD	DRS
Savaskan et al. [16]						
Min et al. [4]	•			-		
Wang and Hsu [5]	•			-		
Paksoy et al. [9]	•	-		-		
Lee et al. [17]	•			-		
O ^{°°} zkir & Başlıgıl [18]	•			-		
Fahimnia et al. [19]	•	-		-		-
Devika et al. [1]		•	•			
Faccio et al. [20]						•
Chen et al. [6]				•		
Soleimani & Kannan [13]	•			•	•	•
Cardoso et al. [14]	•			•		•
Talaei et al. [10]		•		•		
Zhalechain et al. [11]	•	-	-	-		
JinDal & Sangwan [21]	•	-		-		
Özceylan et al. [3]	•	-	-	-		
Sahebjamnia et al. [12]	•	-	-	-		
Jabbarzadeh et al. [7]	•			-		
Jerbia et al. [22]	•			•		
Lie et al. [23]	•		-	•		
Son et al. [8]	•			•	•	
This study	•	-	•	-	•	-

Table 1. A brief review of conventional works in the literature on SCLSC design problems with regard to three factors for sustainability and three distribution channels.

2. Materials and Methods

2.1. Conceptual Structure of SCLSC Design Problem

The conceptual structure of the SCLSC design problem is depicted in Figure 1. The manufacturer produces products and sends a certain proportion of them (α_1 %) to the DC using the NRD and the remaining products (α_2 % = 1 – α_1 %) are sent to customer directly via the DRS. At the DC, a certain proportion (β_1 %) of the incoming products are sent to the retailer via the NRD and the rest (β_2 % = 1 – β_1 %) are sent to customer directly via the DRD. The retailer sends products to the customer via the NRD. A proportion (γ_1 %) of the products returned by the customer are transported to the recovery center via the collection center and the rest (γ_2 % = 1 – γ_1 %) are sent to the disposal center to be disposed. At the recovery center, a certain proportion (δ_1 %) of the returned products are recycled into materials and then returned to the manufacturer, and the rest (δ_2 % = 1 – δ_1 %) are recovered and then are resold to the customer.

Figure 1 also depicts the use of the three factors of sustainability at each stage. The total cost (=the sum of the total fixed costs incurred by the manufacturer, the DC, the retailer, the collection center, the recovery center, and the disposal center + the total transportation costs for all distribution channels + the total handling costs for the manufacturer, the DC, the retailer, the collection center, the recovery center and the disposal center) is considered as the economic factor. The total amount of CO_2 emissions during the manufacture of products at the manufacturer, during the recovery of returned products at the recovery center, and during transportation of products between each stage is considered to constitute the environmental factor. The number of job opportunities created, general unemployment, and the number of lost days due to damage to work at the manufacturer are together used as the relevant social factors.



Figure 1. Conceptual structure of the proposed SCLSC design problem.

2.2. Mathematical Formulation

The following assumptions are made to implement the proposed SCLSC design problem.

- Products of a single type are considered.
- The numbers of facilities considered at each stage at the manufacturer, the DC, the retailer, the customer, the collection center, the recovery center, and the disposal center are fixed and known beforehand.
- Only one facility is opened at each stage at the manufacturer, the DC, the retailer, the collection center, and the recovery center. However, all facilities available at the site of the customer and the disposal center are always considered open.
- The costs to operate the facilities considered at each stage at the manufacturer, the DC, the retailer, the collection center, and the recovery center are all constant, different from each other in value, and known beforehand.
- The unit handling costs of the facilities considered at each stage at the manufacturer, the DC, the retailer, the collection center, and the recovery center are different from each other in value and known beforehand.
- The unit transportation costs among the manufacturer, the DC, the retailer, the customer, the collection center, the recovery center, and the disposal center are different from each other in value and known beforehand.
- The unit amount of CO₂ emitted during transportation at each stage, and those emitted during manufacture and recovery at the manufacturer and the recovery center, respectively, are different from each other in value and known beforehand.
- The proposed SCLSC design problem is considered to be in a steady-state situation.

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

Index Set

- *m*: index of manufacturer; *M*: set of manufacturer, $m \in M$
- *d*: index of DC; *D*: set of DC, $d \in D$
- *r*: index of retailer; *R*: set of retailer, $r \in R$
- *c*: index of customer; *C*: set of customer, $c \in C$

Parameter

 f_m : fixed cost at manufacturer m f_d : fixed cost at DC d f_r : fixed cost at retailer r f_l : fixed cost at collection center l f_e : fixed cost at recovery center e h_m : unit handling cost at manufacturer m h_d : unit handling cost at DC d *hr*: unit handling cost at retailer *r* h_l : unit handling cost at collection center l h_e : unit handling cost at recovery center e ts_{md} : unit transportation cost from manufacturer *m* to DC *d* ts_{mc} : unit transportation cost from manufacturer *m* to customer *c* via DRS ts_{dr} : unit transportation cost from DC d to retailer r ts_{dc} : unit transportation cost from DC *d* to customer *c* via DRD *ts_{rc}*: unit transportation cost from retailer *r* to customer *c* ts_{cl} : unit transportation cost from customer c to collection center l ts_{cp} : unit transportation cost from customer *c* to disposal center *p* ts_{le} : unit transportation cost from collection center l to recovery center e *ts_{ec}*: unit transportation cost from recovery center *e* to customer *c ts_{em}*: unit transportation cost from recovery center *e* to manufacturer *m* d_{md} : distance between manufacturer *m* and DC *d* (unit: kilometer) d_{mc} : distance between manufacturer *m* and customer *c* via DRS (unit: kilometer) d_{dr} : distance between DC *d* and retailer *r* (unit: kilometer) d_{dc} : distance between DC d and customer c via DRD (unit: kilometer) d_{rc} : distance between retailer *r* and customer *c* (unit: kilometer) d_{cl} : distance between customer *c* and collection center *l* (unit: kilometer) d_{cp} : distance between customer *c* and disposal center *p* (unit: kilometer) *d*_{*le*}: distance between collection center *l* and recovery center *e* (unit: kilometer) d_{ec} : distance between recovery center *e* and customer *c* (unit: kilometer) *d_{em}*: distance between recovery center *e* and manufacturer *m* (unit: kilometer) wc: weight allocated to the created job opportunity wl: weight allocated to the number of lost days due to damage to work wu: weight allocated to unemployment se_m : number of the job opportunities created due to the use of technology t at manufacturer m sl_m : number of lost days due to damage to work due to use of technology t at manufacturer m su_m : number of the unemployed workers due to the use of technology t at manufacturer m *CO2V*: amount of CO₂ emitted from a vehicle per kilometer $CO2_m$: unit amount of CO_2 emitted during production process at manufacturer m $CO2_e$: unit amount of CO_2 emitted during recovery process at recovery center e vc: capacity that can be shipped in a vehicle

Decision Variables

 c_m : capacity of manufacturer m c_d : capacity of DC d c_r : capacity of retailer r c_c : capacity of customer c c_l : capacity of collection center l *c_e*: capacity of recovery center *e c*_{*p*}: capacity of disposal center *p* q_{md} : quantity transported from manufacturer *m* to DC *d* q_{mc} : quantity transported from manufacturer *m* to customer *c* via DRS q_{dr} : quantity transported from DC d to retailer r q_{dc} : quantity transported from DC d to customer c via DRD *q_{rc}*: quantity transported from retailer *r* to customer *c* q_{cl} : quantity transported from customer c to collection center l q_{cp} : quantity transported from customer c to disposal center p q_{le} : quantity transported from collection center l to recovery center e *q_{ec}*: quantity transported from recovery center *e* to customer *c* q_{em} : quantity transported from recovery center *e* to manufacturer *m* x_m : takes the value 1 if manufacturer *m* is opened and 0 otherwise x_d : takes the value 1 if DC *d* is opened and 0 otherwise x_r : takes the value 1 if retailer *r* is opened and 0 otherwise x_l : takes the value 1 if collection center *l* is opened and 0 otherwise x_e : takes the value 1 if recovery center *e* is opened and 0 otherwise t_m : takes the value 1 if technology t is used at manufacturer m and 0 otherwise

The first objective function (F_1), corresponding to the economic factor, is defined as follows to minimize the total cost. The total cost is the aggregate of the total fixed cost, the total handling cost, and the total transportation cost.

 $Min. F_1 = Total fixed cost (TFC) + Total handling cost (THC) + Total transportation cost (TTC) (1)$

$$TFC = \left(\sum_{m} f_m \cdot x_m\right) + \left(\sum_{d} f_d \cdot x_d\right) + \left(\sum_{r} f_r \cdot x_r\right) + \left(\sum_{l} f_{l} \cdot x_{l}\right) + \left(\sum_{e} f_e \cdot x_e\right)$$
(2)

$$THC = \left(\sum_{m} h_m \cdot c_m \cdot x_m\right) + \left(\sum_{d} h_d \cdot c_d \cdot x_d\right) + \left(\sum_{r} h_r \cdot c_r \cdot x_r\right) + \left(\sum_{l} h_{l} \cdot c_{l} \cdot x_{l}\right) + \left(\sum_{e} h_e \cdot c_e \cdot x_e\right)$$
(3)

$$TTC = (\sum_{m} \sum_{d} ts_{md} \cdot (\alpha_{1} \otimes c_{m}) \cdot x_{m} \cdot x_{d}) + (\sum_{m} \sum_{c} ts_{mc} \cdot (\alpha_{2} \otimes c_{m}) \cdot x_{m}) + (\sum_{d} \sum_{r} ts_{dr} \cdot (\beta_{1} \otimes c_{d}) \cdot x_{d} \cdot x_{r}) + (\sum_{d} \sum_{c} ts_{dc} \cdot (\beta_{2} \otimes c_{d}) \cdot x_{d}) + (\sum_{c} \sum_{l} ts_{cl} \cdot (\gamma_{1} \otimes c_{c}) \cdot x_{l}) + (\sum_{c} \sum_{p} ts_{cp} \cdot (\gamma_{2} \otimes c_{c})) + (\sum_{l} \sum_{e} ts_{le} \cdot c_{l} \cdot x_{l} \cdot x_{e}) + (\sum_{e} \sum_{m} ts_{em} \cdot (\delta_{1} \otimes c_{e}) \cdot x_{e} \cdot x_{m}) + (\sum_{e} \sum_{c} ts_{ec} \cdot (\delta_{2} \otimes c_{e}) \cdot x_{e})$$

$$(4)$$

The term *TFC* in Equation (2) is calculated as the sum of the fixed costs when the facilities at all manufacturers, DCs, retailers, collection centers and recovery centers are opened. The term *THC* in Equation (3) is the sum of the handling costs incurred to handle products at the facilities opened at manufacturers, DCs, retailers, collection centers, and recovery centers. The term *TTC* in Equation (4) is the sum of the transportation costs of products from one stage to another.

The second objective function (F_2) corresponding to the environmental factor is defined as follows to minimize the total amount of CO₂ emissions during production, recovery and transportation processes.

$$Min. F_2 = Total amount of CO_2 emitted during production and recovery processes (TCP) + Total amount of CO_2 emitted during transportation processes (TCT) (5)$$

$$TCP = \left(\sum_{m} c_{m} \cdot x_{m} \cdot CO2_{m}\right) + \left(\sum_{e} c_{e} \cdot x_{e} \cdot CO2_{e}\right)$$
(6)

$$TCT = CO2V \cdot \left[\left(\sum_{m} \sum_{d} d_{md} \cdot x_{m} \cdot x_{d} \cdot \frac{c_{m} \cdot \alpha_{1} \cdot \%}{v_{c}} \right) + \left(\sum_{m} \sum_{c} d_{mc} \cdot x_{m} \cdot \frac{c_{m} \cdot \alpha_{2} \cdot \%}{v_{c}} \right) + \left(\sum_{d} \sum_{r} d_{dr} \cdot x_{d} \cdot x_{d} \cdot \frac{c_{d} \cdot \beta_{1} \cdot \%}{v_{c}} \right) + \left(\sum_{c} \sum_{c} d_{dc} \cdot x_{d} \cdot \frac{c_{d} \cdot \beta_{2} \cdot \%}{v_{c}} \right) + \left(\sum_{r} \sum_{c} d_{rc} \cdot x_{r} \cdot \frac{c_{r}}{v_{c}} \right) + \left(\sum_{c} \sum_{l} d_{cl} \cdot x_{l} \cdot \frac{c_{l} \cdot \gamma_{1} \cdot \%}{v_{c}} \right) + \left(\sum_{c} \sum_{p} d_{cp} \cdot \frac{c_{c} \cdot \gamma_{2} \cdot \%}{v_{c}} \right) + \left(\sum_{l} \sum_{e} d_{le} \cdot x_{l} \cdot x_{e} \cdot \frac{c_{l}}{v_{c}} \right) + \left(\sum_{e} \sum_{m} d_{em} \cdot x_{e} \cdot x_{m} \cdot \frac{c_{e} \cdot \delta_{1} \cdot \%}{v_{c}} \right) + \left(\sum_{e} \sum_{c} d_{ec} \cdot x_{e} \cdot \frac{c_{e} \cdot \delta_{2} \cdot \%}{v_{c}} \right) \right]$$

$$(7)$$

The term *TCP* in Equation (6) denotes the total amount of CO_2 emitted during production and recovery processes at manufacturers and recovery centers. The term *TCT* denotes the total amount of CO_2 emitted during transportation between each pair of stages. In Equation (7), the parameters values of *vc* and *CO2V* are randomly generated according to the methods described in [3,9].

The third objective function (F_3) corresponding to the social factor is defined as follows to maximize the social influence, which consists of (i) the number of job opportunities created, (ii) the number of lost days due to damage to work, and (iii) the number of unemployed workers at the manufacturers. The three components are already mentioned and studied by many conventional literatures [24–27]. Equation (8) defines F_3 .

$$Max. F_{3} = (weight allocated to created job opportunity number of created job opportunity at manufacturer) - (weight allocated to lost day caused by work/s damage number of lost day caused by work/s damage at manufacturer) - (weight allocated to unemployment number of unemployment at manufacturer) = (wc \cdot \sum_{m} se_{m} \cdot x_{m} \cdot t_{m}) - (wl \cdot \sum_{m} sl_{m} \cdot x_{m} \cdot t_{m}) - (wu \cdot \sum_{m} su_{m} \cdot x_{m})$$
(8)

The three aforementioned objective functions should be optimized with respect to the following constraints.

$$(\alpha_1 \% \cdot \sum_m \sum_d q_{md} \cdot x_m \cdot x_d) - (\sum_d c_d \cdot x_d) \le 0$$
(9)

$$(\alpha_1 \% \cdot \sum_m \sum_d q_{md} \cdot x_m \cdot x_d) - (\sum_d c_d \cdot x_d) \le 0$$
(10)

$$(\beta_1 \stackrel{\text{\tiny oheta}}{\sim} \sum_d \sum_r q_{dr} \cdot x_d \cdot x_r) - (\sum_r c_r \cdot x_r) \le 0$$
(11)

$$(\beta_2^{\circ} \cdot \sum_d \sum_c q_{dc} \cdot x_d) - (\sum_c c_c) \le 0$$
(12)

$$\left(\sum_{r}\sum_{c}q_{rc}\cdot x_{r}\right)-\left(\sum_{c}c_{c}\right)\leq0$$
(13)

$$(\gamma_1 \stackrel{\text{\tiny $\%$}}{\sim} \sum_c \sum_l q_{cl} \cdot x_l) - (\sum_l c_l \cdot x_l) \le 0$$
(14)

$$(\gamma_{2\%} \cdot \sum_{c} \sum_{p} q_{cp}) - (\sum_{p} c_{p}) \le 0$$
(15)

$$\left(\sum_{l}\sum_{e}q_{le}\cdot x_{l}\cdot x_{e}\right) - \left(\sum_{e}c_{e}\cdot x_{e}\right) \le 0$$
(16)

$$(\delta_1 \stackrel{\text{\tiny oh}}{\sim} \sum_e \sum_m q_{em} \cdot x_e \cdot x_m) - (\sum_m c_m \cdot x_m) \le 0$$
(17)

$$(\delta_1 \% \cdot \sum_e \sum_c q_{ec} \cdot x_e) - (\sum_c c_c) \le 0$$
(18)

$$\sum_{m} x_m = 1 \tag{19}$$

$$\sum_{d} x_{d} = 1 \tag{20}$$

$$\sum_{r} x_r = 1 \tag{21}$$

$$\sum_{l} x_{l} = 1 \tag{22}$$

$$\sum_{e} x_e = 1 \tag{23}$$

$$x_m = \{0, 1\}, \ \forall \ m \in M$$
(24)

$$x_d = \{0, 1\}, \ \forall \ d \in D$$
(25)

$$x_r = \{0, 1\}, \ \forall \ r \in R$$
 (26)

$$x_l = \{0, 1\}, \ \forall \ l \in L$$
 (27)

$$x_e = \{0, 1\}, \ \forall \ e \in E$$
(28)

$$c_m, c_d, c_r, c_c, c_l, c_e, c_p \ge 0, \ \forall m \in M, \forall d \in D, \forall r \in R, \forall c \in C, \forall l \in L, \forall e \in E, \forall p \in P$$

$$(29)$$

Equation (9) indicates that the amount of transported goods from a manufacturer to a DC is less than or equal to the capacity of the DC. In a similar vein, inequalities (10) to (18) represent the quantity limitation for transportation between each pair of stages. Equations (19)–(23) impose the restriction that only one facility may be opened at each stage at each manufacturer, DC, retailer, collection center, and recovery center. Relations (24)–(28) represent the fact that each decision variable should take the values of 0 or 1. Inequality (29) represents non-negativity of the variables concerned.

2.3. Proposed HGA Approach

Most complicated network problems are known to be NP-complete [16,28,29], and the SCLSC design problem proposed in this paper is no exception. Existing works in the literature [4,29–31] have shown that meta-heuristics-based approaches such as GA, CS, and Tabu search (TS) have been adapted to solve complicated network problems efficiently. However, there exist many situations in which most conventional single-based meta-heuristics approaches do not perform particularly well [28,31,32]. To address this gap, various hybrid approaches have been developed that use GA or other similar approaches [29,31–37].

Zhang et al. [35] and Xinyu and Liang [36] developed the hybrid GA (HGA) approaches that combine GA with TS to reinforce the hybrid search ability by utilizing GA for global searches and TS for local searches. However, their HGA approaches suffer from weaknesses in applications to complicated network problems. First, the search schemes used in their HGA approaches require considerable computation time, as all individuals in a current population are adapted to produce the TS list and this process is time-consuming. Second, the search quality for locating global optimal solutions via GA sometimes deteriorates, because the Tabu list in TS is produced based on the initial population. Lin et al. [33] developed an HGA approach that utilizes GA for global searches and the iterative hill climbing method for local searches. The approach was adapted to solve complicated network problems of several sizes. Although the authors proved the superior efficiency of the approach compared to that of a conventional GA, its search speed is significantly slower than that of GA, especially for problems of large size.

Therefore, this paper proposes an improved HGA approach, called the pro-HGA approach, that reinforces search speed and search quality to solve the SCLSC design problem efficiently. The pro-HGA approach combines GA for global searches with CS for local searches. First, a new population is produced by using three operators (crossover, mutation, and selection) of GA. Then, CS is applied to the new population produced by GA to locate more respective solutions. To enhance the search speed and search quality of the pro-HGA approach, the respective solutions are continuously produced, and they are used to carry out continuous improvement during GA and CS search processes. For

this strategy, the Lévy flight scheme [38] of CS is adapted to all solutions of the population produced during the GA search process. The implementation procedure of the pro-HGA approach is depicted in detail as follows.

```
procedure: pro-HGA approach
input: problem data, parameters
output: Pareto optimal solutions
begin
              //t: generation number
   t \leftarrow 0
   initialize parent population PP(t) by encoding routine;
   calculate each objective function F_i, i = 1, 2, 3 of PP(t) by decoding routine;
   create Pareto optimal solutions E(P) by non-dominated routine;
   while (t < max generation)
      produce offspring OP(t) from PP(t) by adapting 2X crossover operator [30] and random mutation
      operator [30];
      calculate F_i of OP(t) by decoding routine;
      find current E(P) by non-dominated routine;
      keep best solution set GL_{best} using current E(P);
     for each solution x_i of OP(t) do
          generate a new solution x_{new} from x_i by adapting Lévy flight scheme [38];
          randomly select another solution x_i in OP(t);
          if (F(x_{new}) > F(x_i)) then CP(t) \leftarrow x_{new/}/CP(t): CS population
     end for
     worst solutions with fraction rate (f_r) are abandoned;
     randomly regenerate new solutions x_{r_new} as many as f_r;
     CP(t) \leftarrow x_{r\_new}
     calculate F_i of CP(t) by decoding routine;
     find current E(P) by non-dominated routine;
     keep best solution set CL<sub>best</sub> using current E(P);
     if (\hat{F}(GL_{best}) > F(CL_{best}))
          then update E(P) using GL_{best} by non-dominated routine
          else update E(P) using CL<sub>best</sub> by non-dominated routine
     end if
       reproduce PP(t + 1) using OP(t) and CP(t) by adapting elitist selection scheme [30];
       t \leftarrow t + 1;
     end
     output Pareto optimal solutions E(P);
end;
```

3. Results and Discussions

Via numerical experiments, the mathematical formulation of the SCLSC design problem suggested in Section 2.2 is implemented at five different scales as presented in Table 2.

Scale	Number of Manufacturers	Number of DCs	Number of Retailers	Number of Customers	Number of Collection Centers	Number of Recovery Centers	Number of Disposal Centers
1	5	8	8	1	8	5	1
2	25	30	30	1	30	25	1
3	50	60	60	1	60	50	1
4	100	80	80	1	80	100	1
5	150	100	100	1	100	150	1

 Table 2. The SCLSC design problem at five different scales.

To evaluate the performance of the pro-HGA approach comparatively, two conventional approaches (GA: conventional GA by Gen and Cheng [28], HGA: conventional HGA by Kanagaraj et al. [39]) are chosen. All approaches were programmed using MATLAB Version 2014b and run under the same computational environment (IBM compatible PC 1.3 GHz processor-Intel core I5-1600 CPU, 4GB RAM, and OS-X EI).

The parameter settings to implement the GA, HGA, and pro-HGA approaches are as follows: Total number of generations is 1000, population size is 20, crossover rate is 0.5, and mutation rate is 0.3. The number of host nests is 20, $\alpha = 1$ and $p_a = 0.25$ for the search of CS used in the HGA and pro-HGA approaches. These parameter values were obtained by fine-tuning the procedure of each approach. The parameter values to implement the mathematical formulation in Section 2.2 are defined as follows: CO2V = 3, $CO2_m = 0.5$, $CO2_e = 0.3$, $v_c = 10$, wc = 0.15, wl = 0.15, wu = 0.15, $se_m = U$ [90, 100], $sl_m = U$ [20, 30], $su_m = U$ [15, 20]. To eliminate the randomness in the implementation of each approach, each method is evaluated over 30 independent runs. Various measures of performance are used to compare the performances of the approaches, as recorded in Table 3.

Table 3.	Measures	of	performance
----------	----------	----	-------------

Measure	Description
<i>S_j</i>	Number of Pareto optimal solutions in reference solution set (S^*) [40]
$R_{NDS}(S_i)$	Rates of Pareto optimal solutions in the S^* [40]
$DI_R(S_j)$	Average distance between Pareto optimal solutions and the set S^* [40]
CPU time (sec.)	Average CPU time required for each run

The values of $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$ presented in Table 3 are the averages obtained over 30 independent runs. The three sub-problems generated from the original problem which had been suggested in Section 2.2 are used to aid the analyses of computation results as follows [31]. The experimental results are summarized in Tables 4–8. The boldfaces in Tables 4–8 indicate the best solutions for each measure.

Problem 1: min. F_1 and min. F_2 Problem 2: min. F_1 and max. F_3 Problem 3: min. F_2 and max. F_3

Table 4. Computation	results for each	approach 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_i $	2	1	1	0	2	2	0	0	2	
$R_{NDS}(S_j)$	0.50	0.25	0.25	0.00	0.50	0.50	0.00	0.00	1.00	
$DI_R(S_i)$	574	1715	415	246	0	109	649	645	0	
CPU time	13.7	14.0	14.1	13.7	14.0	14.1	13.7	14.0	14.1	

Table 5. Computation results for each approach 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 $	1	0	4	0	0	3	0	0	3	
$R_{NDS}(S_i)$	0.20	0.00	0.80	0.00	0.00	1.00	0.00	0.00	1.00	
$DI_R(S_i)$	847	256	0	828	437	0	1286	585	0	
CPU time	13.1	13.4	14.6	13.1	13.4	14.6	13.1	13.4	13.4	

	Scale 3									
	Problem	Problem 2			Problem 3					
Measure	GA	HGA	pro-HGA	GA	HGA	pro-HGA	GA	HGA	pro-HGA	
$ S_j $	0	2	5	1	2	2	0	0	3	
$R_{NDS}(S_i)$	0.00	0.29	0.71	0.20	0.40	0.40	0.00	0.00	1.00	
$DI_R(S_i)$	241	394	373	602	292	246	523	440	0	
CPU time	13.2	13.5	14.5	13.2	13.5	14.5	13.2	13.5	14.5	

Table 6. Computation results for each approach in Scale 3.

	Scale 4									
		Problem	1		Problem	2	Problem 3			
Measure	GA	HGA	pro-HGA	GA	HGA	pro-HGA	GA	HGA	pro-HGA	
$ S_j $	0	0	7	0	0	3	0	0	2	
$R_{NDS}(S_j)$	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	
$DI_R(S_i)$	359	406	0	469	235	0	698	573	0	
CPU time	41.3	42.7	43.6	41.3	42.7	43.6	41.3	42.7	43.6	

Table 7. Computation results for each approach in Scale 4.

Table 8. Computation results for each approach in Scale 5.

	Scale 5									
Problem 1 Problem 2								Problem 3		
Measure	GA	HGA	pro-HGA	GA	HGA	pro-HGA	GA	HGA	pro-HGA	
$ S_j $	0	0	5	0	0	2	0	0	3	
$R_{NDS}(S_i)$	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	
$DI_R(S_i)$	569	557	0	707	483	0	670	684	0	
CPU time	41.8	42.1	44.0	41.8	42.1	44.0	41.8	42.1	44.0	

In Table 4, the number of Pareto optimal solutions of Problem 1 obtained via the GA approach is greater than that obtained via the HGA and pro-HGA approaches for the same problem in terms of the values $|S_j|$. However, in Problem 2, the number of the Pareto optimal solutions obtained via the pro-HGA approach is the same as that obtained via the HGA approach, and they are both greater than the number of solutions obtained via the GA approach. In Problem 3, the pro-HGA approach locates two Pareto optimal solutions, but the GA and HGA approaches fail to locate any. The values of $|S_j|$ also influence the rate of Pareto optimal solutions in S^* . In other words, in terms of $R_{NDS}(S_j)$, the rate corresponding to the GA approach is higher than those corresponding to the HGA and pro-HGA approaches in Problem 1. In contrast, the rates corresponding to the HGA and pro-HGA approaches are higher than that corresponding to the GA approach in Problems 2 and 3. In terms of $DI_R(S_j)$, the pro-HGA approach exhibits significantly better results than the GA and HGA approaches in Problems 1 and 3, which can be inferred from the fact that the average distance between the Pareto optimal solutions and elements of S^* is inversely proportional to the quality of the approach.

According to the data presented in Table 5, the pro-HGA approach performs significantly better in terms of $|S_j|$ compared to the GA and HGA approaches in Problems 1, 2, and 3. Similar results are observed in terms of $R_{NDS}(S_j)$ and $DI_R(S_j)$. The computation results based on $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$ indicate that the search scheme used in the pro-HGA approach is more efficient than those used in the GA and HGA approaches.

According to the data presented in Table 6, the pro-HGA approach outperforms the GA and HGA approaches in terms of $|S_j|$ and $R_{NDS}(S_j)$ in Problems 1 and 3, but not for Problem 2. On the other hand, in terms of $DI_R(S_j)$, the performance of the GA approach is slightly better than that of the HGA and pro-HGA approaches in Problem 1. However, for Problems 2 and 3, the performance of the pro-HGA approach is superior to those of the others.

In terms of the average CPU times required, as recorded in Tables 4–6, no significant differences among the approaches are observed, even though the computation speeds of the GA approach were slightly quicker than those of the HGA and pro-HGA approaches.

In the data corresponding to Problems 1, 2, and 3 presented in Table 7, the pro-HGA approach performs the best in terms of $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$ compared to the GA and HGA approaches. A similar observation also follows from the results tabulated in Table 8 in all the Problems, the performances of the pro-HGA approach are significantly superior to those of the GA and HGA approaches in terms of $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$. The search speeds of the GA approach were observed to be slightly quicker than those of the HGA and pro-HGA approaches, but no significant difference was noticed.

Figures 2–4 depict the Pareto optimal solutions of the GA, HGA, and pro-HGA approaches in Problems 1, 2, and 3 at Scale 5.



Figure 2. Pareto optimal solutions for each approach in Problem 1 at Scale 5.



Figure 3. Pareto optimal solutions for each approach in Problem 2 at Scale 5.



Figure 4. Pareto optimal solutions for each approach in Problem 3 at Scale 5.

From Figure 2, it is evident that five Pareto optimal solutions obtained via the pro-HGA approach coincide with the S^* , and that the GA and HGA approaches do not show any advantages compared to it in this regard. Similar results are observed regarding the number of Pareto optimal solutions in terms of $|S_j|$ for Problem 1 as presented in Table 8. Similar situations are also depicted in Figures 3 and 4. The pro-HGA approach exhibits two Pareto optimal solutions in Figure 3 and three solutions in Figure 4 that coincide with those of S^* , but none of the solutions obtained via the GA and HGA approaches coincide in position with elements of S^* .

Based on the experimental results presented in Tables 4–8 and Figures 2–4, we can reach the following conclusion.

• The pro-HGA approach has performed better than the GA and HGA approaches in terms of the metrics $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$, as the problem sizes were increased from scales 1 to scale 5. However, the former does not exhibit any advantage in terms of the CPU times required compared to the latter pair. With respect to the Pareto optimal solutions obtained via each approach in comparison with the *S**, the performance of the pro-HGA approach is superior to those of the GA and HGA approaches, which proves that the search scheme used in the pro-HGA approach is more efficient than those used in the GA and HGA approaches.

As recorded in Table 1, the SCLSC design problem proposed in this paper utilizes various distribution channels (i.e., NRD, DRD, and DRS) and this feature distinguishes it from methods presented in other works in the literature. Therefore, we can compare the performances of the following SCLSC design problems.

- . SCLSC-S: the SCLSC design problem with a single distribution channel, i.e., NRD
- . SCLSC-V: the SCLSC design problem with various distribution channels, i.e., NRD, DRD, and DRS

Tables 9 and 10 present the computation results for SCLSC-S and SCLSC-V at scales 4 and 5. The boldfaces in Tables 9 and 10 indicate the best solutions for each measure.

	Scale 4									
	Prob	lem 1	Prob	lem 2	Problem 3					
Measure	SCLSC-S	SCLSC-V	SCLSC-S	SCLSC-V	SCLSC-S	SCLSC-V				
$ S_i $	1	8	1	2	3	2				
$R_{NDS}(S_i)$	0.11	0.89	0.33	0.66	0.6	0.4				
$DI_R(S_i)$	12,670	0	940	1124	0	0				
CPU time	32.8	43.6	32.8	43.6	32.8	43.6				

Table 9. Computation results for SCLSC-S and SCLSC-V at Scale 4.

Table 10. Computation results for SCLSC-S and SCLSC-V at Scale 5.

	Scale 5									
Problem 1 Problem 2 Problem 3										
Measure	SCLSC-S	SCLSC-V	SCLSC-S	SCLSC-V	SCLSC-S	SCLSC-V				
$ S_i $	2	4	3	2	0	3				
$R_{NDS}(S_j)$	0.33	0.66	0.60	0.40	0.00	1.00				
$DI_R(S_i)$	8899	787	0	0	13,654	0				
CPU time	33.0	44.0	33.0	44.0	33.0	44.0				

From the data presented in case of Problem 1 in Table 9, the performances of SCLSC-V are observed to be significantly better than those of the SCLSC-S in terms of the metrics $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$. In Problem 2, SCLSC-V again exhibits slightly better performances than SCLSC-S in terms of $|S_j|$ and $R_{NDS}(S_j)$, but not for $DI_R(S_j)$. However, in Problem 3, SCLSC-V no longer exhibits any comparative merits in terms of $|S_j|$ and $R_{NDS}(S_j)$. Similar results are gleaned by analyzing the results presented in Table 10. In Problems 1 and 3, SCLSC-V significantly outperforms SCLSC-S in terms of $|S_j|$, $R_{NDS}(S_j)$, and $DI_R(S_j)$, even though the latter performs slightly better in terms of $|S_j|$ and $R_{NDS}(S_j)$ in Problem 2. In Problems 1, 2 and 3 of Tables 9 and 10, the search speeds of SCLSC-S are slightly quicker than those of SCLSC-V as is apparent from the average CPU times required.

Figures 5–7 depict the Pareto optimal solutions for SCLSC-S and SCLSC-V with respect to Problems 1, 2, and 3 at Scale 5.



Figure 5. Pareto optimal solutions for SCLSC-S and SCLSC-V in Problem 1 at Scale 5.



Figure 6. Pareto optimal solutions for SCLSC-S and SCLSC-V in Problems at Scale 5.



Figure 7. Pareto optimal solutions for SCLSC-S and SCLSC-V in Problems 3 at Scale 5.

From Figure 5, it is evident that four Pareto optimal solutions out of five coincide with S^* for SCLSC-V, while the same is true for two out of seven solutions for SCLSC-S. These results are the same as the distributions of Pareto optimal solutions in terms of $|S_j|$ for Problem 1 as presented in Table 10. From Figure 6, we can observe that all Pareto optimal solutions for SCLSC-V and SCLSC-S coincide with S^* . However, in Figure 7, all Pareto optimal solutions for SCLSC-V coincide with S^* , but none of the solutions for the SCLSC-S do.

Based on the experimental results presented in Tables 9 and 10 and Figures 5–7, the following conclusion can be reached.

SCLSC-V outperforms SCLSC-S with respect to most performance measures, although the former
has slightly lower search speeds than the latter. This indicates that the SCLSC design problem
with various distribution channels, i.e., NRD, DRD, and DRS is more efficient in locating optimal
solutions than that with a single distribution channel, i.e., NRD.

4. Conclusions

In this paper, we have proposed an SCLSC design problem. Three factors (economic, environmental, and social factors) and three distribution channels (NRD, DRD, and DRS) have been considered for

the construction of the problem. The economic factor is concerned with minimizing the total cost, which is the aggregate of the total fixed cost, the total handling cost, and the total transportation cost. The environmental factor also is concerned with minimizing the total amount of CO₂ emissions during the transportation and manufacturing processes. On the other hand, the social factor is concerned with maximizing the social influence of the process, which consists of the number of job opportunities created, the number of unemployed workers and the number of lost days due to damage to work. As these three factors have been considered in the proposed SCLSC design problem simultaneously, the problem has been formulated as a multi-objective optimization problem. A pro-HGA approach that combines GA with CS has been proposed to solve the SCLSC design problem.

The SCLSC design problem has been presented in five different scales with the help of numerical experiments and the performance of the pro-HGA approach has been compared with those of two conventional approaches (GA and HGA). Various measures of performance, such as Pareto optimal solutions, have been used for the comparison. The experimental results have conclusively shown that the pro-HGA approach is more efficient than the GA and HGA approaches with respect to various measures of performance, although the former shows no advantage over the latter with respect to the average CPU time required to complete the process.

SCLSC design problems with and without various distribution channels have also been compared in the paper. SCLSC-S (the SCLSC design problem with single distribution channel, i.e., NRD) and SCLSC-V (the SCLSC design problem with various distribution channels, i.e., NRD. DRD, and DRS) have been compared at two separate scales. Experimental results demonstrated that SCLSC-V is more efficient in locating optimal solutions than SCLSC-S with respect to most performance measures, except the average CPU time required.

With regard to the direction of our future studies, we wish to present SCLSC design problems of a larger scale using real field data to compare the performances of SCLSC-V and SCLSC-S. We also wish to consider other meta-heuristic approaches, such as particle swam optimization, ant colony optimization, etc. to construct a more efficient pro-HGA approach.

Author Contributions: Investigation, Y.Y.; Methodology, Y.Y. and M.G.; Software, A.C.; Validation, Y.Y.; Writing—original draft, Y.Y. and M.G.; Review and editing, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Devika, K.; Jafarian, A.; Nourbakhsh, V. Designing a sustatinable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridixation techniques. *Eur. J. Oper. Res.* 2014, 235, 594–615. [CrossRef]
- 2. Eskandarpour, M.; Dejax, P.; Miemczyk, J.; Péton, O. Sustainable supply chain network design: An optimization-oriented review. *Omega* **2015**, *54*, 11–31. [CrossRef]
- 3. Özceylan, E.; Demirel, N.; Çetinkaya, C.; Demirel, E. A closed-loop supply chain network design for automotive industry in Turkey. *Comput. Ind. Eng.* **2017**, *113*, 729–745. [CrossRef]
- 4. Min, H.; Ko, C.S.; Ko, H.J. The spatial and temporal consolidation of returned products in a closed-loop supply chain network. *Comput. Ind. Eng.* **2006**, *51*, 309–320. [CrossRef]
- 5. Wang, H.F.; Hsu, H.W. A closed-loop logistic model with a spanning tree based genetic algorithm. *Comput. Oper. Res.* **2010**, *37*, 376–389. [CrossRef]
- 6. Chen, Y.T.; Chan, F.T.S.; Chung, S.H. An integrated closed-loop supply chain model with location and allocation problem and product recycling decisions. *Int. J. Prod. Res.* **2015**, *53*, 3120–3140. [CrossRef]
- 7. Jabbarzadeh, A.; Haughton, M.; Khosrojerdi, A. Closed-loop supply chain network design under distription risks: A robust approach with real world application. *Comput. Ind. Eng.* **2018**, *116*, 178–191. [CrossRef]
- Son, D.; Kim, S.; Park, H.; Jeong, B. Closed-loop supply chain planning model of rare metals. *Sustainability* 2018, 10, 1061. [CrossRef]

- 9. Paksoy, T.; Bektaş, T.; Özceylan, E. Operational and environmental performance measures in a multi-product closed-loop supply chain. *Transp. Res. Part E* **2011**, *47*, 532–546. [CrossRef]
- 10. Talaei, M.; Moghaddam, B.F.; Pishvaee, M.S.; Bozorgi-Amiri, A.; Gholamnejad, S.A. A robust fuzzy optimization model for carbon-efficient closed-loop supply chain network design problem: A numerical illustration in electronics industry. *J. Clean. Prod.* **2016**, *113*, 662–673. [CrossRef]
- 11. Zhalechian, M.; Tavakkoli-Moghaddam, R.; Zahiri, B.; Mohammadi, M. Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty. *Transp. Res. Part E* **2016**, *89*, 182–214. [CrossRef]
- Sahebjamnia, N.; Fathollahi-Fard, A.M.; Hajiaghaei-Keshteli, M. Sustainable tire closed-loop supply chain network design: Hybrid metaheuristic algorithms for large-scale networks. *J. Clean. Prod.* 2018, 196, 273–296. [CrossRef]
- 13. Soleimani, H.; Kannan, G. A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale network. *Appl. Math. Model.* **2015**, *39*, 3990–4012. [CrossRef]
- 14. Cardoso, S.R.; Barbosa-Póvoa, A.P.; Relvas, S. Integrating financial risk measures into the design and planning of closed-loop supply chains. *Comput. Chem. Eng.* **2016**, *85*, 105–123. [CrossRef]
- 15. Varsei, M.; Polyakovskiy, S. Sustainable supply chain network design: A case of the wine industry in Australia. *Omega* **2017**, *66*, 236–247. [CrossRef]
- 16. Savaskan, R.C.; Bhattacharya, S.; Van Wassenhove, L.V. Closed-loop supply chain models with product remanufacturing. *Manag. Sci.* 2004, *50*, 239–252. [CrossRef]
- 17. Lee, Y.J.; Baker, T.; Jayaraman, V. Redesigning an integrated forward-reverse logistics system for a third party service provider: An empirical study. *Int. J. Prod. Res.* **2012**, *50*, *56*15–*56*34. [CrossRef]
- Özkir, V.; Başlıgıl, H. Modelling product-recovery processes in closed-loop supply-chain network design. *Int. J. Prod. Res.* 2012, *50*, 2218–2233. [CrossRef]
- 19. Fahimnia, B.; Sarkis, J.; Dehghanian, F.; Banihashemi, N.; Rahman, S. The impact of carbon pricing on a closed-loop supply chain: An Australian case study. *J. Clean. Prod.* **2013**, *59*, 210–225. [CrossRef]
- Faccio, M.; Persona, A.; Sgarbossa, F.; Zanin, G. Sustainable SC through the complete reprocessing of end-of-life products by manufacturers: A traditional versus social responsibility company perspective. *Eur. J. Oper. Res.* 2014, 233, 359–373. [CrossRef]
- 21. Jindal, A.; Sangwan, K.S. Multi-objective fuzzy mathematical modelling of closed-loop supply chain considering economic and environmental factors. *Ann. Oper. Res.* **2017**, 257, 95–120. [CrossRef]
- 22. Jerbia, R.; Boujelben, M.K.; Sehli, M.A.; Jemai, Z. A stochastic closed-loop supply chain network design problem with multiple recovery options. *Comput. Ind. Eng.* **2018**, *118*, 23–32. [CrossRef]
- 23. Lie, M.; Liu, R.; Zhu, Z.; Chu, C.; Man, X. A bi-objective green closed-loop supply chain design problem with uncertain demand. *Sustainability* **2018**, *10*, 967. [CrossRef]
- 24. Pishvaee, M.; Razmi, J.; Torabi, S. Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets Syst.* **2012**, *206*, 1–20. [CrossRef]
- 25. Pishvaee, M.; Razmi, J.; Torabi, S. An accelerated Benders decomposition algorithm for sustainable supply chain network design under uncertainty: A case study of medical needle and syringe supply chain. *Transp. Res. Part E* 2014, *E67*, 14–28. [CrossRef]
- 26. Pishvaee, M.; Zanjirani, F.R.; Dullaert, W. A memetic algorithm for bi- objective integrated forward/reverse logistics network design. *Comput. Oper. Res.* **2010**, *37*, 1100–1112. [CrossRef]
- 27. Saffari, M.M.; Shakouri, G.H.; Razmi, J. A new multi objective optimization model for designing a green supply chain network under uncertainty. *Int. J. Ind. Eng. Comput.* **2015**, *6*, 15–32. [CrossRef]
- 28. Gen, M.; Cheng, R. *Genetic Algorithms and Engineering Optimization*; John-Wiley & Sons: New York, NY, USA, 2000.
- 29. Gen, M.; Lin, L.; Yun, Y.S.; Inoue, H. Recent advances in hybrid priority-based genetic algorithms for logistics and SCM network design. *Comput. Ind. Eng.* **2018**, *115*, 394–412. [CrossRef]
- 30. Gen, M.; Cheng, R. Genetic Algorithms and Engineering Design; John Wiley & Son: New York, NY, USA, 1997.
- 31. Yun, Y.S.; Chung, H.S.; Moon, C.U. Hybrid genetic algorithm approach for precedence-constrained sequencing problem. *Comput. Ind. Eng.* **2013**, *65*, 137–147. [CrossRef]
- 32. Yun, Y.S. Hybrid genetic algorithm with adaptive local search scheme. *Comput. Ind. Eng.* **2006**, *51*, 128–141. [CrossRef]

- 33. Lin, L.; Gen, M.; Wang, X. Integrated multistage logistics network design by using hybrid evolutionary algorithm. *Comput. Ind. Eng.* 2009, *56*, 854–873. [CrossRef]
- 34. Yun, Y.S.; Gen, M.; Hwang, R.K. Adaptive genetic algorithm to multi-stage reverse logistics network design for product resale. *Inf. Inte. Interdiscip. J.* **2012**, *15*, 6117–6138.
- 35. Zhang, Q.; Manier, H.; Manier, M.A. A genetic algorithm with Tabu search procedure for flexible job shop scheduling with transportation constraints and bounded processing times. *Comput. Oper. Res.* **2012**, *39*, 1713–1723. [CrossRef]
- 36. Xinyu, L.; Liang, G. An effective hybrid genetic algorithm and Tabu search for flexible job shop scheduling problem. *Int. J. Prod. Econ.* **2016**, *174*, 93–110.
- 37. Gen, M.; Zhang, W.; Lin, L.; Yun, Y.S. Recent advance in hybrid evolutionary algorithms for multiobjective manufacturing scheduling. *Comput. Ind. Eng.* **2017**, *112*, 616–633. [CrossRef]
- 38. Yang, X.S.; Deb, S. Cuckoo search via Levy flights. In Proceedings of the World Congress on Nature and Biologically Inspired Computing (NaBIC 2009), Coimbatore, India, 9–11 December 2009; pp. 210–214.
- 39. Kanagaraj, G.; Ponnambalam, S.G.; Jawahar, N. A hybrid cuckoo search and genetic algorithm for reliability-redundancy allocation problems. *Comput. Chem. Eng.* **2013**, *66*, 1115–1125. [CrossRef]
- 40. Ishibushi, H.; Yoshida, T.; Murata, T. Balance between genetic search and local search in memetic algorithms for multiobjective permutation flowshop scheduling. *IEEE Trans. Evol. Comput.* **2003**, *7*, 204–223. [CrossRef]



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).