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A Hybrid Method for The Closed-loop Supply Chain to Minimize Total Logistics Costs

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Abstract. Crow search algorithm for binary optimization (BinCSA) is currently used in some ideal models of the uncapacitated facility location problem (UFLP), but studies on its use in real-world supply chain cases remain limited. Therefore, this study aimed to address the gap by introducing a hybrid method that combined the BinCSA with an exact method to solve a CLSC problem, including location allocation, transportation, and supplier selection challenges. The initial sections of the study included theoretical foundations and experimental results of the BinCSA. Subsequently, how the BinCSA works in the proposed hybrid method was discussed, and the computational results were showed to evaluate the performance of the proposed method.

Keywords: Crow search algorithm; Closed-loop supply chain; Facility location problem; Hybrid method

1. Introduction

The forward supply chain is a network connecting facilities and distribution mechanisms to manage the transformation of raw materials into finished products and deliver them to end customers. In contrast, the reverse supply chain focuses on the return flow of materials from customers to suppliers, with the aim of maximizing profits from returned products or minimizing the total costs of return processes (Kannan *et al.*, 2010). By emphasizing the backward flow, the reverse supply chain offers significant opportunities for recycling more materials and promoting environmental friendliness throughout supply chain activities.

The Closed-loop Supply Chain (CLSC) includes both the forward and reverse supply chain. The forward supply chain facilitates the movement of material flow from upstream suppliers to downstream customers, while the reverse supply chain manages the return flow from downstream customers back to upstream suppliers for potential recycling and reuse. A holistic manifestation of this concept is the CLSC, which requires a comprehensive assessment of its architectural blueprint. Unlike solely dissecting the forward and reverse supply chain, the CLSC model demands a holistic perspective, evaluating not only the performance of the forward supply chain but also the reverse. The overall performance is considered an entirety, avoiding a simplistic split into two distinct dimensions.

A significant increase in scholarly efforts has been on facility location models,

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addressing questions about the number and allocation of facilities, locations, and the processing of products, including recycling centers in the CLSC network (Zhen, Huang, and Wang, 2019). The significance of sustainability in CLSC network design is sometimes overlooked while existing models often prioritize total cost minimization or total profit maximization. In this study landscape, facility location models for the CLSC network have been defined by some scholars, reflecting a dedicated effort to optimize decision variables in both forward and reverse channels (Amin and Zhang, 2012). In similar studies, total cost minimization or total profit maximization were regarded as fundamental objective functions. Moreover, the relevance of sustainability was easily ignored in CLSC network design despite numerous calls for its importance by international organizations, societies, and governments in recent decades (Pati, Vrat, and Kumar 2008). Although sustainability in supply chain has been recently mentioned in the study, the number of published papers was still limited (Azadi *et al.,* 2015; Brandenburg *et al.,* 2014; Seuring, 2013).

In addressing these challenges, this study introduced Crow Search Algorithm (CSA), a population-based optimization algorithm inspired by the behavior of crow, as introduced by Askarzadeh (2016). Previous studies showed the superior efficiency of CSA when compared to established algorithms such as Genetic Algorithm (GA), Harmony Search (HS), and Particle Swarm Optimization (PSO) (Askarzadeh, 2016). Due to the promising capabilities of CSA and the limited literature on sustainability in supply chain, this study proposed a CLSC network model for a realistic problem including location-allocation, transportation, and supplier selection. A novel hybrid method was used to address this problem which integrated an exact method with CSA for solving the proposed CLSC mathematical model.

2. Literature Review

The concept of a sustainable supply chain includes managing material flows, information, and funds, as well as collaboration between enterprises along supply chain while addressing the three aspects of sustainable development, namely environmental, social, and economic simultaneously (Meixell and Luoma, 2015; Eskandarpour *et al.,* 2015; Brandenburg *et al.,* 2014). Adopting sustainability as a strategic tool can produce various benefits such as improving environmental impacts, enhancing brand image, generating revenue, customer service, and reducing production costs (Qiang *et al.,* 2013).

With advancements in recycling and remanufacturing technologies, scholars are increasingly focusing on integrating forward and reverse logistics as a CLSC network (Xie *et al.,* 2017). The CLSC, a subtype of sustainable supply chain aims to optimize recycling and refurbishing processes for end-of-life products (Das and Posinasetti, 2015). A general CLSC has a manufacturer serving for reverse logistics processes. The returned products and goods are recycled (Ashayeri, Ma, and Sotirov, 2015), and resold in the primary or secondary market after important processing (Turrisi, Bruccoleri, and Cannella 2013). A typical CLSC consists of both forward and reverse supply chain channels including processes like product return, recycling/recovery, remanufacturing, and resale (He, 2015).

CLSC network design treats forward and reverse supply chain networks as a cohesive unit, avoiding local optimality issues associated with separate modelling (Soleimani, Esfahani, and Govindan, 2014). Sustainable CLSC can be modelled based on its network but additional complexities, and increasing computational difficulty are introduced (Eskandarpour *et al.,* 2015). Therefore, capable solution methods are crucial in solving mathematical models.

Meta-heuristic algorithm, such as swarm-based algorithm, have been applied to various optimization problems (Utama, Yurifah, and Garside, 2023; Nitnara and Tragangoon, 2023; Zukhruf *et al.,* 2020). This study focused on a single-objective MILP model which aimed to minimize total costs in solving CLSC, location-allocation, transportation, and supplier selection problem. The proposed hybrid method integrated the Binary Crow Search Algorithm (BinCSA) with an exact method for efficient problem-solving.

3. Methodology

This study proposed a single-objective Mixed-Integer Linear Programming (MILP) model to address the CLSC problem. The model was solved using a hybrid method that combined CSA and an exact method. Specifically, CSA for binary optimization (BinCSA) was adopted to solve the location-allocation problem, which included selecting the location of distribution centers in a scenario modeled after the Incapacitated Facility Location Problem (UFLP). The mathematical model was subsequently solved using the CPLEX solver.

3.1. Problem Description

The CLSC problem depicted in Figure 1, incorporated both the forward and reverse supply chain. The forward supply chain included four distinct echelons, namely ‘supplier’, ‘manufacturers’, ‘distribution centers’, and ‘customers’. This mirrors a conventional forward supply chain, where manufacturers source components from suppliers, and finished products are distributed to customers through distribution centers.

The reverse supply chain consists of ‘recycling centers’, ‘disposal centers’, and ‘manufacturers’. The recycling centers collect used products from customers, inspect and disassemble, and segregate the components into ‘usable’ and ‘disposal parts’. Furthermore, the ‘usable parts’ undergo recycling and refurbishment, while ‘disposal parts’ are sent to 'disposal centers’. The recycled components are then forwarded to the ‘manufacturer’, combined with new parts procured from the ‘supplier' and used in the manufacturing process.

The location of the ‘supplier’, ‘plants’, and ‘customers’ were predetermined while the ‘distribution centers’ and ‘recycling centers’ remained undisclosed. This study operated within a discrete space, limiting choices for these locations to predefined candidates. (Indonesia).

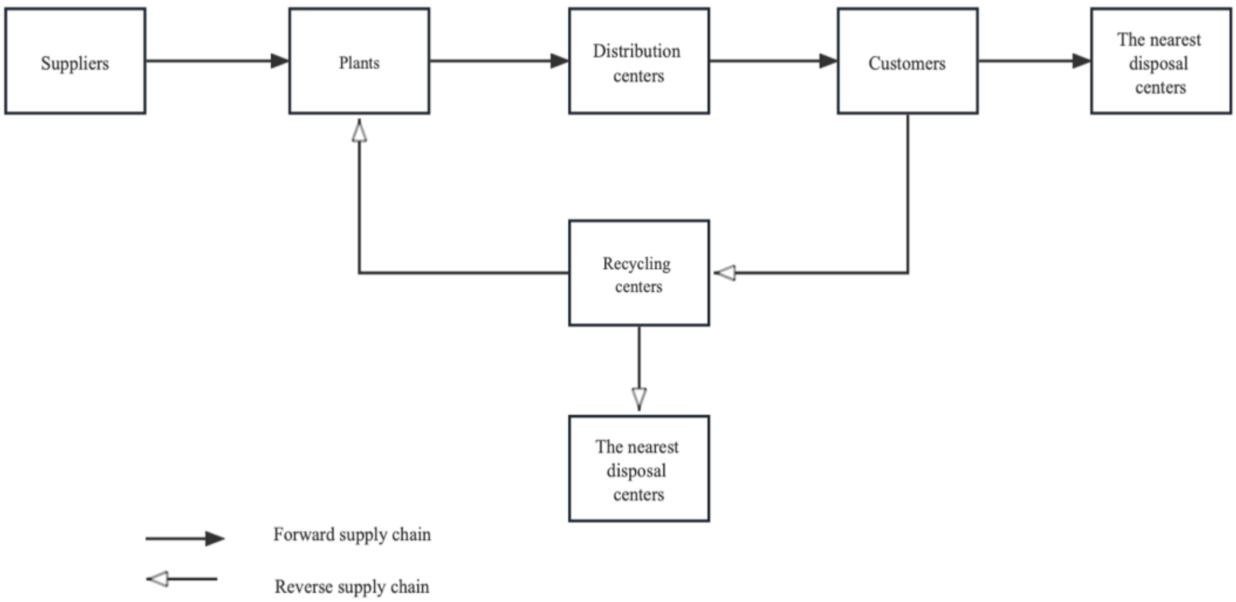

Figure 1 The proposed structure of the proposed CLSC model

This study introduced a single-objective MILP model for the CLSC. The objective function aimed to minimize the logistics costs, which included fixed, transportation, and others. Therefore, fixed costs were defined as the opening costs of each facility, primarily contingent on the quantity of opened facility. The transportation costs were influenced by the transportation expenses between customers' sites and the opened facilities. Other costs included the purchasing costs from suppliers and the recycling costs associated with used products.

3.2. Mathematical Model Description and Explanation

This section presented the mathematical model for the CLSC, outlined in Tables 2, 3, and 4. Table 2 shows the model indices, 3 provides information on model parameters, and Table 4 enumerates the model variables. These components collectively formed the foundation for understanding the complexities and intricacies of the CLSC mathematical model presented in this study.

Table 1 The indices of the CLSC mathematical model

Index	Description
i	Plant set ($i \in I$)
j	Potential distribution centers (DC) set ($j \in J$)
k	Customers set ($k \in K$)
l	Potential recycling centers (RC) set ($l \in L$)
s	Supplier set ($s \in S$)
n	Parts set ($n \in N$)

Table 2 The parameters of the CLSC mathematical model

Parameter	Description
W_i	The capacity of plant $i \in I$
d_k	The demand of customer $k \in K$
O_{ns}	The purchasing costs of part $n \in N$ from supplier $s \in S$
v_n	Unit recycling costs for part $n \in N$
F_j	The fixed costs for opening DC $j \in J$
f_l	The fixed costs for opening RC $l \in L$
T_{ij}^1	The logistics costs to transport per unit product from plant $i \in I$ to DC $j \in J$
T_{jk}^2	The logistics costs to transport all products from DC $j \in J$ to customer $k \in K$
T_{kl}^3	The logistics costs to transport all used products from customer $k \in K$ to RC $l \in L$
T_{li}^4	The logistics costs to transport per unit recycled material from RC $l \in L$ to plant $i \in I$
T_{si}^5	The logistics costs to transport per unit part from supplier $s \in S$ to plant $i \in I$ using
p_i	The minimal number of products transported from plant $i \in I$ to a DC
w_{ni}	The minimal number of recycled parts $n \in N$ transported from RC $l \in L$ to a plant
A_1	The average percentage of used products that can be recycled (collected from a customer)
A_2	The average percentage of used products that can be recycled and transformed into raw material
F_s	The minimum purchase quantity from supplier $s \in S$
A_s	The maximum purchase quantity from supplier $s \in S$
a_{ns}	Internal resource consumption of supplier $s \in S$ to produce one unit of part $n \in N$

Table 3 The decision variables of the CLSC mathematical model

Variables	Description
X_{ij}^{1}	The number of products transported from plant $i \in I$ to DC $j \in J$
X_{nsi}^{5}	The number of part $n \in N$ transported from supplier $s \in S$ to plant $i \in I$
Y_j	Equal to 1, when DC $j \in J$ opens, 0, otherwise
y_l	Equal to 1, when RC $l \in L$ opens, 0, otherwise
U_{ij}^{1}	Equal to 1, when products are transported from plant $i \in I$ to DC $j \in J$, 0, otherwise
U_{jk}^{2}	Equal to 1, when customer $k \in K$ is served by DC $j \in J$, 0, otherwise
U_{kl}^{3}	Equal to 1, when used products of customer $k \in K$ are transported to RC $l \in L$, 0, otherwise
U_{li}^{4}	Equal to 1, when recycled materials are transported from RC $l \in L$ to plant $i \in I$, 0, otherwise
X_{li}^{4}	The amount of equivalent to product's recycled materials transported from RC l $\in L$ to plant $i \in I$
U_{nsi}^{5}	Equal to 1, when part $n \in N$ transferred from supplier $s \in S$ to plant $i \in I$ using vehicle $v \in V^5$, 0, otherwise
u_{ns}	Binary variable for supplier $s \in S$ to transfer part $n \in N$

The mathematical model of this CLSC can be formulated as in equation (1). Its objective is to minimize the sum of the opening costs Z^{oc}, which is the equation (2) the transportation costs Z^{tc} is the equation (3), and other costs Z^{o} is equation (4).

$$Z_c = Z^{oc} + Z^{tc} + Z^{o} \tag{1}$$

$$Z^{oc} = \sum_{j=1}^{J} F_j Y_j + \sum_{l=1}^{L} F_l Y_l \tag{2}$$

$$\begin{aligned} Z^{tc} = & \sum_{i=1}^{I}\sum_{j=1}^{J} U^1{}_{ij} X^1{}_{ij} T^1{}_{ij} + \sum_{j=1}^{J}\sum_{k=1}^{K} U^2{}_{jk} T^2{}_{jk} + \sum_{k=1}^{K}\sum_{l=1}^{L} U^3{}_{kl} T^3{}_{kl} \\ & + \sum_{l=1}^{L}\sum_{i=1}^{I}\sum_{n=1}^{N} U^4{}_{li} X^4{}_{li} o_n T^4{}_{li} + \sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{i=1}^{I} U^5{}_{nsi} X^5{}_{nsi} T^5{}_{nsi} \end{aligned} \tag{3}$$

$$Z^{oc} = \sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{i=1}^{I} O_{ns} X^5{}_{nsi} + \sum_{n=1}^{N}\sum_{l=1}^{L}\sum_{i=1}^{I} v_n X^4{}_{li} o_n \tag{4}$$

Subject to:

$$\sum\nolimits_{s \in S} X_{nsi}^{5} + \sum\nolimits_{l \in L} X_{li}^{4}\, o_n \geq \sum\nolimits_{j \in J} o_n\, X_{ij}^{1}, \forall\, n \in N\,, i \in I \tag{5}$$

$$\sum_{j \in J} X_{ij}^{1} \leq W_i\,, \forall i \in I \tag{6}$$

$$U_{jk}^{2} - Y_j \leq 0\,, \forall j \in J, k \in K \tag{7}$$

$$U_{kl}^{3} - y_l \leq 0\,, \forall k \in K, l \in L \tag{8}$$

$$X_{ij}^{1} \geq p_i U_{ij}^{1}, \forall i \in I, j \in J \tag{9}$$

$$X_{ij}^{1} \leq M U_{ij}^{1}, \forall i \in I, j \in J \tag{10}$$

$$\sum_{j \in J} U_{jk}^{2} \leq 1, \forall k \in K \tag{11}$$

$$\sum_{l \in L} U_{kl}^{3} = 1, \forall k \in K \tag{12}$$

$$\sum_{k \in K} (U_{kl}^{3} d_{kt} o_n A_1 A_2) \geq \sum_{i \in I} X_{li}^{4} o_n, \forall l \in L, n \in \mathrm{N}, t \in \mathrm{T} \tag{13}$$

$$\sum_{l \in L} X_{li}^{4} o_n \leq \sum_{j \in J} o_n X_{ij}^{1}, \forall i \in \mathrm{I}, n \in \mathrm{N} \tag{14}$$

$$X_{li}^{4} o_n \geq w_{ni} U_{nli}^{4}, \forall l \in L, i \in I, n \in \mathrm{N} \tag{15}$$

$$X_{li}^{4} \leq M U_{nli}^{4}, \forall l \in L, i \in I \tag{16}$$

$$U_{nsi}^{5} F \leq U_{nsi}^{5} F \leq U_{nsi}^{5} A_s, \forall i \in I, n \in N, s \in S \tag{17}$$

$$X_{ij}^{1} \geq 0, \forall n \in N, i \in I, j \in J \tag{18}$$

$$X_{li}^{4} \geq 0, \forall n \in N, l \in L, i \in I \tag{19}$$

$$X_{nsi}^{5} \geq 0, \forall n \in N, s \in S, i \in I \tag{20}$$

$$Y_j, y_l, U_{ij}^{1}, U_{jk}^{2}, U_{kl}^{3}, U_{li}^{4}, U_{nsi}^{5} \in \{0, 1\} \tag{21}$$

$$M \text{ is a very large positive number} \tag{22}$$

The objective function (1) targets economic impact aimed at minimizing the sum of total costs. It included fixed costs (equation 2), transportation costs (equation 3), and other costs (equation 4). Formulation (2) showed the sum of all fixed costs, which covered the opening costs of distribution and recycling centers, as well as the purchasing costs of parts from suppliers. Formulation (3) represented the sum of logistic costs, accounting for transportation costs between suppliers, plant distribution centers, customers, and recycling centers. Formulation (4) showed total costs, which comprised purchasing raw materials and recycling used products.

For the explanation of constraints, constraint (5) endured the number of acquired parts from suppliers and recycling centers that met production based on the demands of customers. Constraint (6) limited plant production to its maximum capacity the plant capacity constraints). (7) and (8) guaranteed each customer was served by a distribution and recycling center. (9) and (10) limited the number of products shipped to a distribution center. (11) ensured a customer was served by only one open distribution center. (12) ensured used products from a customer were collected by one open recycling center. (13) limited the number of recycled parts. (14) ensured not all parts were old in remanufacturing. Constraints (15) and (16) restricted the number of recycled parts delivered to a plant. (17) set the minimum and maximum purchasing quantity of parts from a single supplier. Constraints (18), (19), (20), and (21) were binary and non-negativity restrictions on decision variables. Constraint (22) represented a large positive number M.

3.3. Inspiration of CSA

CSA is a population-based optimization algorithm designed for continuous optimization (Sonuç, 2021). Inspired by the intelligent behavior of crows, it mimics characteristics of living in flocks, remembering hidden food location, following others to steal food, by following other animals to discover their secret location and protecting their stash from theft (Askarzadeh, 2016) Recent studies focused on the behavior and brain function of crow. CSA showed significant success in addressing these challenges when applied to various optimization problems. This included but was not limited to studies of Gupta *et al.* (2018) on the healthcare sector, Sonuç (2021) on facility location problem, and Panah *et al.* (2021) on the industrial application. Recent reviews on applications of CSA refer to Meraihi *et al.* (2021). This study showed the potential of CSA as the foundational method to tackle the specific optimization problem under investigation and marked the pioneering attempt to use CSA for solving this particular problem, thereby presenting a novel and innovative method in the field.

3.4. Implementation of CSA for Optimization Problem

The number of crows is denoted as N, the total number of dimensions as D, AP refers to the awareness probability and FL refers to the flight length of crow traveling. The maximum number of CSA iterations is noted as t_max. For each iteration, the notation x^(i,t) is used to denote the spatial position of crow i at iteration t, where i = 1, 2, …, N and t = 1, 2, ..., t_max. m^(i,t) signifies the most successful position that crows have achieved so far and symbolizes the position of the crow's stash. The adjustment of the crow's position is realized through one of two distinct strategies, each contingent upon the value of AP, which determines the specific case to be used.

Within the first scenario, crow i adopts a strategy of shadowing crow j, with the intention of surreptitiously pilfering sustenance from the cache of crow j. Importantly, crow j doesn't notice that crow i is tracking in this case, thereby, the position of crow i is updated based on the equation (23):

$$x^{i,t} = x^{i,t} + r * FL * (m^{j,t} - x^{i,t}) \tag{23}$$

In the alternative scenario, denoted as the second scenario, it is presumed that crow *j* possesses awareness of crow *i*'s pursuit. In response, crow *j* will give up on going to its stash, opting instead to relocate to an alternative spatial position to protect its food. For this case, the new position of crow *i* is expounded upon as the equation (24):

$$\begin{aligned} &if\ r \geq AP: x^{i,t} = x^{i,t} + r * FL * \left(m^{j,t} - x^{i,t}\right), \\ &\text{otherwise: Select a random position as } x^{i,t} \end{aligned} \tag{24}$$

The notation r is a random numerical value drawn from the continuous interval (0,1) with uniform distribution. The parameter AP is bounded within the interval (0,1) and establishes a balance between exploration and exploitation. Importantly, the magnitude of AP imparts an influence upon search dynamics, when the value of AP is equal to zero, CSA becomes a local search method, and when AP is set to be one, the search process is performed as a global search process. The pseudo-code of CSA appears in Figure 2.

Algorithm: Pseudo-code for CSA

Input: Initial values for parameters *N, AP, FL*, t_{max}, *D*
Output: Optimal crow position

Generate the initial position of crow *x* randomly
Evaluate the position of each crow *x* in search space
Initialize crow's memory
while $t < t_{max}$ do
  for *i = 1:N* do
    Choose a random crow *j* to follow
    Generate a random value r_i in the range (0,1)
if $r_i \geq AP$ then
      $x^{i,t+1} = x^{i,t} + r_i * FL * (m^{j,t} - x^{i,t})$
    else
      $x^{i,t+1}$ = A random position in search space
    Check if solutions are in search space
    Evaluate the fitness of each crow
    Update memory of crow based on the objective function

Figure 2 Pseudo-code for CSA

3.5. CSA for Binary Optimization (BinCSA)

The initialization phase of BinCSA included generating random binary numbers using a Bernoulli process. A random number in the range of 0 to 1 was generated, and when it was less than 0.5, it was binarized to 0, otherwise, it was binarized to 1. This process illiterated repeatedly for each of the D variables till the initialization stage was complete. This method produced the first feasible solution for the Uncapacitated Facility Location Problem (ULFP), with the solution size equal to a total number of possible facility locations. Feasible solutions were represented as 1 for the potential facility location to be opened and 0 otherwise. The initial fitness values were calculated using the objective function based on the opening and transportation costs. In the case of discrete location, BinCSA determined the distribution center location through a series of steps outlined in Figure 3.

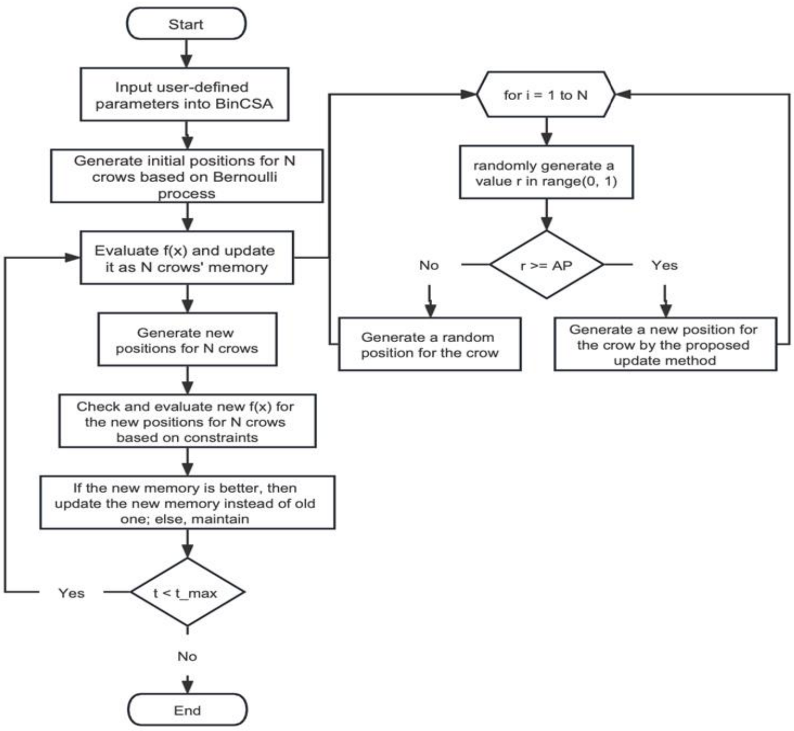

Figure 3 Flowchart of the BinCSA

3.6. A Two-stage Method to Solve the Model

The conceptual framework for the development of the proposed mathematical model was previously illustrated in Figure 1 and had equations (1) through (22). It was planned to be solved with a hybrid method of two stages which integrated both the exact method and the heuristic algorithm. The BinCSA was used at the initial stage to optimize facility location for both distribution centers and recycling centers, subject to uncapacitated constraints. Certain variables important to facility location problem were determined and treated as fixed parameters in the simplified version of the mathematical model after the first stage was completed., The simplified model became more amenable to resolution through the exact method. In the subsequent stage, the CPLEX solver was used to obtain solution for the mathematical model.

4. Results and Discussion

4.1. Numerical Experiment

A benchmark dataset obtained from both Irawan *et al.* (2022) and ORLIB was used to evaluate the performance of the proposed model in this study instead of relying on primary data to evaluate the effectiveness of the proposed model. The dataset included monetary values in US dollars and distances measured in kilometers. The evaluation included three main elements performed such as analysis of parameter settings for BinCSA, presentation of solutions to the uncapacitated location problem for distribution centers, and a discussion of solutions obtained from the MILP CLSC model.

BinCSA was executed on ten datasets obtained from ORLIB. These datasets comprise four sets of data with 25 potential distribution centers and 50 customers in each set, four sets of data with 50 potential distribution centers and 50 customers in each set, and two sets of data with 100 potential distribution centers and 1,000 customers in each set. Each dataset was executed twenty times, and the results of these iterations are presented in Table 5.

4.2. Parameters Tuning and Results

Modifying the parameters of a metaheuristic algorithm had a direct impact on the quality of the outcomes. Therefore, fine-tuning them posed a considerable challenge for scholars because it was a complex process that required conducting numerous computational experiments to determine the optimal settings specific to a given problem. In the BinCSA experiment, each parameter was independently assessed without the influence of other parameters. Optimal configuration could not be assuredly guaranteed even though several repeated attempts to fine-tune the parameters were made in such cases.

The practical implementation of the BinCSA identified three key parameters that significantly impacted its performance: population scale (N), awareness probability (AP), and the maximum number of iterations (t_max). Computational time and solution quality were crucially impacted by these parameters. Preliminary experiments suggested that the BinCSA performed relatively well when N = 400 and AP = 0.1. Therefore, for this experiment, N was set at 400 and AP as 0.1, with t_max being the only variable. The results given in Table 4 showed that increasing t_max could improve the solution quality. For datasets that did not reach the optimal solution, they have close gaps. However, in smaller datasets with optimal results, increasing t_max does not affect the values of the results but increases computational time. Determining the most appropriate t_max for each dataset was essential in achieving better performance within reasonable computational time.

In smaller-scale scenarios, exemplified by 'cap101' and 'cap102', where problem size was based on a '25*50' matrix, it was viable to adjust the value of 't_max' to a smaller range. This aimed to enhance the overall performance of result accuracy and computational efficiency. Conversely, for larger scenarios like 'capa' and 'capb', characterized by larger problem dimensions of '100*1000', fine-tuning the 't_max' parameter across a broader range accommodated search for optimal solutions and maintained computational efficiency. laminates.

Table 4 Results of 10 instances with t_max = 8,000, t_max = 12,000, and t_max = 30,000

N=400	*AP*=0.1		*t_max*= 8,000		*t_max* =12,000		*t_max* =30,000	
	Problem size	ORLIB cost	Costs (CSA)	CPU time	Costs (CSA)	CPU time	Costs (CSA)	CPU time
cap101	25 * 50	796,648.44	796,648.438	1.192	796,648.438	1.728	796,648.438	4.372
cap102	25 * 50	854,704.20	854,704.2	1.128	854,704.2	1.692	854,704.2	4.182
cap103	25 * 50	893,782.11	893,782.113	1.078	893,782.113	1.634	893,782.113	3.81
cap104	25 * 50	928,941.75	928,941.75	1.074	928,941.75	1.576	928,941.75	3.71
cap131	50 * 50	793,439.56	801,071.19	2.0676	793,473.61	3.033	793,439.562	6.649
cap132	50 * 50	851,495.33	856,992.81	1.992	853,782.81	2.882	851,495.325	6.377
cap133	50 * 50	893,076.71	896,083.67	2.008	893,782.11	2.851	893,076.713	6.392
cap134	50 * 50	893,076.71	930,562.36	2.027	928,941.75	2.815	928,941.75	6.095
capa	100 * 1000	17,156,454.48	28,143,242.1	50.989	19,737,461.8	72.794	17,156,454.48	168.991
capb	100 * 1000	12,979,071.58	16,373,178.4	51.35	13,965,251.1	73.128	12,979,071.58	169.549

4.3. The Results of the MILP CLSC Model

After results were obtained from BinCSA, modifications were made to equations from distribution centers to customers and customers to recycling centers in the CLSC model. These equations were deleted, and their values were modified based on BinCSA results. Parameters and constraints related to these equations were also removed. The binary results of the opened facility were modified from binary decision variables to known parameters. This study took the dataset 'cap101' as an example to minimize the total costs of the proposed CLSC mathematical model. Avoiding the opening of both distribution and recycling centers synchronously in the same potential location was the rule of facility opening.

The MILP model, post-modification, comprised 4,137 constraints and 102 variables. The experiment was conducted on a personal computer with an Intel® Core™ i7-8665U CPU @1.90GHz 2.11GHz processor with 16GB of RAM. The model was optimally solved using the IBM ILOG CPLEX optimization studio version 12.11. The CPU time to obtain the CPLEX result was 0.52 seconds. The minimized total costs that covered both the forward and reverse supply chain was $95,514,379.54 for one period. In this scenario, producing one unit of product needed 2 units of part 1, 1 unit of part 2, and 3 units of part 3. A supplier selection problem was solved. According to the results, the plant did not purchase any part from supplier 3; the plant purchased part 1 for 115,636 units, part 2 for 57,818 units, part 3 for 100,000 units from supplier 1; the plant purchased part 3 for 73,454 units from supplier 2.

5. Conclusions

In conclusion, this study successfully applied BinCSA to address the facility location problem in the proposed MILP model for the CLSC. A hybrid method, combining the exact method and BinCSA, effectively solved the proposed model. However, limitations included BinCSA solving impractical ULFP and challenges in tuning parameters at the initial stage. Future studies can improve parameters tuning through adaptive learning methodologies, extending BinCSA to capacitated facility location problem, using simulation-optimization methods, and incorporating environmental objectives in bi-objective CLSC model. Many existing experiences were using a hybrid method to address the CLSC-related problem, which included the amalgamation of two or more distinct meta-heuristics or exact methods but the body of studies applying CSA in combination with other methodologies were scarce. Therefore, it is promising to explore more opportunities to integrate CSA with other meta-heuristics and exact methods to address problems related to CLSC. One of those future study opportunities is currently being studied to correspond with cutting-edge advancements in supply chain study and development.

References

Amin, S.H., Zhang, G., 2012. An Integrated Model for Closed-loop Supply Chain Configuration and Supplier Selection: Multi-objective Approach. *Expert Systems with Applications*, Volume 39(8), pp. 6782–6791

Ashayeri, J., Ma, N., Sotirov, R., 2015. The Redesign of a Warranty Distribution Network with Recovery Processes. *Transportation Research Part E: Logistics and Transportation Review*, Volume 77, pp. 184–197

Askarzadeh, A., 2016. A Novel Metaheuristic Method for Solving Constrained Engineering Optimization Problems: Crow Search Algorithm. *Computers and Structures,* Volume 169, pp. 1–12

Azadi, M., Jafarian, M., Saen, R.F., Mirhedayatian, S.M., 2015. A New Fuzzy DEA Model for Evaluation of Efficiency and Effectiveness of Suppliers in Sustainable Supply Chain Management Context. *Computers and Operations Research*, Volume 54, pp. 274–285

Brandenburg, M., Govindan, K., Sarkis, J., Seuring, S., 2014. Quantitative Models for Sustainable Supply Chain Management: Developments and Directions. *European Journal of Operational Research*, Volume 233(2), pp. 299–312

Das, K., Posinasetti, N.R., 2015. Addressing Environmental Concerns in Closed-loop Supply Chain Design and Planning. *International Journal of Production Economics,* Volume 163, pp. 34–47

Eskandarpour, M., Dejax, P., Miemczyk, J., Péton, O., 2015. Sustainable Supply Chain Network Design: An Optimization-oriented Review. *Omega,* Volume 54, pp. 11–32

Gupta, D., Sundaram, S., Khanna, A., Hassanien, A.E., De Albuquerque, V.H.C., 2018. Improved Diagnosis of Parkinson's Disease using Optimized Crow Search Algorithm. *Computers and Electrical Engineering*, Volume 68, pp. 412–424

He, Y., 2015. Acquisition Pricing and Remanufacturing Decisions in a Closed-loop Supply Chain. *International Journal of Production Economics*, Volume 163, pp. 48–60

Irawan, C. A., Dan-Asabe Abdulrahman, M., Salhi, S., Luis, M., 2022. An Efficient Matheuristic Algorithm for Bi-objective Sustainable Closed-loop Supply Chain Networks. *(Insitute of Mathematics and its Applications) IMA Journal of Management Mathematics*, Volume 33(4), pp. 603–636

Kannan, G., Sasikumar, P., Devika, K., 2010. A Genetic Algorithm Approach For Solving A Closed Loop Supply Chain Model: A Case Of Battery Recycling. *Applied Mathematical Modelling*, Volume 34(3), pp. 655-670

Meixell, M.J., Luoma, P., 2015. Stakeholder Pressure in Sustainable Supply Chain Management: A Systematic Review. *International Journal of Physical Distribution and Logistics Management*, Volume 45(1/2), pp. 69–89

Meraihi, Y., Gabis, A.B., Ramdane-Cherif, A., Acheli, D., 2021. A Comprehensive Survey of Crow Search Algorithm and its Applications. *Artificial Intelligence Review*, Volume 54(4), pp. 2669–2716

Nitnara, C., Tragangoon, K., 2023. Simulation-Based Optimization of Injection Molding Process Parameters for Minimizing Warpage by ANN and GA. *International Journal of Technology*, Volume 14(2), pp. 422–433

Panah, P.G., Bornapour, M., Hemmati, R., Guerrero, J.M., 2021. Charging Station Stochastic Programming for Hydrogen/Battery Electric Buses using Multi-criteria Crow Search Algorithm. *Renewable and Sustainable Energy Reviews*, Volume 144, p. 111046

Pati, R., Vrat, P., Kumar, P., 2008. A goal programming model for paper recycling system. *Omega*, Volume 36(3), pp. 405–417

Qiang, Q., Ke, K., Anderson, T., Dong, J., 2013. The Closed-loop Supply Chain Network with Competition, Distribution Channel Investment, and Uncertainties. *Omega*, Volume 41(2), pp. 186–194

Seuring, S., 2013. A Review of Modeling Approaches for Sustainable Supply Chain Management. *Decision Support Systems*, Volume 54(4), pp. 1513–1520

Soleimani, H., Esfahani, M.S., Govindan, K., 2014. Incorporating Risk Measures in Closed-loop Supply Chain Network Design. *International Journal of Production Research,* Volume 52(6), pp. 1843–1867

Sonuç, E., 2021. Binary Crow Search Algorithm for the Uncapacitated Facility Location Problem. *Neural Computing and Applications*, Volume 33(21), pp. 14669–14685

Turrisi, M., Bruccoleri, M., Cannella, S., 2013. Impact of Reverse Logistics on Supply Chain Performance. *International Journal of Physical Distribution and Logistics Management*, Volume 43(7), pp. 564–585

Utama, D.M., Yurifah, A., Garside, A.K., 2023. A Novel Hybrid Spotted Hyena Optimizer: An Algorithm for Fuel Consumption Capacitated Vehicle Routing Problem. *International Journal of Technology*, Volume 14(5), pp. 1049–1059

Xie, J., Liang, L., Liu, L., Ieromonachou, P., 2017. Coordination Contracts of Dual-channel with Cooperation Advertising in Closed-loop Supply Chains. *International Journal of Production Economics*, Volume 183, pp. 528–538

Zhen, L., Huang, L., Wang, W., 2019. Green and Sustainable Closed-loop Supply Chain Network Design Under Uncertainty. *Journal of Cleaner Production*, Volume 227, pp. 1195–1209

Zukhruf, F., Frazila, R.B., Widhiarso, W., 2020. A Comparative Study on Swarm-based Algorithms to Solve the Stochastic Optimization Problem in Container Terminal Design. *International Journal of Technology*, Volume 11(2), pp. 374–387