

A Hybrid Butterfly-Genetic Algorithm for Sustainable Closed-Loop Supply Chain Network Design with Pricing Consideration: An Application to the Home Appliance Industry

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KEYWORDS

Closed Loop Supply Chain,

Sustainability,

Metaheuristic Algorithm,

Genetic Algorithm,

Butterfly Optimization Algorithm,

Home Appliance Industry,

Reverse Logistics,

Multi Objective Optimization

ABSTRACT

This article addresses the mounting pressure on industries to adopt sustainable practices by first developing a multi-echelon, multi-product, and multi-period closed-loop supply chain network model that integrates forward and reverse logistics for the home appliance sector. The model jointly pursues three objectives, namely economic efficiency, environmental impact, and social responsibility, combined into a single weighted fitness function, and explicitly differentiates pricing between original and remanufactured products. To solve the resulting large-scale mixed integer linear program, a novel hybrid metaheuristic algorithm is then proposed, embedding the crossover and mutation operators of the genetic algorithm (GA) into the butterfly optimization algorithm (BOA) to strengthen exploration of the search space and curb premature convergence. The hybrid algorithm, the GA, and the BOA are compared on six test problems of increasing size. Across these instances, the hybrid algorithm consistently outperforms the two standalone algorithms, improving the normalized revenue, environmental, and social criteria while reducing the normalized cost, with changes of up to about 0.05-0.10 (on a 0-1 normalized scale) relative to the BOA and the GA respectively; a sensitivity analysis on the objective weights further confirms the stability of these gains. These results demonstrate the superior solution quality of the hybrid metaheuristic algorithm and underline the importance of jointly addressing economic, environmental, and social objectives in closed-loop supply chain design. By contributing both an integrated sustainable network model and an efficient solution method, this study supports the adoption of closed-loop supply chain practices that reduce environmental footprints and promote social responsibility in the home appliance industry.

1. Introduction

Effective supply chain management is crucial for organizations to gain competitive advantage, ensure customer satisfaction, and promote sustainability in today's globalized economy. A supply chain is a complex network of organizations, activities, and resources that facilitate the movement of goods from producers to customers throughout a product's life cycle. Optimizing the flow of goods,

services, and resources within this network reduces costs, waste, and environmental impacts while improving overall system efficiency. Successful supply chain management not only enhances profitability and customer satisfaction but also fosters sustainable practices, particularly as organizations increasingly collaborate with suppliers and distributors across various regions worldwide [1]. Successful organizations prioritize strong supplier relationships, advanced technology implementation, and continuous process

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improvement within their supply chain networks to meet customer needs effectively and efficiently. The integration of forward and reverse logistics, known as the closed-loop supply chain, has gained attention due to environmental concerns and social regulations [2]. Decision-makers are increasingly focused on designing closed-loop supply chain networks to address sustainability challenges and meet stakeholder expectations in the modern business landscape.

A closed-loop supply chain is a sustainable approach to supply chain management that recycles, reuses, and reprocesses products and materials at the end of their life cycle. This circular model has been applied in various industries such as e-waste [3], textiles [4], automotive [5], packaging [6], construction [7], food [8], plastics [9], batteries [10], and medical devices [11]. By minimizing waste, conserving resources, and reducing environmental impacts, closed-loop supply chains offer a more sustainable alternative to the traditional linear model, challenging the conventional one-way flow of resources from source to consumption.

A sustainable closed-loop supply chain optimizes the flow of goods, services, and information while prioritizing environmental conservation, social responsibility, and economic viability [12,13]. This system facilitates a circular flow of materials, products, and waste, where recycling and remanufacturing processes extend the life cycle of resources and minimize waste generation. The integration of environmental, social, and economic dimensions in supply chain management is essential for fostering long-term sustainability in the closed-loop model.

A multi-objective mathematical model for a sustainable closed-loop supply chain network should incorporate forward and reverse logistics. Due to the inherent complexity and NP-Hard nature of designing such networks [14], meta-heuristic algorithms are well-suited to tackle these challenges [15-17]. These algorithms have proven effective in addressing various aspects of supply chain optimization, making them a viable option for solving complex problems in sustainable closed-loop supply chain network design.

This paper presents a multi-echelon, multi-product, and multi-period sustainable closed-loop supply chain network for the home appliance industry. The proposed network features a circular cycle for recycling home appliances and aims to achieve three key objectives: minimizing costs, reducing environmental pollution, and maximizing social impacts. These objectives are combined into a final objective function using a weighted approach. The model employs different pricing strategies for forward and reverse logistics, recognizing their importance for customer satisfaction and the successful implementation of sustainability measures across the product life cycle. By addressing diverse customer purchasing power, this tailored pricing strategy contributes to a more effective and sustainable closed-loop supply chain network in the home appliance sector.

Our research employs a multi-objective linear programming model with various binary, discrete, and continuous decision variables to address the complexities of a sustainable closed-loop supply chain network. Multi-objective linear programming models aim to optimize multiple objective functions concurrently while adhering to linear constraints [18]. In this context, our goal is to find an optimal balance between the competing objectives of cost reduction, environmental pollution minimization, and social impact maximization. Recognizing the potential conflicts between these objectives, the model seeks to effectively address the complexities and trade-offs inherent in sustainable supply chain management [19].

In this paper, we implement a hybrid metaheuristic algorithm combining the Butterfly Optimization Algorithm (BOA) [20] and the Genetic Algorithm (GA) [21]. Both algorithms have demonstrated their effectiveness in solving complex optimization problems. The hybrid algorithm leverages the strengths of both algorithms to enhance the overall performance in addressing the multi-objective

linear programming model for the sustainable closed-loop supply chain network.

The necessity of this research stems from the growing pressure on the home appliance industry to adopt sustainable practices while remaining economically competitive. Existing closed-loop supply chain (CLSC) models and solution methods struggle to jointly satisfy three requirements that this industry faces simultaneously: (i) coordinating forward and reverse product flows with differentiated pricing for original and remanufactured items, (ii) balancing economic, environmental, and social objectives rather than cost alone, and (iii) solving the resulting large, mixed integer formulation efficiently. This research addresses these challenges by proposing an integrated sustainable CLSC model together with a hybrid BOA-GA metaheuristic tailored to solve it.

This research makes the following main contributions:

- A multi-echelon, multi-product, multi-period sustainable closed-loop supply chain network model is developed for the home appliance industry, jointly optimizing economic, environmental, and social objectives while explicitly differentiating the pricing of original (forward) and remanufactured (backward) products.
- A novel hybrid metaheuristic algorithm is designed by embedding the GA's crossover and mutation operators into the BOA, specifically to mitigate the premature convergence and local-optima entrapment that limit the standalone BOA and GA on this large mixed integer linear program.
- The proposed hybrid algorithm is benchmarked against the standalone GA and BOA on six problem instances of increasing scale, showing consistent improvements in solution quality across all three sustainability criteria, with results corroborated by a sensitivity analysis on the objective weights.
- Managerial insight is offered into the trade-offs between economic, environmental, and social objectives in closed-loop supply chain design for the home appliance sector, providing guidance for decision-makers seeking to balance profitability with sustainability.

In doing so, this research addresses gaps in the current literature: it combines industry-specific modeling of the home appliance sector, explicit forward/backward pricing differentiation, and a three-dimensional sustainability objective within a single model, and it proposes a solution method designed to handle the resulting large numbers of continuous and discrete decision variables more effectively than the standalone GA or BOA. This study is distinct from the authors' related review [19], which surveys the broader literature on sustainable closed-loop supply chains and enabling technologies; the present work instead develops and computationally validates an original network model and a novel hybrid metaheuristic algorithm.

This paper consists of six main sections: Section 2 provides a comprehensive literature review on sustainable closed-loop supply chains. Section 3 presents the proposed sustainable closed-loop supply chain network model, including its assumptions, indicators, objective (fitness) functions, constraints, network parameters, and decision variables. Section 4 describes the proposed hybrid BOA-GA metaheuristic algorithm developed to solve this model. Section 5 reports and analyzes the computational results, comparing the performance of the proposed approach with the standalone GA and BOA. Finally, Section 6 summarizes the main findings, highlights the

contributions of the proposed strategy, and suggests potential future research directions.

2. Literature review

In this section, we will explore the research background and provide an overview of recent studies on sustainable closed-loop supply chain networks across various applications. The concept of sustainable closed-loop supply chains has been widely researched, with a focus on optimizing supply chain networks to minimize costs and environmental impacts while maximizing social benefits.

Yun et al. [22] introduced a sustainable closed-loop supply chain network using hybrid genetic algorithms. Their study aimed to reduce environmental pollution by minimizing carbon dioxide emissions while ensuring the goal of increasing social impacts through job creation and the employment of local workers. Additionally, reducing the total cost in the network cycle was considered as another sustainability objective, demonstrating the importance of balancing economic, environmental, and social aspects in supply chain management. The authors proposed a hybrid approach that combines GA and Simulated Annealing (SA) to address the optimization problem [22].

Oliveira et al. [23] presented a survey on the application of optimization methods in closed-loop supply chain networks. Their study analyzed research conducted between 2008 and 2020, revealing that over 70% of the studies focused on optimization algorithms with economic goals such as cost reduction and revenue increase. This finding highlights the relatively limited attention paid to sustainability aspects in closed-loop supply chain network research. Additionally, around 21% of the studies employed hybrid approaches, indicating the popularity of such strategies in this domain. The selection of appropriate methods for solving multi-objective optimization problems, considering the nature of the problem and its conditions, was also emphasized in their study, underscoring the importance of tailored solutions for complex supply chain network challenges [23].

Fathollahi-Fard et al. [24] proposed a two-channel closed-loop supply chain network for the automotive tire industry under uncertainty. They developed two hybrid metaheuristic strategies using four metaheuristic algorithms: GS, SA, Whale Optimization Algorithm (WOA), and Red Deer Algorithm (RDA). Cost reduction was chosen as the fitness function for the metaheuristic algorithms. The comparative evaluation demonstrated that the hybrid strategy combining WOA and SA outperformed other approaches in addressing the optimization problem, highlighting the potential benefits of this tailored solution for the automotive tire industry [24]. Chiang et al. [25] conducted a comprehensive review of multi-objective optimization in sustainable closed-loop supply chains and logistics management. The study highlighted the importance of balancing multiple, often conflicting objectives such as cost reduction, environmental impact minimization, and social responsibility enhancement. To effectively navigate these complex trade-offs, multi-objective optimization techniques were identified as suitable approaches. The review explored various multi-objective optimization techniques applied in this domain, including weighted sum method, goal programming, constraint method, evolutionary algorithms, and interactive methods. Each technique possesses unique strengths and weaknesses, and the selection of an appropriate technique depends on the specific problem context and decision makers' preferences [25].

Salehi-Amiri et al. [26] developed a sustainable closed-loop supply chain network for the walnut industry using mixed-integer linear programming to optimize the overall costs of the chain. While the objective function primarily focused on cost optimization, the network integrated forward and reverse logistics for both product delivery and returned product management. Five different meta-heuristic algorithms were employed to solve the optimization problem. The mixed-integer linear programming model aimed to minimize the overall costs in the walnut industry, with the network incorporating forward and reverse logistics to meet market demand and facilitate the reuse of returned products [26].

Mehrjerdi et al. [27] introduced a flexible and sustainable closed-loop supply chain model that incorporated multiple sourcing and information sharing strategies. The primary objectives of this research included examining the role of multiple sources and information sharing, as well as exploring strategies to enhance supply chain network resilience. The proposed model was applied to the automotive tire industry, with an improved version of the augmented epsilon constraint algorithm employed to solve the multi-objective optimization problem. This algorithm is a conventional method for addressing multi-objective optimization challenges. The model integrated various dimensions of sustainability by minimizing total cost, energy consumption, and pollution while maximizing job opportunities, thus encompassing a comprehensive approach to sustainable supply chain management [27].

Dastani et al. [28] developed a green closed-loop supply chain model utilizing the multi-objective Gray Wolf Optimization Algorithm (GWOA). The model incorporated two primary objectives: cost reduction and environmental impact minimization. The GWOA was employed to solve this multi-objective optimization problem. The network's forward logistics processes encompassed suppliers, manufacturers, distributors, retailers, and customers, while the backward logistics processes addressed the collection, inspection, and reprocessing of returned products. This holistic approach aimed to enhance both the economic and environmental performance of the supply chain network [28].

Rajabi-Kafshgar et al. [16] developed a closed-loop supply chain network for the agricultural industry, focusing on pistachio products, using a hybrid metaheuristic approach. A mixed linear mathematical model was formulated based on the proposed problem, and three hybrid metaheuristic algorithms were introduced and evaluated. The primary objective of this research was to design a sustainable supply chain network for agricultural products, with a specific focus on pistachios. The network integrated various stages, including farming, processing, distribution, and waste management. The authors created a sustainable closed-loop supply chain network that incorporated multiple objectives, constraints, and decision variables, representing key components such as transportation, inventory, production, and waste management. This comprehensive approach aimed to promote sustainability throughout the agricultural supply chain [16].

Afshar et al. [29] introduced a multi-objective optimization model for a multi-commodity closed-loop supply chain network that incorporated disruption risk considerations. The proposed model was designed for a supply chain with manufacturing and distribution components. This model aimed to determine the optimal location and allocation of items within the supply chain while controlling environmental, economic, and social factors. A unique aspect of the study was the integration of different scenarios in the closed-loop supply chain to account for product perishability and quality.

Furthermore, the model included carbon dioxide emission minimization to address environmental concerns [29].

Gholipour et al. [30] developed a multi-objective optimization model for a sustainable closed-loop supply chain network in the agricultural industry, focusing on pomegranate production in Iran. This novel model aimed to address gaps in previous research by considering factors such as waste separation, artificial intelligence costs for pest control, and maintenance costs for processed products. The integration of reverse logistics enabled the conversion of wasted pomegranates into valuable recycled products, including ethanol, renewable energy, and compost for organic fertilizer. The proposed model sought to minimize supply chain costs, reduce risks, and increase profits for orchardists. To solve the multi-objective optimization problem, two meta-heuristic algorithms, namely the non-dominated sorting genetic algorithm (NSGA) and the multi-objective particle swarm optimization algorithm (MOPSO), were employed, demonstrating the potential for improved supply chain management in the pomegranate industry [30].

Wang et al. [31] introduced a closed-loop supply chain network within a fuzzy environment, utilizing an enhanced genetic algorithm. The primary focus of this research was the establishment of a network that facilitates the reuse, renovation, and recycling of industrial waste. The proposed model incorporated three objectives: cost reduction, environmental impact minimization, and social responsibility maximization. Environmental performance was addressed through the reduction of carbon dioxide emissions, while social responsibility was enhanced by increasing job opportunities. An optimized version of the genetic algorithm, integrating electromagnetic concepts, was developed to solve the multi-objective optimization problem. This novel approach aimed to design a closed-loop supply chain network that effectively combined forward and reverse logistics while considering customer demands and conflicting objectives. To address the uncertainty of customer demands, fuzzy parameters were incorporated into the model, further emphasizing the need for robust and adaptable supply chain management strategies [31].

Valizadeh et al. [32] introduced a novel approach to managing sustainability risks in closed-loop supply chains through a hybrid optimization model. Drawing from previous research, a questionnaire was developed, encompassing four sustainability risks and 18 sub-criteria. Additionally, a two-level mathematical model was proposed to address government concerns regarding sustainability risks and decisions related to manufacturers' activities within the network. The four sustainability risks identified in the model included economic, social, environmental pollution, and operational risks. The findings of this research indicated that economic risks exerted the most significant impact on the network cycle, highlighting the importance of addressing financial considerations in supply chain management strategies [32].

Tavana et al. [33] explored a comprehensive framework for sustainable closed-loop supply chain network design using a multi-objective linear programming model. The model incorporated various factors such as routing, inventory, time windows, location, supplier selection, order allocation, and different modes of transportation, while considering uncertainties [33].

Dehshiri et al. [34] developed a multi-objective optimization model for a closed-loop supply chain network. The model focused on reducing costs, increasing customer responsiveness by minimizing product transfer times, and addressing environmental concerns by reducing gas emissions [34].

A mathematical model was presented for designing a closed-loop supply chain network in the hydrogen field, taking pipeline routing and pollutant gas emissions into account. The objectives included reducing supply constraints, pollutant emissions, and total network costs within a specified timeframe [35].

Bortolini et al. [36] introduced a three-objective optimization model for designing a medium-term sustainable closed-loop supply chain network. The linear programming model aimed to reduce costs, pollution, and inventory levels in distribution centers and customer warehouses. Successful implementation in a European company resulted in reduced inventory levels [36].

Cao et al. [37] investigated optimal pricing strategies for material recycling in the garment industry supply chain. A closed-loop supply chain model was presented with three leadership models (manufacturer, retailer, and collector) to select the optimal recycling strategy. The findings indicated that customer sensitivity to recycling prices affected the decision-making of other supply chain components [37].

A closed-loop supply chain network was examined, considering pricing decisions and queuing systems in production centers. The model aimed to maximize the net present value, real demand sensitivity to final product pricing, and re-production. A flexible fuzzy optimization method was used to handle uncertainties, and four optimization algorithms were employed to solve the problem [38].

Although the existing literature on sustainable closed-loop supply chain design and optimization has made significant contributions, several gaps remain: most studies rely on generic rather than industry-specific models; few integrate comprehensive forward/backward pricing strategies; existing solution methods for these multi-objective problems remain susceptible to local optima and premature convergence; social impact is rarely modeled as an explicit objective alongside cost and environmental impact; and hybrid meta-heuristic strategies for this class of problems remain under-explored.

3. Model formulation

This section outlines the design and development of a sustainable closed-loop supply chain network for the home appliance industry. To achieve optimal results, a hybrid strategy combining the BOA and GA is proposed to solve the optimization problem. The multi-objective linear programming model is designed to consider various aspects of the supply chain network, such as the circular economy, environmental pollution, and social impacts, along with economic goals.

A key feature of this proposed network is the integration of the circular economy concept. By enabling the reproduction or repair of original products, the network creates an opportunity for a wider customer base, including those with lower financial capacity, to purchase products. Furthermore, the model addresses environmental concerns by incorporating pollution considerations, as well as social impacts along with economic objectives. The sustainable closed-loop supply chain network ultimately includes three primary goals within its sustainability model: economic, environmental, and social impacts. By accounting for these diverse factors, the proposed network seeks to strike a balance between financial viability, ecological responsibility, and social welfare.

The general schematic representation of the proposed sustainable closed-loop supply chain network for the home appliance industry is depicted in Figure 1. The network consists of two primary components: forward logistics and backward logistics. Forward

logistics encompasses five key units: suppliers, manufacturers, distributors, retailers, and customers of original products. This chain ensures the smooth flow of products from raw materials to finished goods and ultimately to end consumers. On the other hand, backward logistics involves four units: collection, remanufacturing, waste management, and customers of remanufactured products. This section of the supply chain deals with product returns, recycling, and waste disposal, promoting the reuse and repurposing of materials. A noteworthy aspect of this network is the distinction between customers in the forward and backward logistics components. This separation enables the establishment of different pricing strategies for manufactured and remanufactured products.

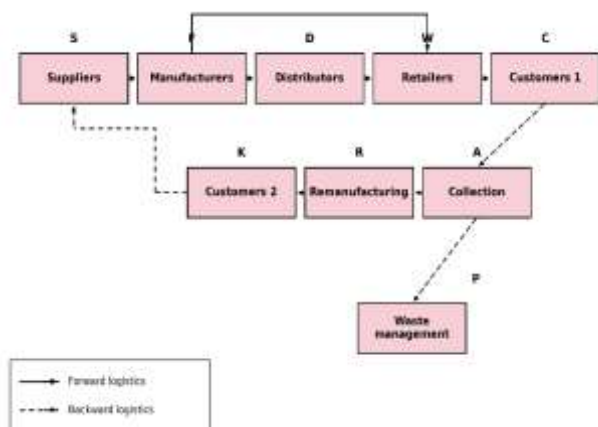


Fig.1. The general schematic representation of the proposed sustainable closed-loop supply chain network

3.1. Model assumptions

The proposed sustainable closed-loop supply chain network model operates under several key assumptions. These assumptions are as follows:

- Multi-echelon, multi-product, and multi-period model: The network comprises nine main entities, namely suppliers, manufacturers, distributors, retailers, customers of primary products, collection centers, remanufacturing facilities, customers of secondary products, and waste management.
- Differentiation between primary and secondary products: The quality, demand, and pricing of returned products differ from primary products. Consequently, distinct pricing strategies are applied to primary and secondary products.
- Multi-objective optimization: The model incorporates three objectives (economic, social, and environmental impacts) within the sustainable closed-loop supply chain network.
- Predetermined parameters: Key factors such as potential facility locations, capacities, and cost parameters are specified in advance.

3.2. Model indicators

This section presents a comprehensive list of indicators for the proposed sustainable closed-loop supply chain network model. Table 1 provides an organized overview of these indicators.

Tab. 1. Organized overview of model indicators

No.	Indicator	Set	Define
1	s	$S = \{1, 2, \dots, s\}$	Supplier
2	f	$F = \{1, 2, \dots, f\}$	Manufacturer
3	d	$D = \{1, 2, \dots, d\}$	Distributor
4	w	$W = \{1, 2, \dots, w\}$	Retailer

5	c	$C = \{1, 2, \dots, c\}$	Customers 1
6	a	$A = \{1, 2, \dots, a\}$	Collection
7	r	$R = \{1, 2, \dots, r\}$	Remanufacturer
8	k	$K = \{1, 2, \dots, k\}$	Customers 2
9	p	$P = \{1, 2, \dots, p\}$	Waste
10	u	$U = \{1, 2, \dots, u\}$	Product
11	t	$T = \{1, 2, \dots, t\}$	Time

3.3. Fitness function

The proposed sustainable closed-loop supply chain network model incorporates three key objectives. Differentiating product prices in forward logistics (original products) and backward logistics (reproduced products), this section presents the final weighted fitness function that combines these goals in the form of efficiency, serving as the fitness function for the hybrid metaheuristic algorithm. Equation (1) represents the fitness function for the proposed hybrid metaheuristic algorithm.

$$\text{Max: } \text{Fitness}_{\text{final}} = W_1 \times (\text{Fit}_{38} - \text{Fit}_{31}) + W_2 \times \frac{1}{\text{Fit}_{39}} + W_3 \times \text{Fit}_{58} \quad (1)$$

Where W_1 , W_2 and W_3 denote the weights assigned to each objective, ensuring their relative importance is accounted for. To maintain a balanced weight distribution, equation (2) must always hold true:

$$W_1 + W_2 + W_3 = 1 \quad (2)$$

It is important to note that the proposed sustainable closed-loop supply chain network model is inherently multi-objective, comprising economic, environmental, and social objectives. To obtain a single scalar value that population-based metaheuristics such as the BOA and the GA can directly optimize, these three objectives are aggregated using a weighted-sum (scalarization) approach, as formalized in Equations (1)-(2). This is a widely used and computationally efficient strategy for multi-objective supply chain optimization when decision-makers can express their relative priorities through the weights W_1 , W_2 and W_3 ; the resulting single-objective formulation is what is solved by the GA, the BOA, and the proposed hybrid algorithm in Section 4, and the sensitivity analysis in Section 5.6 examines how the solution changes as these weights vary. Unlike Pareto-based multi-objective methods (e.g., NSGA-II), the weighted-sum approach yields a single non-dominated solution per weight combination rather than an explicit approximation of the full Pareto front; extending the proposed hybrid algorithm to a Pareto-based multi-objective variant is identified in Section 6 as a direction for future research.

In order to establish the comprehensive final fitness function that integrates economic, social, and environmental objectives, a total of 58 distinct sub-functions have been carefully identified and detailed in Table 2. These sub-functions contribute to the overall evaluation of the sustainable closed-loop supply chain network, ensuring that all relevant aspects are considered for a well-rounded assessment of the system's performance and efficiency.

Tab. 2. All sub-functions

No.	Metric	Equation
1	Cost	$\text{Fit}_1 = \sum_{s=1}^S F_s \times L_s$
2	Cost	$\text{Fit}_2 = \sum_{f=1}^F F_f \times L_f$
3	Cost	$\text{Fit}_3 = \sum_{d=1}^D F_d \times L_d$

4	Cost	$Fit_4 = \sum_{w=1}^W F_w \times L_w$
5	Cost	$Fit_5 = \sum_{a=1}^A F_a \times L_a$
6	Cost	$Fit_6 = \sum_{r=1}^R F_r \times L_r$
7	Cost	$Fit_7 = \sum_{p=1}^P F_p \times L_p$
8	Cost	$Fit_8 = \sum_{f=1}^F \sum_{d=1}^D \sum_{u=1}^U \sum_{t=1}^T Q_{fdut} \times B_{fu} \times FC_{fut}$
9	Cost	$Fit_9 = \sum_{f=1}^F \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{fwut} \times B_{fu} \times FC_{fut}$
10	Cost	$Fit_{10} = \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \times B_{fu} \times FC_{fut}$
11	Cost	$Fit_{11} = \sum_{s=1}^S \sum_{f=1}^F \sum_{u=1}^U \sum_{t=1}^T Q_{sfut} \times B_{su} \times TC_{ut} \times DS_{sf}$
12	Cost	$Fit_{12} = \sum_{f=1}^F \sum_{d=1}^D \sum_{u=1}^U \sum_{t=1}^T Q_{fdut} \times B_{fu} \times TC_{ut} \times DS_{fd}$
13	Cost	$Fit_{13} = \sum_{f=1}^F \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{fwut} \times B_{fu} \times TC_{ut} \times DS_{fw}$
14	Cost	$Fit_{14} = \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \times B_{fu} \times TC_{ut} \times DS_{fc}$
15	Cost	$Fit_{15} = \sum_{d=1}^D \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{dwut} \times B_{du} \times TC_{ut} \times DS_{dw}$
16	Cost	$Fit_{16} = \sum_{w=1}^W \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{wcut} \times B_{wu} \times TC_{ut} \times DS_{wc}$
17	Cost	$Fit_{17} = \sum_{c=1}^C \sum_{a=1}^A \sum_{u=1}^U \sum_{t=1}^T Q_{caut} \times B_{cu} \times TC_{ut} \times DS_{ca}$
18	Cost	$Fit_{18} = \sum_{a=1}^A \sum_{p=1}^P \sum_{u=1}^U \sum_{t=1}^T Q_{aput} \times B_{au} \times TC_{ut} \times DS_{ap}$
19	Cost	$Fit_{19} = \sum_{a=1}^A \sum_{r=1}^R \sum_{u=1}^U \sum_{t=1}^T Q_{arut} \times B_{au} \times TC_{ut} \times DS_{ar}$
20	Cost	$Fit_{20} = \sum_{a=1}^A \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{akut} \times B_{au} \times TC_{ut} \times DS_{ak}$

21	Cost	$Fit_{21} = \sum_{a=1}^A \sum_{s=1}^S \sum_{u=1}^U \sum_{t=1}^T Q_{asut} \times B_{au} \times TC_{ut} \times DS_{as}$
22	Cost	$Fit_{22} = \sum_{r=1}^R \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{rkut} \times B_{ru} \times TC_{ut} \times DS_{rk}$
23	Cost	$Fit_{23} = \sum_{a=1}^A \sum_{p=1}^P \sum_{u=1}^U \sum_{t=1}^T Q_{aput} \times B_{au} \times PC_{put}$
24	Cost	$Fit_{24} = \sum_{a=1}^A \sum_{r=1}^R \sum_{u=1}^U \sum_{t=1}^T Q_{arut} \times B_{au} \times PRC_{rut}$
25	Cost	$Fit_{25} = \sum_{a=1}^A \sum_{s=1}^S \sum_{u=1}^U \sum_{t=1}^T Q_{asut} \times B_{au} \times RC_{sut}$
26	Cost	$Fit_{26} = \sum_{c=1}^C \sum_{a=1}^A \sum_{u=1}^U \sum_{t=1}^T Q_{caut} \times B_{cu} \times DAC_{aut}$
27	Cost	$Fit_{27} = \sum_{s=1}^S \sum_{f=1}^F \sum_{u=1}^U \sum_{t=1}^T Q_{sfut} \times B_{su} \times MC_{sut}$
28	Cost	$Fit_{28} = \sum_{f=1}^F \sum_{d=1}^D \sum_{u=1}^U \sum_{t=1}^T Q_{fdut} \times B_{fu} \times RR_{dut}$
29	Cost	$Fit_{29} = \sum_{d=1}^D \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{dwut} \times B_{du} \times RR_{wut}$
30	Cost	$Fit_{30} = \sum_{s=1}^S \sum_{f=1}^F \sum_{u=1}^U \sum_{t=1}^T Q_{sfut} \times B_{su} \times RR_{fut}$
31	Cost	$Fit_{31} = \sum_{i=1}^{30} Fit_i$
32	Revenue	$Fit_{32} = \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \times B_{fu} \times SS_{cut}$
33	Revenue	$Fit_{33} = \sum_{w=1}^W \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{wcut} \times B_{wu} \times SS_{cut}$
34	Revenue	$Fit_{34} = \sum_{i=32}^{33} Fit_i$
35	Revenue	$Fit_{35} = \sum_{a=1}^A \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{akut} \times B_{au} \times SC_{kut}$
36	Revenue	$Fit_{36} = \sum_{r=1}^R \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{rkut} \times B_{ru} \times SC_{kut}$
37	Revenue	$Fit_{37} = \sum_{i=35}^{36} Fit_i$

38	Revenue	$Fit_{38} = Fit_{34} + Fit_{37}$
39	Environmental	$Fit_{39} = Fit_{40} + Fit_{44} + Fit_{49} + Fit_{50}$
40	Environmental	$Fit_{40} = \sum_{i=41}^{43} Fit_i$
41	Environmental	$Fit_{41} = \sum_{f=1}^F \sum_{d=1}^D \sum_{u=1}^U \sum_{t=1}^T Q_{fdut} \times B_{fu} \times EP_{fu}$
42	Environmental	$Fit_{42} = \sum_{f=1}^F \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{fwut} \times B_{fu} \times EP_{fu}$
43	Environmental	$Fit_{43} = \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \times B_{fu} \times EP_{fu}$
44	Environmental	$Fit_{44} = \sum_{i=45}^{48} Fit_i$
45	Environmental	$Fit_{45} = \sum_{a=1}^A \sum_{p=1}^P \sum_{u=1}^U \sum_{t=1}^T Q_{aput} \times B_{au} \times EP_{au}$
46	Environmental	$Fit_{46} = \sum_{a=1}^A \sum_{r=1}^R \sum_{u=1}^U \sum_{t=1}^T Q_{arut} \times B_{au} \times EP_{au}$
47	Environmental	$Fit_{47} = \sum_{a=1}^A \sum_{s=1}^S \sum_{u=1}^U \sum_{t=1}^T Q_{asut} \times B_{au} \times EP_{au}$
48	Environmental	$Fit_{48} = \sum_{a=1}^A \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{akut} \times B_{au} \times EP_{au}$
49	Environmental	$Fit_{49} = \sum_{r=1}^R \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{rkut} \times B_{ru} \times EP_{ru}$
50	Environmental	$Fit_{50} = \sum_{a=1}^A \sum_{p=1}^P \sum_{u=1}^U \sum_{t=1}^T Q_{aput} \times B_{pu} \times EP_{pu}$
51	Social	$Fit_{51} = \sum_{s=1}^S EMP_s \times L_s$
52	Social	$Fit_{52} = \sum_{f=1}^F EMP_f \times L_f$
53	Social	$Fit_{53} = \sum_{d=1}^D EMP_d \times L_d$
54	Social	$Fit_{54} = \sum_{w=1}^W EMP_w \times L_w$
55	Social	$Fit_{55} = \sum_{a=1}^A EMP_a \times L_a$
56	Social	$Fit_{56} = \sum_{p=1}^P EMP_p \times L_p$
57	Social	$Fit_{57} = \sum_{r=1}^R EMP_r \times L_r$

58	Social	$Fit_{58} = \sum_{i=51}^{57} Fit_i$
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3.4. Model constraints

Table 3 presents the constraints of the proposed sustainable closed-loop supply chain network model. These constraints define the operational boundaries and conditions that must be adhered to within the network (e.g., capacity, flow-balance, and facility-count restrictions), ensuring that the system functions effectively while meeting the desired economic, social, and environmental objectives. Satisfying these constraints is crucial for the feasibility of any candidate solution produced by the solution algorithm in Section 4.

Tab. 3. The constraints of the proposed model

No.	Constraint
1	$LI_{sf} \leq \sum_{s=1}^S \sum_{f=1}^F \sum_{u=1}^U \sum_{t=1}^T Q_{sfut} \leq LMI_{sf}$
2	$LI_{fd} \leq \sum_{f=1}^F \sum_{d=1}^D \sum_{u=1}^U \sum_{t=1}^T Q_{fdut} \leq LMI_{fd}$
3	$LI_{fw} \leq \sum_{f=1}^F \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{fwut} \leq LMI_{fw}$
4	$LI_{fc} \leq \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \leq LMI_{fc}$
5	$LI_{dw} \leq \sum_{d=1}^D \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{dwut} \leq LMI_{dw}$
6	$LI_{wc} \leq \sum_{w=1}^W \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{wcut} \leq LMI_{wc}$
7	$LI_{ca} \leq \sum_{c=1}^C \sum_{a=1}^A \sum_{u=1}^U \sum_{t=1}^T Q_{caut} \leq LMI_{ca}$
8	$LI_{ap} \leq \sum_{a=1}^A \sum_{p=1}^P \sum_{u=1}^U \sum_{t=1}^T Q_{aput} \leq LMI_{ap}$
9	$LI_{ar} \leq \sum_{a=1}^A \sum_{r=1}^R \sum_{u=1}^U \sum_{t=1}^T Q_{arut} \leq LMI_{ar}$
10	$LI_{ak} \leq \sum_{a=1}^A \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{akut} \leq LMI_{ak}$
11	$\leq \sum_{r=1}^R \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{rkut} \leq LMI_{rk}$
12	$\sum_{s=1}^S L_s \leq S$
13	$\sum_{f=1}^F L_f \leq F$
14	$\sum_{d=1}^D L_d \leq D$
15	$\sum_{w=1}^W L_w \leq W$
16	$\sum_{a=1}^A L_a \leq A$
17	$\sum_{p=1}^P L_p \leq P$
18	$\sum_{r=1}^R L_r \leq R$

$$\begin{aligned}
& \sum_{s=1}^S \sum_{f=1}^F \sum_{u=1}^U \sum_{t=1}^T Q_{sfut} \times B_{su} \\
& = \sum_{f=1}^F \sum_{d=1}^D \sum_{u=1}^U \sum_{t=1}^T Q_{fdut} \\
& \quad \times B_{fu} \\
& + \sum_{f=1}^F \sum_{w=1}^W \sum_{u=1}^U \sum_{t=1}^T Q_{fwut} \\
& \quad \times B_{fu} \\
& + \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \\
& \quad \times B_{fu} \\
& \sum_{c=1}^C \sum_{a=1}^A \sum_{u=1}^U \sum_{t=1}^T Q_{caut} \times B_{cu} \\
& = \sum_{a=1}^A \sum_{p=1}^P \sum_{u=1}^U \sum_{t=1}^T Q_{aput} \\
& \quad \times B_{au} \\
& + \sum_{a=1}^A \sum_{r=1}^R \sum_{u=1}^U \sum_{t=1}^T Q_{arut} \\
& \quad \times B_{au} \\
& + \sum_{a=1}^A \sum_{s=1}^S \sum_{u=1}^U \sum_{t=1}^T Q_{asut} \\
& \quad \times B_{au} \\
& + \sum_{a=1}^A \sum_{k=1}^K \sum_{u=1}^U \sum_{t=1}^T Q_{akut} \\
& \quad \times B_{au} \\
& \sum_{f=1}^F \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{fcut} \times B_{fu} \\
& + \sum_{w=1}^W \sum_{c=1}^C \sum_{u=1}^U \sum_{t=1}^T Q_{wcut} \\
& \quad \times B_{wu} \geq \frac{7}{10} \times DDD_{cut}
\end{aligned}$$

3.5. Network parameters

In the preceding sections, a comprehensive outline of the objective functions was provided, encompassing economic, social, and environmental aspects of the proposed sustainable closed-loop supply chain network model. Additionally, the constraints governing the model were also clearly defined. Table 4 offers a consolidated overview of all parameters pertaining to this network, serving as a valuable reference point for understanding the intricacies of the model and facilitating its implementation.

Tab. 4. All network Parameters

No.	Parameter	Define
1	F_s	Fixed cost of supplier opening
2	F_f	Fixed cost of manufacturer opening
3	F_d	Fixed cost of distributor opening
4	F_w	Fixed cost of retailer opening
5	F_a	Fixed cost of collection opening
6	F_r	Fixed cost of remanufacturing opening
7	F_p	Fixed cost of waste opening
8	B_{fu}	Package size of product u from manufacturer f
9	B_{su}	Package size of product u from supplier s
10	B_{du}	Package size of product u from distributor d
11	B_{wu}	Package size of product u from retailer w
12	B_{ru}	Package size of product u from remanufacturing r

13	FC_{fut}	Cost of producing product u at time t from manufacturer f
14	TC_{ut}	Transportation cost of product u at time t
15	DS_{sf}	Distance between supplier s and manufacturer f
16	DS_{fd}	Distance between manufacturer f and distributor d
17	DS_{fw}	Distance between manufacturer f and retailer w
18	DS_{fc}	Distance between manufacturer f and customer c
19	DS_{dw}	Distance between distributor d and retailer w
20	DS_{wc}	Distance between retailer w and customer c
21	DS_{ca}	Distance between customer c and Collection a
22	DS_{ap}	Distance between collection a and waste p
23	DS_{as}	Distance between collection a and supplier s
24	DS_{ar}	Distance between collection a and recycling r
25	DS_{ak}	Distance between collection a and customer k
26	PC_{put}	Cost of waste of product u at time t by waste unit p
27	PRC_{rut}	Cost of reproducing product u at time t by reproducing unit r
28	RC_{sut}	Cost of recycling product u at time t by supplier unit s
29	DAC_{aut}	Cost of collecting product u at time t by collection unit a
30	MC_{sut}	Cost of materials of product u at time t by supplier unit s
31	RR_{dut}	Cost of storing product u at time t by distributor unit d
32	RR_{wut}	Cost of storing product u at time t by retailer unit w
33	SS_{cut}	Price of product u at time t for customer c
34	SC_{kut}	Price of product u at time t for customer k
35	EP_{fu}	Environmental impact of producing product u from producer unit f
36	EP_{au}	Environmental impact of producing product u from collection unit a
37	EP_{ru}	Environmental impact of producing product u from reproducing unit r
38	EMP_s	Number of jobs created If supplier is open
39	EMP_f	Number of jobs created if producer is open
40	EMP_d	Number of jobs created if distributor is open
41	EMP_w	Number of jobs created if retailer is open
42	EMP_a	Number of jobs created if collection is open
43	EMP_p	Number of jobs created if waste unit is open
44	EMP_r	Number of jobs created if reproduction is open
45	B_{cu}	Package size of product u from customer c
46	B_{au}	Package size of product u from Collection a
47	DS_{rk}	Distance between remanufacturing r a and customer k

48	RR_{fut}	Cost of storing product u at time t by manufacturer f
49	B_{pu}	Package size of product u from waste p
50	EP_{pu}	Environmental impact of producing product u from waste p

3.6. Decision variables

Table 5 displays the decision-making variables associated with the proposed sustainable closed-loop supply chain network. These variables serve as essential components in the optimization process, as they represent the controllable factors that can be adjusted to achieve the desired balance between economic, social, and environmental objectives while adhering to the specified constraints. Analyzing and understanding these variables is crucial for effectively managing and optimizing the supply chain network's performance.

Tab. 5. The decision-making variables

No.	Variable	Define
1	L_s	Binary decision variable in the supplier domain
2	L_f	Binary decision variable in the producer domain
3	L_d	Binary decision variable in the distributor domain
4	L_w	Binary decision variable in the retailer domain
5	L_a	Binary decision variable in the collection domain
6	L_r	Binary decision variable in the recycling domain
7	L_p	Binary decision variable in the waste domain
8	Q_{fdut}	Product package flow u at time t from producer f to distributor d
9	Q_{fwut}	Product package flow u at time t from producer f to retailer w
10	Q_{fcut}	Product package flow u at time t from producer f to customer c
11	Q_{sfut}	Product package flow u at time t from supplier s to producer f
12	Q_{dwut}	Product package flow u at time t from distributor d to retailer w
13	Q_{wcut}	Product package flow u at time t from retailer w to customer c
14	Q_{caut}	Product package flow u at time t from customer c to collection a
15	Q_{aput}	Product package flow u at time t from collection a to waste p
16	Q_{arut}	Product package flow u at time t from collection a to recycling r
17	Q_{asut}	Product package flow u at time t from collection a to supplier s
18	Q_{rkut}	Product package flow u at time t from reproduction r to customer k
19	Q_{akut}	Product package flow u at time t from collection a to customer k

4. Solution Algorithm

This section provides an overview of the two meta-heuristic algorithms used in the proposed hybrid strategy: The BOA and the GA.

4.1. Butterfly Optimization Algorithm (BOA)

The BOA is a nature-inspired, population-based meta-heuristic algorithm introduced by Arora and Singh (2019). Drawing inspiration from the natural behavior of butterflies, BOA models their food-seeking and mating processes to perform global and local searches, respectively. Its simplicity and low number of parameters make it an attractive choice for solving complex optimization problems.

In BOA, each butterfly represents a potential solution within the problem's search space. The algorithm iteratively evolves these solutions through generations, employing a global search mechanism that mimics the butterflies' foraging behavior and a local search mechanism that simulates their mating process. This combination of exploration and exploitation strategies enhances the algorithm's ability to converge towards the optimal solution.

Due to its effectiveness in solving optimization problems, BOA has been widely applied in various domains. Additionally, a binary version of the algorithm has been developed, enabling its application to optimization problems with binary coding. The pseudo-code of the BOA is presented in Algorithm 1, providing an overview of its core structure and functionality.

Algorithm 1: Butterfly Optimization Algorithm (BOA)

Input: maximum iteration number (Max), population size (Size), sensory modality (c), power exponent (a), and switch probability (P) and fitness function $f(x)$

Output: Find the best butterfly (g^*)

01. Initialization of input parameters
02. Generate initial population of butterflies
03. Stimulus intensity I_i at x_i is determined by $f(x_i)$
04. for $i=1$: Max
05. for $j=1$: Size
06. Calculate fragrance for all butterflies using Eq. 3
07. Find the best butterfly
08. Generate a random number r from $[0, 1]$
09. if $r < P$
10. Move towards best butterfly using Eq. 4
11. else
12. Move randomly using Eq. 5
13. end if
14. end for
15. Update the value of a
16. end for

In nature, butterflies possess sensory receptors that enable them to perceive the scent of flowers. Drawing inspiration from this phenomenon, the BOA assumes that butterflies can emit a variety of fragrances, which their neighbors can detect with varying intensity. This intensity is modeled through the equation 3, where variable ' c ' represents the sensory state, ' I ' denotes the butterfly's merit derived from the objective function, and ' a ' signifies the power, which gradually increases from 0.1 to 0.3 as the algorithm iterates. The variable ' a ' plays a crucial role in balancing the global and local search components of the algorithm, facilitating the exploration and exploitation of the solution space. By incorporating the concept of fragrance intensity, BOA captures the complex dynamics of butterfly behavior, enabling the algorithm to navigate and converge towards the optimal solution effectively.

$$pfi = cI^a \quad (3)$$

The BOA comprises two primary phases: global search and local search. In the global search phase, the algorithm updates the candidate solutions using the best solution in the population, drawing inspiration

from the food-seeking behavior of butterflies. This process encourages exploration of the search space, enhancing the chances of finding the optimal solution. On the other hand, the local search phase in BOA updates the solutions based on a randomly selected individual from the population. This mechanism simulates the mating process of butterflies, promoting exploitation of the search space around promising regions. By combining these global and local search strategies, BOA achieves an effective balance between exploration and exploitation, ultimately leading to more efficient optimization outcomes. During the global search phase of the BOA, candidate solutions are updated using the best solution from the population, as shown in equation 4.

$$x_i^{t+1} = x_i^t + (r^2 \times g^* - x_i^t) \times pf_i \quad (4)$$

In the local search phase of the BOA, the solutions are updated using a randomly chosen individual from the current population, as depicted in equation 5. This process simulates the mating behavior of butterflies, allowing the algorithm to exploit promising areas within the search space.

$$x_i^{t+1} = x_i^t + (r^2 \times x_j^t - x_k^t) \times pf_i \quad (5)$$

The BOA employs a switch probability, denoted by variable 'P', to manage the transition between the global and local search phases. This probability facilitates the decision-making process for each individual butterfly, determining whether it participates in the global or local search phase for solution updating.

Essentially, the switch probability 'P' serves as a random conditional control mechanism within BOA. By dynamically adjusting the focus between exploration and exploitation, the algorithm achieves a more comprehensive coverage of the solution space. This adaptive balance contributes to the overall efficiency and effectiveness of the BOA in solving complex optimization problems.

4.2. Genetic Algorithm (GA)

The GA is a potent tool for solving large-scale optimization problems, categorized as a heuristic optimization method based on random search. At its core, GA operates with chromosomes, which represent potential solutions within the problem's search space. Each chromosome is composed of genes that describe the problem's parameters. GA initiates the search process with an initial population of random chromosomes, evolving towards the optimal solution with each iteration. The algorithm's performance relies heavily on its population size, which is determined based on the optimization problem's characteristics. GA commences with a global search using the initial chromosome population. Each iteration generates a new population through three key operators: selection, crossover, and mutation. The selection operator chooses chromosomes based on their merit within the population, prioritizing those with higher fitness for maximization problems or lower fitness for minimization problems. The crossover operator combines two selected chromosomes from the previous population, introducing changes to create new offspring. Crossover can be implemented using single-point or multi-point techniques. Lastly, the mutation operator manipulates specific genes within a chromosome, enabling the algorithm to explore new regions of the search space and prevent premature convergence. The pseudocode for the GA is presented in Algorithm 2.

Algorithm 2: Genetic Algorithm (GA)

Input:

- S (population size)
- P_c (crossover probability)
- P_m (mutation probability)
- Imax (iteration)

Output:

- C* (best chromosome)
- 01. Generate initial population with S chromosome, randomly.
- 02. for i ← 1 to Imax
- 03. Evaluate fitness value of each chromosome in population
- 04. Select number of chromosomes with selection strategies
- 05. Generate ran \\\ ran is a random number between 0 and 1
- 06. if ran ≤ P_c
- 07. Operate crossover on selected chromosomes
- 08. end
- 09. Generate ran \\\ ran is a random number between 0 and 1
- 10. if ran ≤ P_m
- 11. Operate mutation on crossovered chromosomes
- 12. end
- 13. end
- 14. Evaluate fitness value of each chromosome in final population
- 15. Select C* as a best chromosome

In summary, the GA leverages the principles of natural selection and genetic inheritance to effectively solve complex optimization problems. By employing selection, crossover, and mutation operators, GA achieves an efficient balance between exploration and exploitation, enhancing its optimization capabilities across various domains.

4.3. Comparison of algorithms

The proposed hybrid algorithm effectively combines the strengths of two metaheuristic algorithms while mitigating their individual weaknesses. Each metaheuristic algorithm possesses unique advantages and disadvantages, as depicted in Table 6. This hybrid approach leverages the complementary characteristics of both algorithms to enhance overall performance, resulting in improved optimization capabilities for the closed-loop supply chain network. By capitalizing on the strengths of each algorithm and minimizing their drawbacks, the hybrid algorithm demonstrates superior problem-solving capacity in the context of sustainable supply chain network management.

Tab. 6. Comparison of metaheuristic algorithms

No.	characteristic	GA	BOA	Proposed algorithm
1	Population-based	Yes	Yes	Yes
2	Random initial population	Yes	Yes	Yes
3	Fitness function-based	Yes	Yes	Yes
4	Evolutionary strategy	Yes	Yes	Yes
5	Crossover strategy	Yes	No	Yes
6	Mutation strategy	Yes	No	Yes
7	Effect of the best solution	No	Yes	Yes

4.4. Hybrid metaheuristic algorithm

The proposed hybrid metaheuristic algorithm draws from the strengths of two population-based metaheuristic algorithms inspired by natural phenomena. The core algorithm employed is the BOA, which has been enhanced through the integration of the genetic algorithm's crossover and mutation operators. This strategic combination aims to capitalize on the unique advantages of both algorithms, thereby achieving superior optimization results within the sustainable closed-loop supply chain network. The synergistic effect of these algorithms enables the exploration and exploitation of the

solution space more effectively, leading to improved decision-making and overall performance.

Each candidate solution (butterfly/chromosome) in the population directly encodes the complete set of decision variables of the model in Section 3: the binary facility-selection variables for the seven facility-type domains (supplier, manufacturer, distributor, retailer, collection, remanufacturing, and waste-management, Table 5), and the continuous flow variables that determine the quantity of each product shipped along every forward and backward arc of the network in each period (Table 5). This direct encoding allows the fitness function in Equation (1) to be evaluated for any candidate solution by substituting its facility and flow values into the sub-functions of Table 2. The crossover and mutation operators described below act directly on this vector of decision variables, so that every offspring produced by the algorithm remains a representation of the same decision variables as its parents.

4.4.1. Crossover operator

The two-point crossover operator is applied to a pair of parent chromosomes, with the crossover probability (p_c) taken into consideration. This process generates two offspring chromosomes through the recombination of the parental chromosomes. The cut points are chosen at random along the chromosome's length, effectively swapping corresponding segments between the parent chromosomes. Figure 2 provides an illustrative example of the two-point crossover operator in action. It is noteworthy that the time complexity of this operator is $O(n^2)$, where n represents the length of the chromosome. This indicates that the computational time required for the two-point crossover operation increases with the size of the chromosome.

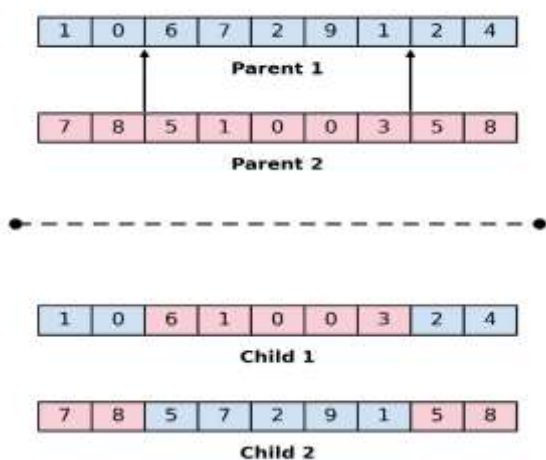


Fig. 2. An example of the two-point crossover operator

4.4.2. Mutation operator

In the GA, the mutation operator is applied to chromosomes with a specified mutation probability, (P_m). This involves generating a random number between zero and one; if this number is smaller than the designated P_m value, the mutation operation is executed on the chromosome. The primary function of the mutation operator is to alter the search direction within the GA, which is achieved by manipulating a subset of genes within the chromosome. The swap mutation operator, a specific type of mutation operator, aims to increase population diversity. This operator randomly selects two genes and transposes their values, potentially leading to novel solutions within the problem's search space. The time complexity of the transposition

mutation operator is $O(n)$, where n denotes the length of the chromosome. As a result, the computational time for this operator scales linearly with the chromosome's size. Figure 3 provides an example of the swap mutation operator in action, demonstrating its ability to promote solution diversity and facilitate the exploration of the problem's search space.

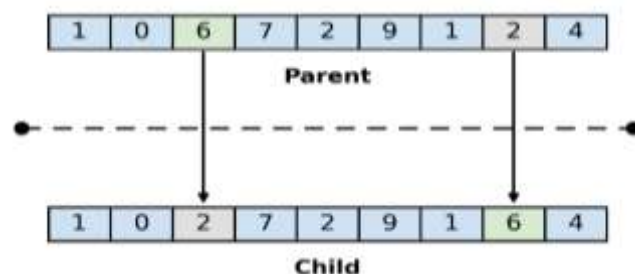


Fig. 3. An example of the swap mutation operator

4.4.3. Challenges

To address the challenges of premature convergence and local optima in the BOA, two solutions are proposed:

- Inclusion of the crossover operator from the GA: By incorporating GA's crossover operator, BOA can avoid local optima entrapment. The crossover operator facilitates the generation of diverse solution combinations, enhancing exploration of the search space and reducing the likelihood of converging to suboptimal solutions.
- Inclusion of the mutation operator from the GA: The integration of GA's mutation operator into BOA helps prevent premature convergence. By introducing various mutations in the solutions, the mutation operator fosters a more comprehensive exploration of the problem domain, promoting the identification of the global optimal solution.

4.4.4. Improved strategies

The first strategy for escaping local optima involves employing the two-point crossover operator. Implemented in each iteration of the BOA, this strategy entails randomly selecting a specified maximum number of butterfly pairs from the population. The two-point crossover operator is then applied to generate two offspring, after which a decision is made based on the fitness function to determine the best solutions among the four candidates (two parents and two children). Algorithm 3 presents a comprehensive description of this strategy, demonstrating how the two-point crossover operator contributes to preventing entrapment in local optima.

Algorithm 3: First improved strategy

In each round

01. $max_i = 10\%$ of population size
02. for $i = 1$ to max_i
03. parent_1 = a random butterfly in population
04. parent_2 = a random butterfly in population
05. (child_1, child_2) = Two-point crossover(parent_1, parent_2)
06. sort parent_1, parent_2, child_1, child_2 based on fitness
07. parent_1 = First best solution
08. parent_2 = Second best solution
09. end

The second strategy designed to prevent premature convergence involves employing the swap mutation operator. This strategy is executed during each iteration of the BOA, targeting the best solution within the population. This approach is applied a predetermined maximum number of times, with the swap mutation operator being used on the best population solution to produce a new offspring.

Subsequently, a decision is made based on the fitness function to determine the best solution between the parent and child. The fitness function can be designed for either maximization or minimization and guides the selection process. Ultimately, the superior solution is chosen to progress in the algorithm. Algorithm 4 provides an overview of this strategy, illustrating how the swap mutation operator contributes to mitigating premature convergence issues.

Algorithm 4: Second improved strategy

In each round

01. $\text{maxi} = 10\%$ of population size
 02. $\text{parent} = \text{the best butterfly } (g^*)$
 03. for $i = 1 : \text{maxi}$
 04. $\text{child} = \text{swap-mutation}(\text{parent})$
 05. if $\text{fit}(\text{child}) > \text{fit}(\text{parent})$ // Fitness as max
 06. $\text{parent} = \text{child}$
 07. end
 08. end
-

Algorithm 5 presents a hybrid algorithm that combines the GA and BOA to overcome the challenges of premature convergence and local optima entrapment. By incorporating these GA operators into the BOA framework, the hybrid strategy effectively addresses the inherent issues related to early convergence and local optima in the optimization process. This combined approach leverages the exploration and exploitation capabilities of both algorithms, yielding improved performance and enhanced optimization outcomes. As a result, the proposed hybrid method offers a robust solution for addressing complex supply chain network problems and other optimization challenges.

Algorithm 5: Hybrid algorithm

Input: maximum iteration number (Max), population size (Size), sensory modality (c), power exponent (a), and switch probability (P) and fitness function $f(x)$

Output: Find the best butterfly (g^*)

01. Initialization of input parameters
 02. Generate initial population of butterflies
 03. Stimulus intensity I_i at x_i is determined by $f(x_i)$
 04. for $i = 1 : \text{Max}$
 05. for $j = 1 : \text{Size}$
 06. Calculate fragrance for all butterflies using Eq. 3
 07. Find the best butterfly based on algorithm 4
 08. Generate a random number r from $[0, 1]$
 09. if $r < P$
 10. Move towards best butterfly using Eq. 4
 11. else
 12. Move randomly using Eq. 5
 13. end if
 14. end for
 15. Update the value of a
 16. Perform algorithm 3
 17. end for
-

Candidate solutions generated and modified by the BOA movement equations, the crossover operator, and the mutation operator are evaluated against the constraints in Table 3 (e.g., facility-count and flow-capacity bounds). Solutions that violate these constraints are corrected through a repair procedure that rescales and reassigns the affected flow and facility variables back to the nearest feasible values, ensuring that the butterfly retained in the population at the end of each iteration satisfies the model's constraints.

Figure 4 summarizes the complete hybrid BOA-GA procedure described in this section as a flow chart, from initialization through the two improved strategies to the output of the best butterfly found.

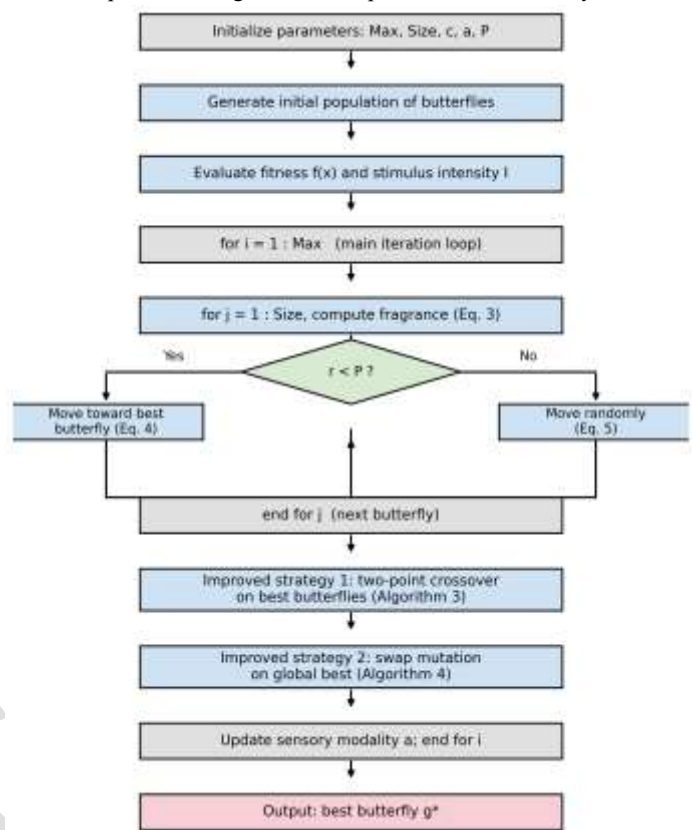


Fig. 4. Flow chart of the proposed hybrid BOA-GA algorithm

5. Simulation Results

This section details the simulation of the proposed sustainable closed-loop supply chain network model on networks of varying scales, utilizing the MATLAB simulation software version 2017. The simulation is executed on a server computer equipped with a 32 Threads processor, 32 GB RAM, and Windows operating system. The computational time for the proposed model is assessed in seconds. The simulation process employs the proposed hybrid metaheuristic algorithm, which effectively combines the strengths of two metaheuristic algorithms. By leveraging the unique advantages of each algorithm, the hybrid approach demonstrates superior problem-solving capabilities in the context of sustainable supply chain management.

5.1. Network scales

The assessment of the proposed sustainable closed-loop supply chain network model for the home appliance industry involves testing it on various small and large-scale networks. Small-scale networks are typically evaluated using GAMS software, which can provide accurate results but often requires substantial computational time as the problem Dimensions increase. To overcome this challenge and solve large-scale problems more efficiently, meta-heuristic methods are employed. Table 7 presents the problem dimensions used for evaluating the proposed model, offering insights into the range of network scales under consideration. Furthermore, Figure 5 provides a visual representation of the various scales of the sustainable closed-loop supply chain network model.

Tab. 7. The problem dimensions

Test	Value									
	u	p	k	r	a	c	w	d	f	s
P ₁	16	12	107	11	35	101	38	21	16	13
P ₂	18	14	205	16	37	203	39	23	19	15
P ₃	19	16	359	19	40	347	45	32	19	17
P ₄	60	57	1238	54	76	1117	83	62	60	59
P ₅	66	63	1345	54	84	1201	78	71	66	62
P ₆	67	65	1307	57	85	1304	82	73	67	63

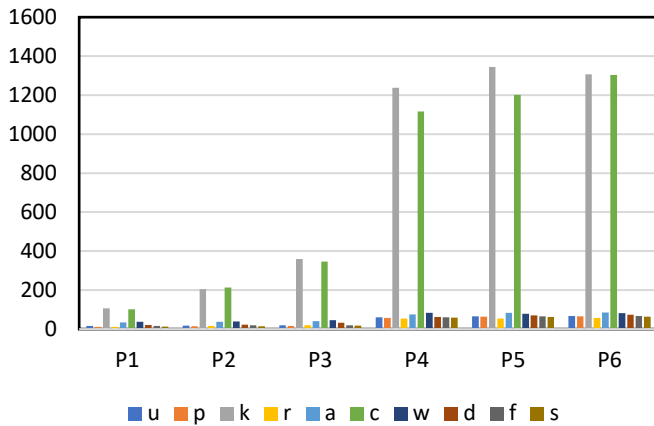


Fig. 5. A visual representation of the various scales of the model

5.2. Setting parameters

To ensure the generation of more precise scientific results, the proposed sustainable closed-loop supply chain networks are resolved using various heuristic parameters. This approach enhances the quality of solutions obtained from the proposed hybrid metaheuristic algorithm by fine-tuning its performance to different problem scenarios. Table 8 displays the initialization of various heuristic parameters associated with the hybrid metaheuristic algorithm.

Key parameters requiring initialization include population size, number of algorithm iterations, control parameter, and the weight of objectives within the fitness function. These parameters play a crucial role in determining the efficiency and effectiveness of the algorithm in solving the supply chain network problems. By adjusting these parameters, the proposed model can adapt to diverse supply chain scenarios, ensuring optimal performance and a better balance between economic, social, and environmental objectives.

In conclusion, the use of varying heuristic parameters allows for a more comprehensive evaluation of the proposed sustainable closed-loop supply chain network model, leading to more accurate results and better decision-making within the home appliance industry.

Tab. 8. The initialization of various parameters

# Run	Population size	Iteration	Control parameter	W ₁	W ₂	W ₃	W ₁ +W ₂ +W ₃
1	50	50	0.6	0.34	0.33	0.33	1
2	50	100	0.7	0.34	0.33	0.33	1
3	100	100	0.6	0.50	0.25	0.25	1
4	100	50	0.6	0.25	0.50	0.25	1
5	150	150	0.7	0.25	0.25	0.50	1
6	150	200	0.7	0.60	0.20	0.20	1

7	200	100	0.6	0.34	0.33	0.33	1
8	200	150	0.6	0.20	0.60	0.20	1
9	200	200	0.7	0.50	0.25	0.25	1

5.3. Normalization

Normalizing objective functions within the range of 0 to 1 is a common practice in multi objective optimization problems, as it streamlines the interpretation of objective values and maintains consistency across different problem instances. This approach enhances the balance between various objectives and facilitates exploration of the search space, ultimately promoting convergence behavior.

The selection of a normalization technique and the range of normalized values may depend on the specific problem and the characteristics of the objective functions. Min/max normalization is a popular and effective method for scaling objective functions, particularly in metaheuristic algorithms.

Min/max normalization transforms objective function values into a range between 0 and 1 by utilizing the minimum and maximum objective function values among all solutions in the population. By employing min/max normalization, decision-makers can more easily compare and interpret objective function values, enabling better analysis and understanding of the trade-offs between different objectives. In the context of the proposed sustainable closed-loop supply chain network model, this approach would aid in evaluating the balance between economic, social, and environmental aspects, ultimately supporting more informed decision-making within the home appliance industry.

5.4. Network setting

It is essential for all parameters of the proposed sustainable closed-loop supply chain network model to be assigned numerical values for effective evaluation and optimization. In the defined case study, random and uniform distribution strategies have been utilized to allocate these values. Table 9 provides a detailed overview of the values assigned to each parameter within the proposed model. Using random and uniform distribution strategies allows for a comprehensive assessment of the model's performance under various conditions, reflecting the real-world variability of supply chain networks. By incorporating these strategies, the proposed model can be tested and optimized for diverse scenarios, ensuring robustness and adaptability to the dynamic nature of the home appliance industry.

Tab. 9. The values of network parameters

Parameter	Value	Parameter	Value
F _s	Rand (5,6,7,8,9)	DS _{as}	Rand (21,22,23,...,29)
F _f	Rand (5,6,7,8,9)	DS _{ar}	Rand (21,22,23,...,29)
F _d	Rand (4,5,6,7,8)	DS _{ak}	Rand (21,22,23,...,29)
F _w	Rand (4,5,6,7,8)	PC _{put}	Rand (1,2)
F _a	Rand (3,4,5,6,7)	PRC _{rut}	Rand (1,2)
F _r	Rand (4,5,6,7,8)	RC _{sut}	Rand (1,2)
F _p	Rand (3,4,5,6,7)	DAC _{aut}	Rand (1,2)
B _{fu}	U (0,0/2)	MC _{sut}	Rand (1,2)
B _{su}	U (0,0/2)	RR _{dut}	Rand (1,2)
B _{du}	U (0,0/2)	RR _{wut}	Rand (1,2)
B _{wu}	U (0,0/2)	SS _{cut}	U (0,1)
B _{ru}	U (0,0/2)	SC _{kut}	U (0,1)
FC _{fut}	U (0,0/2)	EP _{fu}	Rand (1,2,3,...,10)

TC _{ut}	Rand (1,2,3,4,5)	EP _{au}	Rand (1,2,3,...,10)
DS _{sf}	Rand (21,22,23,...,29)	EP _{ru}	Rand (1,2,3,...,10)
DS _{fd}	Rand (21,22,23,...,29)	EMP _s	Rand (6,7,8,...,9)
DS _{fw}	Rand (21,22,23,...,29)	EMP _f	Rand (6,7,8,...,9)
DS _{fc}	Rand (21,22,23,...,29)	EMP _d	Rand (6,7,8,...,9)
DS _{dw}	Rand (21,22,23,...,29)	EMP _w	Rand (6,7,8,...,9)
DS _{wc}	Rand (21,22,23,...,29)	EMP _a	Rand (6,7,8,...,9)
DS _{ca}	Rand (21,22,23,...,29)	EMP _p	Rand (6,7,8,...,9)
DS _{ap}	Rand (21,22,23,...,29)	EMP _r	Rand (6,7,8,...,9)
B _{cu}	U (0,0/2)	RR _{fut}	Rand (1,2)
B _{au}	U (0,0/2)	B _{pu}	U (0,0/2)
DS _{rk}	Rand (21,22,23,...,29)	EP _{pu}	Rand (1,2,3,...,10)

Owing to the unavailability of proprietary operational data from a specific home appliance manufacturer, the numerical parameters in Table 9 were generated using random and uniform distributions over ranges chosen to be broadly consistent with the problem scales reported in related closed-loop supply chain studies (Section 2), rather than drawn from a single firm's records. This is consistent with common practice in the metaheuristic optimization literature for benchmarking solution methods, and the resulting case should be read as an illustrative numerical experiment rather than an audit of a specific company. Calibrating the model with real operational data from a home appliance manufacturer is a natural direction for future work.

5.5. Results

Tables 10 through 15 present the results obtained from solving problems P1 to P6, respectively, utilizing three distinct metaheuristic algorithms: the genetic algorithm, the butterfly optimization algorithm, and the hybrid optimization algorithm. Each problem was solved with nine separate runs, employing various heuristic parameters to ensure a comprehensive evaluation of the proposed sustainable closed-loop supply chain network model. This systematic approach to problem-solving allows for a thorough assessment of each algorithm's performance and the model's adaptability to different heuristic parameters. By analyzing the results obtained from each algorithm and across multiple runs, decision-makers can better understand the strengths and weaknesses of each approach, as well as the model's overall effectiveness in addressing economic, social, and environmental objectives within the home appliance industry.

Tab. 10. The results obtained from solving problem P₁

# Run	GA				BOA				Proposed hybrid algorithm			
	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}
1	0.81	0.32	0.37	0.70	0.86	0.28	0.34	0.72	0.91	0.24	0.29	0.75
2	0.84	0.30	0.36	0.72	0.89	0.25	0.31	0.76	0.93	0.22	0.27	0.77
3	0.85	0.27	0.40	0.63	0.91	0.23	0.35	0.68	0.95	0.19	0.32	0.71

4	0.82	0.32	0.29	0.65	0.87	0.28	0.25	0.69	0.92	0.25	0.21	0.72
5	0.82	0.34	0.35	0.74	0.86	0.28	0.31	0.79	0.91	0.23	0.26	0.82
6	0.86	0.23	0.37	0.62	0.91	0.21	0.32	0.64	0.96	0.18	0.27	0.67
7	0.83	0.24	0.38	0.71	0.88	0.29	0.34	0.71	0.92	0.25	0.30	0.76
8	0.75	0.36	0.29	0.68	0.79	0.34	0.25	0.68	0.85	0.31	0.19	0.74
9	0.81	0.35	0.31	0.69	0.84	0.33	0.29	0.71	0.89	0.29	0.22	0.73

Tab. 11. The results obtained from solving problem P₂

# Run	GA				BOA				Proposed hybrid algorithm			
	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}
1	0.79	0.42	0.46	0.59	0.83	0.37	0.42	0.64	0.88	0.31	0.37	0.69
2	0.83	0.40	0.44	0.60	0.85	0.34	0.38	0.66	0.89	0.29	0.35	0.71
3	0.83	0.34	0.48	0.53	0.87	0.28	0.45	0.59	0.92	0.25	0.41	0.63
4	0.75	0.44	0.41	0.58	0.81	0.38	0.38	0.61	0.87	0.32	0.32	0.65
5	0.80	0.38	0.45	0.63	0.86	0.33	0.41	0.68	0.89	0.28	0.36	0.74
6	0.81	0.34	0.50	0.52	0.85	0.28	0.44	0.58	0.91	0.24	0.39	0.64
7	0.79	0.42	0.50	0.63	0.82	0.38	0.46	0.67	0.87	0.33	0.43	0.73
8	0.71	0.50	0.38	0.53	0.76	0.44	0.35	0.58	0.80	0.41	0.31	0.61
9	0.75	0.50	0.44	0.61	0.79	0.45	0.39	0.64	0.83	0.39	0.33	0.68

Tab. 12. The results obtained from solving problem P₃

# Run	GA				BOA				Proposed hybrid algorithm			
	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}
1	0.79	0.41	0.45	0.61	0.80	0.39	0.42	0.64	0.86	0.33	0.39	0.68
2	0.81	0.38	0.41	0.64	0.84	0.35	0.40	0.69	0.87	0.31	0.37	0.72
3	0.82	0.37	0.52	0.59	0.86	0.31	0.49	0.62	0.91	0.29	0.44	0.65
4	0.78	0.39	0.41	0.60	0.82	0.36	0.38	0.63	0.85	0.35	0.35	0.65
5	0.75	0.41	0.48	0.66	0.78	0.36	0.45	0.68	0.84	0.32	0.41	0.71
6	0.83	0.35	0.55	0.58	0.86	0.32	0.51	0.59	0.89	0.28	0.47	0.62
7	0.74	0.38	0.56	0.69	0.77	0.36	0.53	0.71	0.83	0.36	0.49	0.74
8	0.69	0.48	0.40	0.59	0.73	0.45	0.36	0.62	0.77	0.42	0.33	0.66
9	0.71	0.45	0.43	0.64	0.74	0.44	0.41	0.67	0.79	0.41	0.36	0.70

Tab. 13. The results obtained from solving problem P₄

# Run	GA				BOA				Proposed hybrid algorithm			
	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}
1	0.76	0.36	0.44	0.57	0.80	0.30	0.39	0.60	0.83	0.27	0.33	0.64
2	0.74	0.35	0.38	0.58	0.79	0.31	0.35	0.62	0.84	0.25	0.31	0.66

3	0.76	0.29	0.47	0.52	0.81	0.26	0.41	0.55	0.86	0.22	0.35	0.60
4	0.73	0.37	0.36	0.49	0.79	0.32	0.31	0.55	0.85	0.28	0.25	0.61
5	0.72	0.38	0.38	0.65	0.78	0.32	0.34	0.69	0.81	0.26	0.29	0.72
6	0.78	0.31	0.38	0.50	0.83	0.26	0.35	0.53	0.87	0.21	0.32	0.59
7	0.73	0.38	0.43	0.57	0.77	0.34	0.37	0.61	0.82	0.29	0.33	0.64
8	0.66	0.43	0.36	0.54	0.71	0.37	0.30	0.59	0.74	0.34	0.24	0.63
9	0.66	0.43	0.37	0.52	0.71	0.37	0.32	0.58	0.77	0.32	0.26	0.62

Tab. 14. The results obtained from solving problem P₅

# Run	GA				BOA				Proposed hybrid algorithm			
	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}
1	0.79	0.37	0.46	0.59	0.80	0.35	0.42	0.60	0.81	0.29	0.35	0.63
2	0.80	0.36	0.42	0.59	0.80	0.34	0.35	0.61	0.82	0.28	0.33	0.64
3	0.81	0.27	0.47	0.53	0.82	0.27	0.44	0.55	0.84	0.25	0.38	0.59
4	0.78	0.39	0.39	0.54	0.79	0.36	0.34	0.56	0.82	0.30	0.29	0.59
5	0.71	0.36	0.40	0.63	0.76	0.36	0.35	0.64	0.78	0.28	0.31	0.68
6	0.82	0.35	0.42	0.47	0.83	0.32	0.39	0.49	0.85	0.32	0.35	0.53
7	0.75	0.42	0.43	0.57	0.77	0.39	0.39	0.58	0.79	0.36	0.36	0.61
8	0.66	0.42	0.36	0.56	0.67	0.41	0.33	0.59	0.71	0.35	0.28	0.61
9	0.68	0.45	0.37	0.74	0.70	0.43	0.34	0.79	0.75	0.36	0.29	0.79

Tab. 15. The results obtained from solving problem P₆

# Run	GA				BOA				Proposed hybrid algorithm			
	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fit ₃₀	Fi _{t38}	Fi _{t56}	Fi _{t37}	Fi _{t30}	Fi _{t38}	Fi _{t56}
1	0.71	0.44	0.40	0.58	0.75	0.4	0.39	0.59	0.79	0.31	0.36	0.61
2	0.69	0.43	0.38	0.59	0.73	0.4	0.37	0.61	0.81	0.31	0.35	0.63
3	0.72	0.48	0.42	0.56	0.77	0.4	0.43	0.56	0.83	0.27	0.40	0.57
4	0.73	0.39	0.35	0.52	0.74	0.3	0.33	0.53	0.80	0.32	0.31	0.56
5	0.68	0.41	0.35	0.64	0.71	0.4	0.35	0.65	0.75	0.29	0.33	0.66
6	0.74	0.46	0.46	0.47	0.77	0.4	0.39	0.49	0.84	0.33	0.38	0.51
7	0.72	0.48	0.45	0.53	0.72	0.4	0.42	0.57	0.77	0.39	0.38	0.58
8	0.59	0.39	0.32	0.52	0.65	0.3	0.33	0.56	0.68	0.38	0.29	0.59
9	0.66	0.41	0.34	0.54	0.67	0.3	0.32	0.56	0.72	0.37	0.31	0.57

5.6. Analysis

In the initial analysis, the average results from solving problem P₁ were examined, with Figure 6 illustrating the outcomes. The findings indicate that the proposed hybrid optimization algorithm outperforms the BOA and the GA across all four criteria: Revenue, cost,

environmental effects, and social effects. Specifically, the hybrid optimization algorithm demonstrated a 0.05 improvement in revenue compared to the BOA and a 0.09 improvement compared to the GA. Furthermore, it reduced the cost criterion by 0.03 and 0.06 compared to the BOA and the GA, respectively. The hybrid optimization algorithm also showed a reduction in environmental effects by 0.05 and 0.09 compared to the BOA and the GA, respectively. Lastly, it exhibited an improvement of 0.04 in social effects compared to the BOA and 0.06 compared to the GA, highlighting the hybrid algorithm's superior performance in optimizing sustainable closed-loop supply chain networks in the home appliance industry.

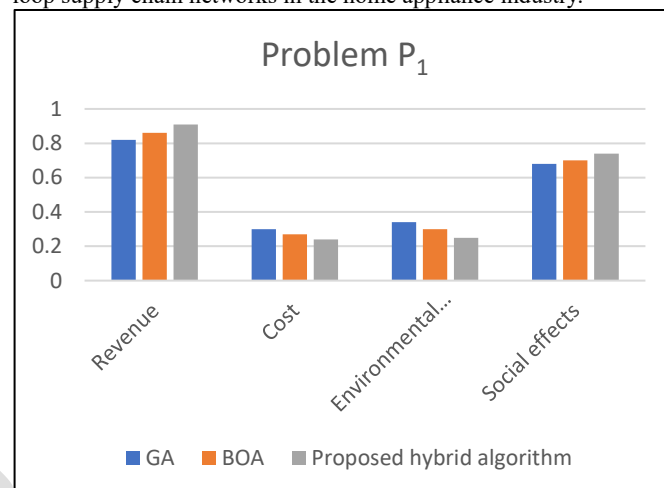


Fig. 6. The average results from solving problem P₁

In the subsequent analysis, the average results obtained from solving problem P₂ were scrutinized, as depicted in Figure 7. The outcomes demonstrated that the proposed hybrid optimization algorithm outperformed the BOA and the GA across all four assessment criteria. Specifically, the hybrid optimization algorithm exhibited a 0.05 improvement in revenue compared to the BOA and a 0.09 improvement compared to the GA. Additionally, it achieved a reduction in the cost criterion by 0.05 and 0.10 compared to the BOA and the GA, respectively. The hybrid optimization algorithm also demonstrated a decrease in environmental impact by 0.04 and 0.09 compared to the BOA and the GA, respectively. Finally, it showed an improvement of 0.05 in social impact compared to the BOA and 0.09 compared to the GA.

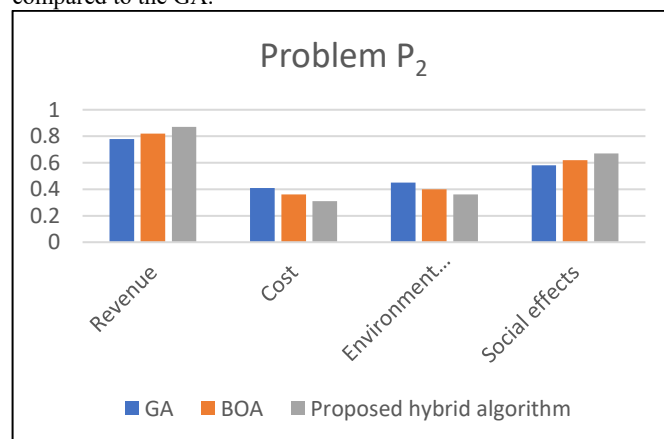


Fig. 7. The average results from solving problem P₂

In the third analysis, the average results from solving problem P₃ were investigated, as illustrated in Figure 8. The findings revealed that the proposed hybrid optimization algorithm outperformed the BOA and

the GA across all four evaluation criteria. Notably, the hybrid optimization algorithm demonstrated a 0.04 improvement in revenue compared to the BOA and a 0.08 improvement compared to the GA. Furthermore, it achieved a reduction in the cost criterion by 0.06 and 0.09 compared to the BOA and the GA, respectively. The hybrid optimization algorithm also exhibited a decrease in environmental impact by 0.03 and 0.06 compared to the BOA and the GA, respectively. Lastly, it showed an improvement of 0.03 in social impact compared to the BOA and 0.06 compared to the GA.

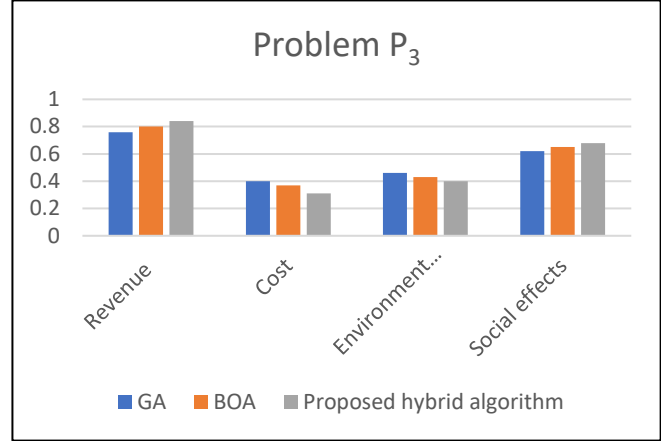


Fig. 8. The average results from solving problem P3

Figures 9 to 11 present the average results obtained from solving large-dimensional problems. It is evident from the results that the proposed hybrid metaheuristic algorithm outperforms both the butterfly optimization algorithm and the genetic algorithm across all criteria. This highlights the superior performance of the hybrid metaheuristic algorithm in optimizing sustainable closed-loop supply chain networks within the home appliance industry, even when dealing with complex, large-scale problems.

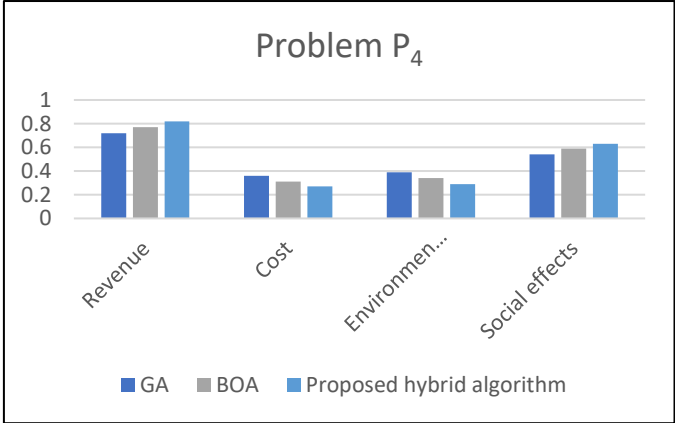


Fig. 9. The average results from solving problem P4

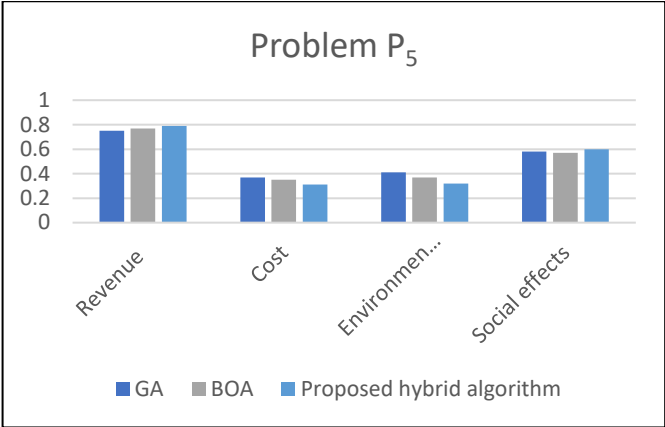


Fig. 10. The average results from solving problem P5

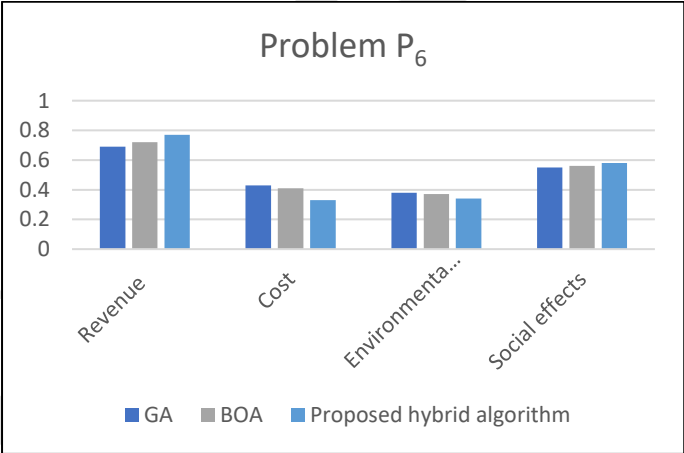


Fig. 11. The average results from solving problem P6

This section delves into the sensitivity analysis of the objective weights within the fitness function. Considering the significant impact of these coefficients on the overall system performance, a separate experiment was conducted to examine their influence. All heuristic parameters of the proposed hybrid metaheuristic algorithm were set in accordance with Table 16, keeping them constant to focus solely on the effect of the objective weights in the fitness function. Table 17 showcases the results of the sensitivity analysis for the objective weights based on problem P₁.

Tab. 16. Setting of the sensitivity analysis for the objective weights

Run	Population size	Iteration	Control parameter	W ₁	W ₂	W ₃
1	100	100	0.7	0.50	0.25	0.25
2	100	100	0.7	0.25	0.50	0.25
3	100	100	0.7	0.25	0.25	0.50

Tab. 17. Results of the sensitivity analysis for the objective weights

Algorithm	Objective	Run 1	Run 2	Run 3
GA	Fit ₃₇	0.91	0.86	0.87
	Fit ₃₀	0.29	0.31	0.35
	Fit ₃₈	0.37	0.32	0.36
	Fit ₅₆	0.66	0.65	0.70
BOA	Fit ₃₇	0.92	0.88	0.89

Proposed algorithm	Fit30	0.26	0.29	0.33
	Fit38	0.35	0.30	0.34
	Fit56	0.69	0.67	0.72
	Fit37	0.94	0.91	0.92
	Fit30	0.21	0.23	0.22
	Fit38	0.32	0.28	0.33
	Fit56	0.72	0.71	0.75

The sensitivity test results reveal that all three metaheuristic algorithms effectively responded to the varying weights of the objectives within the fitness function. It is evident that a higher weight assigned to an objective lead to a more significant impact on the fitness function, while a lower weight results in a reduced influence. This highlights the importance of carefully selecting and adjusting the weights of objectives in the fitness function to prioritize specific aspects, such as economic, environmental, or social factors, within the home appliance industry's sustainable closed-loop supply chain network. Consequently, decision-makers can utilize this information to fine-tune the balance between different objectives according to their specific goals and requirements.

This section delves into the sensitivity analysis of the control parameter within the proposed hybrid metaheuristic algorithm. Given the suggested values of 0.6, 0.7, and 0.8 for this parameter, the sensitivity test is conducted to assess the impact of these different settings. To ensure a focused examination, all other heuristic parameters of the hybrid metaheuristic algorithm are fixed according to Table 18. Table 19 presents the results of the control parameter sensitivity test. The findings demonstrate that the best value for this parameter is 0.6, as it effectively strikes a balance between the exploitation and exploration phases. By evaluating the sensitivity of the control parameter, decision-makers can fine-tune its value to optimize the performance of the sustainable closed-loop supply chain network model in the home appliance industry. This analysis emphasizes the importance of considering various control parameter settings to ensure optimal results when addressing economic, environmental, and social objectives in supply chain management.

Tab. 18. Setting of the sensitivity analysis for the control parameter

Run	Population size	Iteration	Control parameter	W ₁	W ₂	W ₃
1	100	100	0.6	0.50	0.25	0.25
2	100	100	0.7	0.50	0.25	0.25
3	100	100	0.8	0.50	0.25	0.25

Tab. 19. Results of the sensitivity analysis for the control parameter

Algorithm	Objective	Run 1	Run 2	Run 3
GA	Fit37	0.80	0.78	0.75
	Fit30	0.29	0.31	0.33
	Fit38	0.46	0.48	0.50
	Fit56	0.59	0.59	0.56
BOA	Fit37	0.81	0.79	0.78
	Fit30	0.26	0.28	0.28
	Fit38	0.42	0.45	0.46
	Fit56	0.61	0.59	0.57
Proposed algorithm	Fit37	0.83	0.82	0.81
	Fit30	0.24	0.26	0.29
	Fit38	0.41	0.44	0.45
	Fit56	0.62	0.60	0.59

In this analysis, the computational time of the metaheuristic algorithms is evaluated, with time measured in seconds. Across both

small and large-scale problems, the BOA consistently exhibits the shortest computational time. Table 20 showcases the average computational time for each metaheuristic algorithm across the six defined problems.

Although the proposed hybrid metaheuristic algorithm requires more computational time due to the additional computational load imposed by the crossover and mutation processes, its overall performance in terms of solution quality remains superior.

Tab. 20. The average computational time for algorithms

Problem	GA	BOA	Proposed hybrid algorithm
1	3711	3654	3844
2	3752	3677	3875
3	3794	3699	3912
4	14401	14324	14621
5	14456	14356	14654
6	14479	14399	14678

5.7. Validation

Validation of the proposed model and algorithm rests on two complementary checks in this study. First, comparative validation: the hybrid algorithm, the GA, and the BOA are applied to the same six problem instances (P1-P6, Table 7) under identical parameter settings (Table 8), and the hybrid algorithm's consistent improvement across all four performance criteria (Section 5.6) validates its relative solution quality against these two established baselines as problem size grows. Second, robustness validation: the sensitivity analysis in Tables 16-19 shows that the relative ranking of the three algorithms is stable as the objective weights W₁, W₂ and W₃ are varied, indicating that the hybrid algorithm's advantage is not an artifact of one particular weighting. An exact-solution comparison against a solver such as GAMS or CPLEX was not pursued for the tested instances given their scale, and is noted in Section 6 as a direction for future validation work.

6. Conclusion

This research focuses on addressing the escalating need for sustainable practices in the home appliance industry by proposing an innovative closed-loop supply chain network model. The primary objective is to enhance economic, environmental, and social performance by effectively integrating forward and reverse logistics. This study contributes to the advancement of sustainable supply chain management strategies by addressing the interconnected challenges within the industry and promoting closed-loop practices to reduce environmental footprints and promote social responsibility. To achieve the desired outcomes, a novel hybrid metaheuristic algorithm is introduced, combining the strengths of the BOA and the GA. By incorporating the crossover and mutation operators from the GA into the BOA, the hybrid metaheuristic algorithm significantly improves the exploration of the problem space. This innovative solution method is applied to a mixed integer linear programming model to optimize the proposed sustainable closed-loop supply chain network.

A comparative analysis between the hybrid metaheuristic algorithm, the GA, and the BOA demonstrates the superior performance of the hybrid metaheuristic algorithm in terms of solution quality. The results indicate improvements in revenue, cost reduction, decreased environmental impacts, and enhanced social effects. Furthermore, a sensitivity analysis of the control parameter within the hybrid

metaheuristic algorithm reveals that a value of 0.6 effectively balances the exploitation and exploration phases, leading to optimal performance. Lastly, an evaluation of computational time highlights the efficiency of the BOA, emphasizing the importance of considering both computational efficiency and solution quality when optimizing supply chain management strategies.

In conclusion, this research presents a sustainable closed-loop supply chain network model for the home appliance industry, coupled with a novel hybrid metaheuristic optimization algorithm. The proposed method offers several notable advantages:

- **Sustainability:** By incorporating economic, social, and environmental dimensions, the proposed approach fosters a holistic view of sustainability in the home appliance sector.
- **Resource Efficiency:** The closed-loop supply chain network maximizes resource utilization through the integration of forward and reverse logistics, thereby minimizing waste and promoting the use of recycled materials.
- **Optimization Performance:** The hybrid metaheuristic algorithm combines the strengths of the BOA and GA, improving search space exploration and preventing premature convergence to local optima.
- **Differentiated Pricing:** By distinguishing between customers in forward and reverse logistics, the proposed method facilitates unique pricing strategies for original and refurbished products, bolstering the overall sustainability goals of the supply chain network.
- **Real-world Applicability:** The proposed method addresses complex, multi-variable problems, making it a practical solution for real-world challenges in the home appliance industry and potentially other sectors.

While the proposed method in this research offers numerous advantages, it is crucial to also consider potential limitations and challenges that may arise. These include:

- **Computational complexity:** The hybrid metaheuristic algorithm may require more computational resources and time to converge to an optimal solution, potentially impacting its efficiency.
- **Data accessibility:** The performance and decision-making of the proposed model heavily rely on access to accurate and reliable data related to various aspects of the supply chain network. Inaccuracies or missing information could affect its overall effectiveness.
- **Industry adoption:** Encouraging widespread adoption of the proposed method within the home appliance industry or other sectors could face challenges due to resistance to change, infrastructure limitations, or regulatory barriers.
- **External factors:** Unpredictable external factors such as market demand fluctuations, changes in government policies, or disruptions within the supply chain network could affect the model's performance but may not be accounted for in its design.
- **Multi-objective solution approach:** the three sustainability objectives are combined through a weighted-sum formulation (Section 3.3); this is computationally efficient but yields a single non-dominated solution per weight combination rather than an explicit Pareto front, so extending the proposed hybrid algorithm to a Pareto-based multi-objective variant (e.g., NSGA-II) is a promising direction for future research.
- **Validation scope:** validation in this study relies on comparative performance against the GA and BOA and

on sensitivity analysis of the objective weights (Section 5.7); benchmarking against an exact-solution method (e.g., GAMS or CPLEX) on a small-scale instance was outside the scope of this study and is left for future validation work.

AUTHOR CONTRIBUTIONS

All authors contributed equally to the main contributor to this paper.

All authors read and approved the final paper.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to our supervisor, Professor Iraj Mahdavi, for his valuable guidance and support throughout the research process. His expertise and insights were invaluable in shaping our research and helping us to overcome challenges.

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