Management Strategies and Engineering Sciences 2027; 9(1):1-18

Improving the Distribution Network Process in a Reverse Supply Chain by Incorporating Environmental Indicators Using Metaheuristic Algorithms in the Plastic Recycling Industry

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Received: 2026-04-15 **Revised:** 2026-08-27 **Accepted:** 2026-09-05 **Initial Publish:** 2026-09-21 **Final Publish:** 2027-01-01

Abstract

Since the beginning of the past decade, the fate of industrial products and goods during the consumption phase has become one of the major concerns of supply chain researchers. This process begins from the moment a product is delivered and its warranty and after-sales support period commences and continues through to the reuse of the obsolete product at the end of its life cycle. Subsequently, with the expansion of environmental concerns on the one hand and the emergence of considerable economic benefits on the other, the concepts of reverse logistics and reverse supply chains for recovering used products have received increasing attention. Accordingly, the primary objective of the present study is to develop a multi-objective, multi-stage, and multi-product strategic planning model for a closed-loop supply chain. The proposed model is designed for the plastic recycling industry and simultaneously pursues two objective functions. The first objective is to minimize the total cost of the closed-loop supply chain, including fixed investment, transportation, and collection costs. The second objective seeks to select the best routes for transferring products among different components of the network such that transportation time is minimized. The results obtained from implementing the model indicate that the proposed approach improves supply chain processes and significantly enhances productivity in the plastic recycling industry.

Keywords: *reverse logistics, metaheuristic algorithms, plastic recycling industry, multi-objective integer programming.*

How to cite this article:

Zarrati, M., Saleh, H., Vaez, M., & Hosseinzadeh Lotfi, F. (2027). Improving the Distribution Network Process in a Reverse Supply Chain by Incorporating Environmental Indicators Using Metaheuristic Algorithms in the Plastic Recycling Industry. Management Strategies and Engineering Sciences, 9(1), 1-18.

1. Introduction

The growing volume of post-consumption products, industrial residues, packaging materials, and municipal solid waste has intensified the pressure on firms and public institutions to reconsider the conventional linear model of production and distribution. In traditional forward supply chains, managerial attention is primarily directed toward the movement of raw materials and finished goods from suppliers to manufacturers, distributors, retailers, and final customers. However, contemporary supply chain management increasingly recognizes that products continue to generate economic, operational, and environmental consequences after reaching end users. Reverse logistics therefore has emerged as a critical field concerned with the collection, transportation, inspection, sorting, reuse, remanufacturing, recycling, recovery, and disposal of returned or end-of-life products. Recent reviews show that reverse logistics research has moved beyond isolated return processes toward integrated network design, sustainability, digitalization, risk management, and circular-economy-oriented decision making [1, 2]. This development reflects a broader shift from open-loop systems toward closed-loop and circular supply chains in which forward and reverse flows are coordinated to preserve the economic value of materials while reducing environmental burdens [3, 4].

The relevance of reverse logistics is particularly evident in industries characterized by high-volume waste streams and significant opportunities for material recovery. Plastic waste constitutes one of the most challenging of these streams because of its widespread use, long persistence in the environment, and dependence on effective collection, sorting, recycling, and disposal infrastructures. From a supply chain perspective, plastic recycling cannot be treated merely as a waste-handling activity; rather, it requires a structured reverse network that connects geographically dispersed waste generators or customers with collection–inspection centers, recycling facilities, and disposal centers. Research on plastic waste management has demonstrated that network configuration directly influences transportation costs, recovery rates, facility utilization, and the environmental performance of recycling systems [5, 6]. Similarly, closed-loop network models developed for distributed plastic recycling have shown that facility location and material-flow decisions are fundamental to achieving economically and environmentally viable recycling systems [7]. Therefore, the design of an efficient reverse distribution network for plastic products requires simultaneous consideration of where facilities should be established, how returned products should be allocated, which routes should be used, and how recyclable and non-recyclable fractions should be separated.

A central challenge in reverse supply chain design is that managerial decisions frequently involve several conflicting objectives. Cost minimization remains a core concern because establishing collection, recycling, and disposal facilities requires substantial fixed investment, while transportation, handling, inspection, processing, and disposal generate recurring operating expenses. At the same time, decisions that minimize monetary cost do not necessarily minimize transportation time, environmental emissions, energy consumption, service delays, or social impacts. Consequently, sustainable reverse logistics increasingly relies on multi-objective mathematical programming rather than single-objective cost models. Multi-objective reverse supply chain models have been developed to simultaneously address economic and sustainability criteria, particularly where facility location and product-flow decisions must be coordinated under capacity and operational constraints [8, 9]. Bi-objective eco-efficient reverse logistics models also demonstrate that network configuration can be substantially affected when environmental measures are considered alongside economic criteria [10]. Likewise, research on reverse supply chains has emphasized the simultaneous management of cost and delivery delay, highlighting the importance of time-sensitive network decisions in addition to traditional financial objectives [11]. These findings support the need for models that explicitly capture trade-offs among cost, time, environmental performance, and network responsiveness.

Environmental considerations further complicate reverse logistics network design because transportation and facility operations themselves consume energy and generate emissions. A reverse network may recover valuable materials while still producing considerable environmental impacts if products are transported over inefficient routes or if facilities operate far from collection points. Accordingly, sustainable reverse logistics models increasingly incorporate emission reduction, energy use, fleet configuration, routing efficiency, and environmental performance into their objective functions and constraints. Hashemi developed a fuzzy multi-objective model for sustainable municipal waste collection that explicitly considered emission reduction, illustrating the importance of environmental criteria in reverse logistics network design [12]. Cao et al. similarly addressed recyclables collection routing in a two-echelon collaborative reverse logistics system from both circular-economic and environmental perspectives, indicating that fleet and routing decisions can significantly influence sustainability outcomes [13]. Energy-aware logistics modeling has also shown how transportation technology, uncertainty, and network structure can be incorporated into optimization frameworks for urban distribution systems [14]. These studies collectively indicate that environmental performance should not be considered as a secondary consequence of network design but as a fundamental decision criterion.

At the same time, reverse logistics problems are inherently difficult from a computational perspective. Facility location, allocation, routing, capacity, and product-flow decisions create large combinatorial search spaces, particularly when binary and continuous decision variables are combined. The complexity increases substantially when multiple products, multiple echelons, uncertainty, disruption risk, routing decisions, and sustainability objectives are incorporated. Integrated location-routing approaches in reverse logistics demonstrate how the simultaneous consideration of facility decisions and transportation paths can substantially increase model complexity [15]. Integrated forward–reverse logistics systems with routing and cross-docking decisions likewise require coordinated optimization of several interdependent network components [16]. In addition, network disruption and uncertainty can affect the resilience of third-party reverse logistics systems and alter optimal facility and allocation decisions [17]. Such characteristics often make exact solution methods computationally demanding for realistic or large-scale problems, thereby motivating the use of decomposition, heuristic, and metaheuristic solution approaches. Although decomposition methods such as Benders decomposition can effectively address certain capacitated supply chain network design problems [18], their applicability may become limited when nonlinear penalties, multiple objectives, or highly complex decision structures are introduced.

The rapid development of artificial intelligence and metaheuristic optimization has therefore created new opportunities for solving complex reverse logistics and closed-loop supply chain problems. Artificial intelligence is increasingly used for prediction, facility planning, routing, inventory control, decision support, and adaptive optimization across closed-loop supply chains [19]. Bibliometric evidence also indicates a growing integration of artificial intelligence techniques into reverse logistics, reflecting the need for more flexible computational approaches capable of handling nonlinear, uncertain, and dynamic decision environments [20]. Recent theoretical and application-oriented studies similarly demonstrate that artificial intelligence can improve different stages of reverse logistics processes, including information processing, return management, routing, forecasting, and operational coordination [21]. From the perspective of developing economies, artificial-intelligence-enabled reverse logistics can also strengthen circular economy performance by improving the efficiency of recovery and resource recirculation processes [22]. These developments suggest that advanced optimization and intelligent algorithms are becoming integral components of sustainable reverse supply chain management rather than merely supplementary analytical tools.

Among metaheuristic methods, the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are particularly relevant because both are capable of exploring large and complex solution spaces without requiring the strong mathematical assumptions associated with many exact optimization approaches. Genetic algorithms imitate evolutionary processes through selection, crossover, mutation, and survival mechanisms and have been widely employed in supply chain network design, especially where facility-selection and flow variables coexist. The use of fuzzy genetic algorithms in reverse supply chains has demonstrated the capacity of evolutionary search to address network design problems involving uncertainty and multiple decision criteria [23]. More recently, genetic algorithms have been combined with reinforcement learning to solve green reverse logistics problems, indicating that evolutionary approaches can be enhanced through adaptive learning mechanisms for improved search performance [24]. PSO, in contrast, is based on collective learning and coordinated movement within a swarm of candidate solutions and is often valued for its relatively simple structure, limited parameter requirements, and rapid convergence. For both algorithms, however, performance depends strongly on solution representation, initialization, penalty design, parameter tuning, and the balance between exploration and exploitation.

The increasing use of metaheuristics also reflects the broader transition toward digitally enabled and data-driven supply chain optimization. Technologies associated with Industry 4.0 facilitate information sharing, traceability, automation, and real-time decision making, thereby strengthening the connection between reverse logistics and circular-economy strategies [3]. Blockchain-enabled supply chain models have illustrated how digital infrastructures can improve integration and information reliability under uncertainty [25]. Internet of Things technologies have similarly been incorporated into sustainable closed-loop supply chain optimization models supported by multi-objective metaheuristic algorithms [26]. Artificial intelligence and multi-criteria decision analysis are also increasingly being combined to support governance and optimization decisions in reverse supply chains for solid waste [27]. Together, these developments indicate that reverse supply chain optimization is progressively evolving toward intelligent decision ecosystems in which mathematical models, real-time information, and computational intelligence are integrated.

Nevertheless, intelligent optimization should not be separated from the practical realities of supply chain participation, production planning, and operational control. The effectiveness of any reverse network ultimately depends on the behavior and participation of actors who generate, collect, process, and return materials into the chain. Supply chain participation research has shown that organizational and operational factors influence whether actors engage effectively in structured supply chain arrangements [28]. At the operational level, neural-network-supported control models have demonstrated the potential of artificial intelligence for coordinating inventory and production decisions in multi-echelon supply chains with reverse logistics [29]. More broadly, control-oriented optimization studies illustrate the value of designing adaptive mechanisms capable of coordinating local decisions with system-level objectives, even though the specific application domain may differ from reverse logistics [30]. Such perspectives reinforce the view that the performance of reverse supply chains depends not only on selecting facilities but also on ensuring coordinated material flows and responsive decision rules throughout the network.

Another important issue is uncertainty. Returned-product quantities, quality levels, transportation conditions, recycling yields, processing capacities, and market demand for recovered materials are often difficult to predict accurately. For this reason, robust, stochastic, and fuzzy optimization approaches have become prominent in reverse supply chain design. Robust optimization has been applied specifically to plastic waste reverse logistics networks to reduce sensitivity to uncertain parameters and improve the reliability of facility and flow decisions [5]. Uncertainty-aware integrated network models have also been developed using digital technologies such as blockchain, emphasizing that reliable information and resilient decision structures are increasingly necessary in contemporary supply chains [25]. The design of reverse logistics networks under disruption risk further demonstrates that uncertainty can fundamentally alter optimal facility locations and allocation patterns [17]. Accordingly, even when a deterministic formulation is employed, solution methods should ideally possess sufficient flexibility to search broad solution spaces and identify robust network configurations.

Recent research also indicates that sustainable supply chain design increasingly requires integration across strategic, tactical, and operational decision levels. Strategic decisions involve the opening or closing of facilities and the configuration of the overall network; tactical decisions include allocation and capacity utilization; and operational decisions concern transportation flows, routing, and scheduling. Integrated forward and reverse network design studies show that separating these decisions can lead to suboptimal system-wide performance [4]. Similarly, optimization models combining routing with cross-docking demonstrate the managerial value of simultaneously determining network structure and material movement [16]. In plastic recycling systems, this integration is especially important because collected waste must first be inspected and classified before recyclable material is directed to recycling facilities and rejected material is routed to disposal centers. The location and capacity of each facility therefore directly influence both transportation time and total network cost.

Furthermore, the circular economy perspective emphasizes that reverse logistics should be designed not only to remove waste from the forward chain but also to recover material value and maintain resources within productive use for as long as technically and economically feasible. Research on circular supply chain network design indicates that optimization models are increasingly being used to operationalize circularity through decisions related to recovery, reuse, remanufacturing, recycling, and closed-loop flows [2]. Artificial intelligence applications in closed-loop supply chains likewise demonstrate the potential of computational methods to improve the efficiency with which recovered products and materials are reintegrated into supply networks [19]. This is particularly relevant to plastic recycling because the viability of circularity depends substantially on collection efficiency, recycling accessibility, transportation distance, processing capacity, and the proportion of material that must ultimately be disposed of. Therefore, a well-designed reverse network can simultaneously contribute to resource conservation, lower disposal volumes, reduced operational inefficiency, and improved economic performance.

Despite the substantial literature on reverse logistics network design, several challenges remain. First, many studies focus on either facility location or routing in isolation, while real-world plastic recycling requires simultaneous location, allocation, capacity, and flow decisions. Second, environmental objectives are increasingly recognized, yet cost and transportation time remain critical managerial criteria that must be jointly evaluated. Third, exact optimization approaches may become computationally burdensome when multiple facilities, product flows, binary decisions, and nonlinear penalty mechanisms are considered. Fourth, although metaheuristic algorithms are widely used, their comparative behavior in the same reverse supply chain setting is highly problem-dependent. Different algorithms may yield substantially different network structures, convergence patterns, levels of solution stability, and trade-offs between global exploration and local exploitation. Recent developments in green reverse logistics, artificial intelligence, and multi-objective network optimization highlight the importance of systematically comparing alternative intelligent search approaches rather than assuming the superiority of a single method [8, 24, 27].

Accordingly, there is a practical and methodological need for reverse supply chain models that can represent the specific structure of plastic recycling networks while simultaneously minimizing economically and operationally important criteria. A multi-stage network containing customers, collection–inspection centers, recycling centers, and disposal centers captures the essential physical movement of post-consumption plastic and allows facility-selection decisions to be linked directly to transportation flows and capacity restrictions. Comparing GA and PSO within such a model provides an opportunity to evaluate not only objective-function performance but also convergence speed, solution stability, facility-selection patterns, and the concentration or dispersion of customer allocations. This comparative perspective is important because an algorithm that produces a numerically competitive solution may still be less desirable operationally if it requires an unnecessarily complex network or exhibits substantial variability across independent runs. Conversely, an algorithm with rapid convergence and stable allocation patterns may offer significant managerial advantages in practical recycling environments.

Therefore, the aim of the present study is to develop and solve a multi-objective, multi-stage reverse supply chain network model for the plastic recycling industry that minimizes total network cost and transportation time while incorporating environmental considerations, and to compare the performance of Genetic Algorithm and Particle Swarm Optimization in identifying efficient facility-location and product-flow configurations.

2. Methodology

The objective of this section is to develop a mathematical model for a multi-product reverse supply chain network that addresses product returns and decisions concerning material procurement, production, distribution, recycling, and disposal in order to prevent further resource depletion, reduce environmental pollution, and achieve profitability alongside other social and commercial considerations in the plastic recycling industry. As shown in Figure 1, the reverse supply chain network proposed in this article is a multi-stage network comprising customers, collection–inspection centers, and disposal centers with limited capacities. Returned products from customers are collected at collection–inspection centers and, following quality inspection, are classified into recyclable and disposable products. Products suitable for recycling are transferred to recycling centers, whereas products that do not meet the required quality standards are transferred to disposal centers.

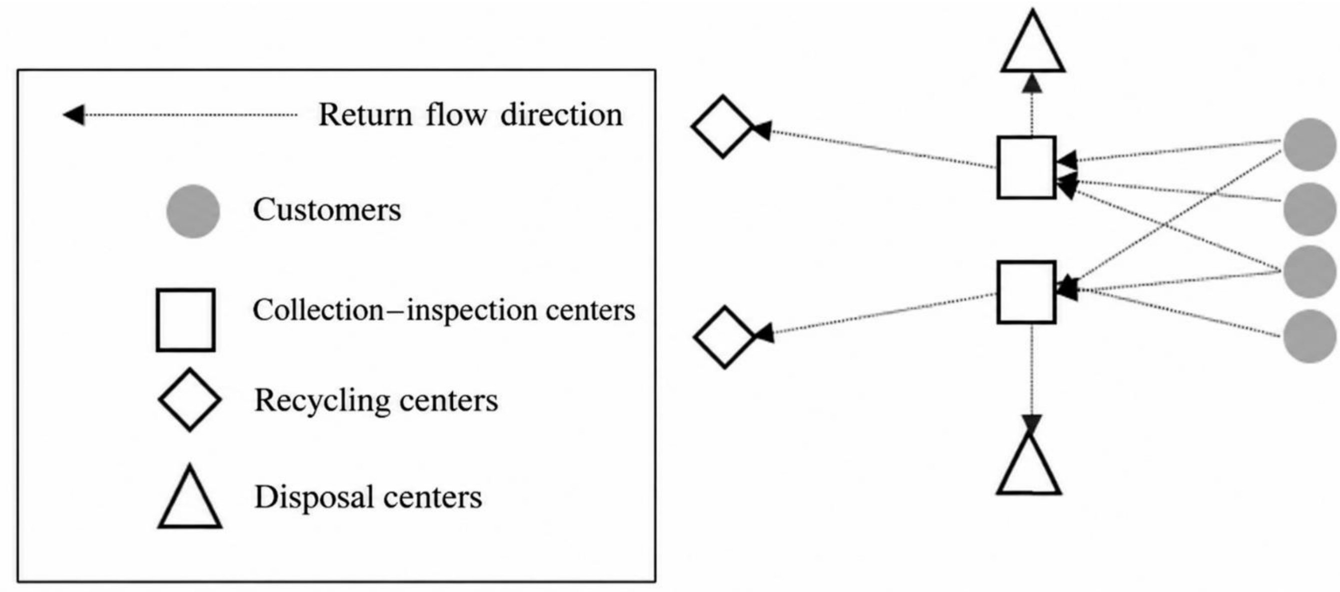

Figure 1. Structure of the Reverse Supply Chain Network

The initial assumptions of the problem are as follows:

- All products returned by customers must be collected.
- Customer locations are predetermined.
- The transportation times for all product types from customers to collection–inspection centers, from collection–inspection centers to recycling centers, and from collection–inspection centers to disposal centers are assumed to be equal.

As previously stated, the objectives of this problem are to reduce both cost and time; therefore, the problem is multi-objective. After specifying the supply chain structure and considering the initial assumptions, the mathematical model required to achieve the predetermined objectives is formulated as follows. In the first step, the required objective functions are derived.

The model is defined in terms of two objective functions. The first objective function seeks to select the best locations for collection–inspection, recycling, and disposal centers, as well as an optimal route for transferring products among the different network components, such that costs are minimized. Let:

i: index corresponding to potential locations for collection–inspection centers,

j: index corresponding to potential locations for recycling centers,

k: index corresponding to potential locations for disposal centers,

l: index corresponding to predetermined customer locations,

p: index corresponding to returned products.

Then:

$$\min Z_1 = \sum_{i\in I} f_i\, y_i + \sum_{j\in J} f_j'\, y_j' + \sum_{k\in K} f_k''\, y_k'' + \sum_{l\in L}\sum_{i\in I}\sum_{p\in P} c\,f_{li}X_{lip} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} c\,s_{ij}Z_{ijp} + \sum_{i\in I}\sum_{k\in K}\sum_{p\in P} c\,t_{ik}W_{ikp} \tag{1}$$

where f_i, f_j', and f_k''represent, respectively, the fixed establishment cost of collection–inspection center i, the fixed establishment cost of recycling center j, and the fixed establishment cost of disposal center k. The variables y_i, y_j', and $y_k''$are binary variables. They take the value 1 if a collection–inspection center is established at location i, a recycling center is established at location j, or a disposal center is established at location k, respectively; otherwise, they take the value 0. cf_{li}denotes the transportation cost of one unit of product from customer $l$to collection–inspection center i; cs_{ij}denotes the transportation cost of one unit of product from collection–inspection center $i$to recycling center j; and ct_{ik}denotes the transportation cost of one unit of product from collection–inspection center $i$to disposal center k.

Furthermore:

$X_{ilp}$is the quantity of returned product type $p$transported from customer $l$to collection–inspection center i.

$Z_{ijp}$is the quantity of returned product type $p$transported from collection–inspection center $i$to recycling center j.

$W_{ikp}$is the quantity of returned product type $p$transported from collection–inspection center $i$to disposal center k.

Similar to the first objective function, the second objective function is defined using Equation (2). The second objective function seeks to select the best product transportation routes among the network components such that transportation time is minimized.

$$\min Z_2 = \sum_{i\in I}\sum_{l\in L}\sum_{p\in P} t_{il}\, X_{ilp} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P} t_{ij}'\, Z_{ijp} + \sum_{i\in I}\sum_{k\in K}\sum_{p\in P} t_{ik}''\, W_{ikp} \tag{2}$$

where t_{il}denotes the transportation time for one unit of product from customer $l$to collection–inspection center i; t_{ij}'denotes the transportation time for one unit of product from collection–inspection center $i$to recycling center j; and t_{ik}''denotes the transportation time for one unit of product from collection–inspection center $i$to disposal center k.

The remaining variables are defined similarly to those in the preceding section. Following the definition of the objective functions, the constraints of the problem are specified by Equations (3)–(12), as follows.

To ensure that all products returned by customers are collected at the collection–inspection centers, Equation (3) is defined as the first constraint:

$$\sum_{i\in I} X_{ilp} = r_{lp}\ \forall l \in L,\, p \in P \tag{3}$$

where r_{lp}represents the quantity of product type $p$returned by customer l.

$$\sum_{j\in J} Z_{ijp} = \left(1 - d_p\right)\sum_{l\in L} X_{ilp}\ \ \forall i \in I,\, p \in P \tag{4}$$

where d_p represents the proportion of product p that is disposed of.

$$\sum_{k\in K} W_{ikp} = d_p \sum_{l\in L} X_{ilp} \;\; \forall i \in I,\, p \in P \qquad (5)$$

Next, Equation (6) prevents the quantity of products transferred to a collection–inspection center from exceeding its capacity.

$$\sum_{l\in L} X_{ilp} \le y_i\, caf_{ip} \; \forall i, p \qquad (6)$$

where caf_{ip} denotes the capacity of collection center i for product type p.

Finally, Equations (7) and (8) prevent the quantities transferred to recycling and disposal centers from exceeding their respective capacities.

$$\sum_{i\in I} Z_{ijp} \le cas_{jp} y'_j \; \forall j, p \qquad (7)$$

where cas_{jp} denotes the capacity of recycling center j for product type p, and cat_{kp} denotes the capacity of disposal center k for product type p.

$$\sum_{i\in I} W_{ikp} \le cat_{kp} y''_k \; \forall k, p \qquad (8)$$

Equations (9)–(11) correspond to the binary decision variables, while Equation (12) ensures nonnegative values for the decision variables.

(9)

(10)

(11)

(12)

The Genetic Algorithm (GA) is one of the most powerful and widely used metaheuristic algorithms and is inspired by the process of natural evolution and Darwinian selection. This algorithm is used to find approximately optimal solutions to complex problems, particularly NP-hard problems such as supply chain network design. To understand the genetic algorithm, several key concepts, all derived from evolutionary biology, must first be introduced:

- **Chromosome:** A chromosome represents a potential solution to the problem and consists of a set of genes. For example, if the problem involves finding optimal values for the variables of a function, each chromosome may be represented as an array of numbers corresponding to the values of those variables.
- **Population:** A population is a set of chromosomes, or potential solutions, evaluated at each stage or generation of the algorithm.
- **Fitness Function:** The fitness function is a measure used to evaluate the quality of each chromosome. It determines how close each potential solution is to the optimal solution. Chromosomes with better fitness values—for example, lower cost or higher profit—have a greater probability of survival and reproduction.
- **Generation:** A generation refers to each stage of the algorithm in which an entire population is evaluated and a new population is generated from it.

Through an iterative process, the genetic algorithm guides a population of solutions toward an optimal solution. This process consists of the following stages:

1. **Initialization:** The algorithm begins by generating a random population containing a specified number of chromosomes or potential solutions. This provides initial diversity within the search space.
2. **Evaluation:** At this stage, the quality of all chromosomes in the current population is calculated using the fitness function. This determines which solutions perform better.
3. **Selection:** Superior chromosomes with better fitness values are selected to generate the next generation. The objective is to transmit desirable genes to subsequent generations. Various selection methods can be used, including roulette-wheel selection, which assigns better chromosomes a higher probability of selection, and tournament selection, in which several chromosomes are randomly selected and the best among them is chosen.
4. **Crossover:** This operator is the primary mechanism for generating new offspring. Two parent chromosomes selected in the previous stage are combined to generate new offspring chromosomes.
5. **Mutation:** With a very low probability, usually less than 1%, this operator introduces small random changes into one or more genes of an offspring chromosome. The purpose of mutation is to preserve genetic diversity within the population and prevent premature convergence of the algorithm

toward local rather than global optima. For example, in a binary chromosome, mutation may change a bit from 0 to 1 or vice versa.

6. **Termination:** Steps 2–5 are repeated iteratively until one of the termination criteria is satisfied. These criteria may include:
   - Reaching a predetermined number of generations.
   - No significant change in the best fitness value over several consecutive generations.
   - Reaching a predetermined threshold value for the fitness function.

Types of Encoding: The representation of a solution, or chromosome, has a substantial effect on algorithm performance. Common encoding methods include:

- **Binary Encoding:** The most common method, in which each gene is represented by a single bit, either 0 or 1.
- **Real-Valued Encoding:** In problems with numerical variables, each gene may be represented by a real number.
- **Permutation/Order Encoding:** This method is used for problems in which ordering is important, such as the traveling salesperson problem, and each chromosome is represented by a sequence of numbers or symbols.
- **Tree Encoding:** This method is used to represent hierarchical structures such as mathematical expressions or computer programs.

Inspired by biological evolution, the genetic algorithm is a stochastic yet intelligent search method. By generating, evaluating, selecting, recombining, and mutating a population of potential solutions, the algorithm gradually moves toward optimal solutions. Its high flexibility and capability to solve large-scale and complex problems make it a highly valuable tool in various fields, including reverse supply chain network optimization.

Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart (1995), is one of the most powerful and widely used metaheuristic algorithms based on swarm intelligence. The algorithm is inspired by the social and movement behavior of bird flocks and fish schools in nature. In nature, birds searching for food or a safe location move collectively toward the best location by sharing individual information. PSO searches the solution space according to precisely this logic. In other words, inspired by the collective intelligent behavior of birds, PSO is a stochastic yet highly efficient search method that effectively explores the solution space through simultaneous updates of particle velocities and positions. Its simple structure, rapid convergence, and requirement for fewer tuning parameters make it an ideal option for solving complex optimization problems in reverse supply chains, particularly when the problem dimension is large and rapid solutions are required.

To understand PSO, the following key concepts, all derived from collective bird behavior, should be considered:

- **Particle:** Each particle represents a potential solution to the problem. Each particle has a position in the search space corresponding to the values of the problem's decision variables.
- **Swarm:** A collection of particles, or potential solutions, that simultaneously explore the search space is referred to as a swarm or population.
- **Position:** The coordinates of each particle in the search space, represented by the vector x_i.
- **Velocity:** Each particle has a velocity vector v_i, which determines the direction and magnitude of its movement in the search space.
- **Personal Best ($pbest$):** The best position that a particular particle has found so far during the search process.
- **Global Best ($gbest$):** The best position discovered thus far among all particles in the swarm. In another variant, known as local PSO, the neighborhood best or $lbest$ is used instead.

The core of the PSO algorithm consists of two primary equations used to update the velocity and position of each particle at each iteration.

1. Velocity Update: The velocity of each particle is calculated based on three components:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

- v_i^t: the current velocity of particle i at iteration t.
- w: the inertia weight, which controls the influence of the previous velocity on the new velocity. A higher value promotes global exploration, whereas a lower value promotes local exploitation.
- c_1: the cognitive coefficient, which determines the weight of the particle's movement toward its personal best position ($pbest$).
- c_2: the social coefficient, which determines the weight of the particle's movement toward the global best position ($gbest$).

- r_1, r_2: uniformly distributed random numbers between 0 and 1, incorporated into the equation to generate stochastic and nondeterministic movement.
- $(pbest_i - x_i^t)$: the vector directing the particle toward its personal best position.
- $(gbest - x_i^t)$: the vector directing the particle toward the global best position.

2. Position Update: After calculating the new velocity, the position of the particle is updated as follows:

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

The execution process of the algorithm proceeds iteratively and step by step as follows:

- **Initialization:** The algorithm begins by generating a population or swarm of Nparticles. Each particle is assigned a random initial position $(X_i)$and a random initial velocity (V_i)in the search space.
- **Fitness Evaluation:** For each particle, the value of the objective or fitness function is calculated using its current position. This value represents the quality of the particle's solution.
- **Updating $pbest$and $gbest$:**
  - If the calculated fitness value for particle $i$is better than the value stored in $pbest_i$, then $pbest_i$is replaced by the current position.
  - If the calculated fitness value for particle $i$is better than the value stored in $gbest$, then $gbest$is replaced by the current position of that particle.
- **Velocity and Position Update:** The velocity and position of each particle are calculated and updated using Equations (1) and (2). Typically, particle velocity is restricted to a specified range to prevent particles from leaving the search space.
- **Termination:** Steps 2–4 are repeated until one of the following termination conditions is satisfied:
  - The maximum number of iterations is reached.
  - No significant change in $gbest$is observed over several consecutive iterations.
  - A desired threshold value of the objective function is reached.

The performance of PSO depends strongly on appropriate parameter tuning:

- **Inertia Weight (w):** This parameter is generally set between 0.4 and 0.9. A common strategy is to decrease $w$linearly during execution, for example, from 0.9 to 0.4, so that the algorithm initially emphasizes exploration and subsequently focuses on exploitation.
- **Acceleration Coefficients (c_1, c_2):** Both coefficients are generally set within the range of 1.5–2.5. A commonly used setting is $c_1 = c_2 = 2$.
- **Swarm Size:** Depending on the dimensionality of the problem, the swarm size is generally selected between 20 and 200 particles.

PSO has several variants, including:

- **Multi-Objective PSO (MOPSO):** For problems involving more than one conflicting objective, such as the present study in which both cost and environmental indicators are optimized, the multi-objective version of PSO can be used. In MOPSO, instead of using a single $gbest$, an external repository is employed to store a set of nondominated solutions, constituting the Pareto front, and a leader-selection mechanism is defined to select the most appropriate particle from this repository.
- **Binary PSO (BPSO):** This version is designed for problems involving binary decision variables, in which particle positions are represented using binary values.

In the present study, given the bi-objective nature of the problem involving cost and environmental considerations, the multi-objective version, MOPSO, is used to identify a set of Pareto solutions and to compare its performance with that of the multi-objective genetic algorithm.

3. Findings and Results

This section evaluates the proposed model in practice through a case study in the plastic recycling industry. First, the specifications of the case study and the data used are presented. The performance of the model is then analyzed using the GA and PSO algorithms through various quantitative indicators and, finally, compared with conventional optimization methods.

The data required for this study were obtained through interviews with managers and experts of an active recycling company and through a review of annual reports issued by the Waste Management Organization. To preserve confidentiality, the data are presented in aggregated and normalized form.

Location-allocation problems in supply chains are particularly important because of their direct effects on costs and service levels. In many real-world applications, decision-makers seek a trade-off between conflicting objectives such as cost reduction and increased response speed. In this study, a three-layer network consisting of 5 customers, 6 collection centers, 6 recycling centers, and 6 disposal centers is considered, with limited capacities of 220 units and a disposal ratio of 20%. The decision variables include facility selection variables, which are binary, and product flows between layers, which are continuous. Given the moderate dimensionality of the problem and the nonlinear nature of the penalty functions, metaheuristic algorithms are employed.

Tables 1–5 present the model parameter values considered for a plastic recycling company. The objective of this problem is to determine the optimal locations for establishing disposal, recycling, and collection centers, together with the quantity of product transferred from each center to another. The numerical data, including fixed costs, cost and time matrices, and demands, were used in accordance with the accompanying dataset.

Table 1. Facility Establishment Costs for Each of the Six Candidate Locations for Collection, Recycling, and Disposal Centers

Facility Type	Candidate 1	Candidate 2	Candidate 3	Candidate 4	Candidate 5	Candidate 6
Collection centers, $\boldsymbol{F}$	8,271	6,315	8,010	5,828	7,643	6,556
Recycling centers, $\boldsymbol{F'}$	9,567	6,145	5,419	7,253	8,741	8,446
Disposal centers, $\boldsymbol{F''}$	7,213	5,390	9,981	7,692	9,129	5,762

Table 2. Cost Matrix $\boldsymbol{CF_{li}}$

Customer	$\boldsymbol{i=1}$	$\boldsymbol{i=2}$	$\boldsymbol{i=3}$	$\boldsymbol{i=4}$	$\boldsymbol{i=5}$	$\boldsymbol{i=6}$
$\boldsymbol{l=1}$	84	18	24	22	69	78
$\boldsymbol{l=2}$	92	35	98	48	13	77
$\boldsymbol{l=3}$	21	59	97	93	87	45
$\boldsymbol{l=4}$	93	97	54	82	94	69
$\boldsymbol{l=5}$	67	97	82	97	71	25

Table 3. Cost Matrix $\boldsymbol{CS_{ij}}$

Recycling Center	$\boldsymbol{i=1}$	$\boldsymbol{i=2}$	$\boldsymbol{i=3}$	$\boldsymbol{i=4}$	$\boldsymbol{i=5}$	$\boldsymbol{i=6}$
$\boldsymbol{j=1}$	78	20	74	79	73	74
$\boldsymbol{j=2}$	33	55	78	82	38	12
$\boldsymbol{j=3}$	56	97	35	27	96	35
$\boldsymbol{j=4}$	73	40	71	54	13	14
$\boldsymbol{j=5}$	91	63	69	50	49	18
$\boldsymbol{j=6}$	97	30	24	68	44	84

Table 4. Cost Matrix $\boldsymbol{CT_{ik}}$

Origin	$\boldsymbol{k=1}$	$\boldsymbol{k=2}$	$\boldsymbol{k=3}$	$\boldsymbol{k=4}$	$\boldsymbol{k=5}$	$\boldsymbol{k=6}$
$\boldsymbol{j=1}$	59	84	66	93	16	61
$\boldsymbol{j=2}$	22	32	53	36	14	52
$\boldsymbol{j=3}$	23	94	42	78	58	11
$\boldsymbol{j=4}$	33	41	85	78	80	40
$\boldsymbol{j=5}$	86	27	63	44	94	24
$\boldsymbol{j=6}$	33	32	60	61	21	82

Table 5. Customer Loads to Be Delivered to Collection Centers

Customer	$\boldsymbol{l=1}$	$\boldsymbol{l=2}$	$\boldsymbol{l=3}$	$\boldsymbol{l=4}$	$\boldsymbol{l=5}$
Load	55	99	50	89	91

The capacity of the disposal, collection, and recycling centers is assumed to be 220 units. The disposal ratio is assumed to be:

$$d = 0.2$$

This section presents the solution framework for the location-allocation problem involving collection, recycling, and disposal centers using two metaheuristic algorithms: Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA). Because of the NP-hard nature of the problem and the existence of two conflicting objectives, the weighted-sum method is used to transform the problem into a composite single-objective function:

$$\min Z = w_1 Z_1 + w_2 Z_2,\ w_1 + w_2 = 1$$

In this study, the weights are specified as:

$$w_1 = 0.6,\ w_2 = 0.4$$

thereby assigning greater priority to cost. For validation purposes, each algorithm was independently executed 30 times.

Each potential solution is defined as a vector of length:

$$nVar = 18 + 30 + 36 + 36 = 120$$

- 18 binary variables for facility selection $(6 + 6 + 6)$.
- 90 continuous variables for the flows: 30 customer-to-collection flows, 36 collection-to-recycling flows, and 36 collection-to-disposal flows.

The genetic algorithm was executed with a population of 100 chromosomes over 500 generations. For initialization, half of the population was generated intelligently based on lower fixed costs, while the other half was generated randomly. Tournament selection with a tournament size of 2 was used. For crossover, the BLX-α method with $\alpha = 0.5$was applied to the continuous variables, while weighted arithmetic crossover was used for the entire chromosome. Mutation was implemented in two forms: binary mutation with a probability of 0.05 for facility-selection variables, and Gaussian mutation with a standard deviation equal to $0.1\ \times$the variable range for the flow variables. In addition, the four best chromosomes in each generation were retained as elites and transferred to the next generation. Based on the preceding discussion, the initial GA implementation settings were specified as follows:

- Population size: 100.
- Number of generations: 500.
- Parent selection: tournament selection with a tournament size of 2.
- Crossover: arithmetic crossover (BLX) with $\alpha = 0.5$and a crossover probability of 0.8.
- Mutation: bit-flip mutation with a probability of 0.05 for binary variables and Gaussian mutation with a standard deviation of $0.1 \times (ub - lb)$and a probability of 0.1 for continuous variables.
- Replacement: preservation of the four elite chromosomes together with the generated offspring (elitism).
- Initialization: similar to PSO, using a combination of random and greedy initialization.
- Fitness function and constraint handling: exactly the same as in PSO.

The continuous version of PSO was implemented with 100 particles over 500 iterations. The inertia weight was reduced linearly from 0.9 to 0.4 to establish an appropriate balance between exploration and exploitation. The cognitive and social coefficients were both set equal to 2. Initialization was conducted similarly to the GA. To handle binary variables, following each position update, the facility-selection variables were rounded to the nearest integer. If fewer than two facilities of a particular type were selected, additional centers were randomly activated. No independent mutation operator was defined in PSO. For the implementation of the PSO algorithm, the initial parameter settings were specified as follows:

- Number of particles: 100.
- Number of iterations: 500.
- Inertia weight: linear reduction from 0.9 to 0.4.
- Cognitive and social coefficients:

$$c_1 = c_2 = 2$$

- Initialization: a combination of random and greedy methods; half of the particles were initialized by selecting lower-cost centers.
- Management of binary variables: after each position update, the binary portion was rounded using the round operator; when fewer than two centers were selected, additional centers were randomly activated.
- Fitness function: the composite objective function plus a quadratic penalty for constraint violations, with penalty coefficient:

$$M = 10^6$$

The following criteria were used to compare the performance of the two algorithms:

- Best, worst, mean, standard deviation, and median fitness-function values, including penalties, across 30 runs.
- Actual values of the two objectives, $Z_1$and Z_2, excluding penalties, for the best solution.
- Selected centers and the flow-allocation pattern in the best solution.
- Convergence curve of the best solution across generations/iterations.

All implementations were performed in MATLAB R2020b on a system equipped with a Core i7 processor and 16 GB of RAM.

In the best GA solution, all six collection centers, all six recycling centers, and five disposal centers, excluding Center 1, were activated. The product flow from each customer was distributed among several collection centers, resulting in a dispersed allocation pattern. In contrast, the best PSO solution also activated all collection centers, but selected only four recycling centers, namely Centers 2, 3, 4, and 6, and four disposal centers, namely Centers 1, 2, 3, and 6. The allocation pattern obtained through PSO was concentrated, such that each customer sent its entire requirement to only one collection center: Customer 1 → Center 2, Customer 2 → Center 5, Customer 3 → Center 1, Customer 4 → Center 3, and Customer 5 → Center 6. In addition to reducing transportation costs, this simpler structure facilitates operational management.

The customer-to-collection-center allocation flows are presented in Tables 6 and 7.

Table 6. Customer-to-Collection-Center Flows in the Optimal GA Solution

Customer	Demand	Center 1	Center 2	Center 3	Center 4	Center 5	Center 6
1	55	25	11	12	1	5	5
2	99	4	15	1	23	59	2
3	50	26	0	3	1	15	12
4	89	30	2	40	12	1	12
5	91	2	1	7	23	0	61

Table 7. Customer-to-Collection-Center Flows in the Optimal PSO Solution

Customer	Demand	Center 1	Center 2	Center 3	Center 4	Center 5	Center 6
1	55	0	55	0	0	0	0
2	99	0	0	0	0	95	0
3	50	50	0	0	0	0	0
4	89	0	0	86	0	0	0
5	91	0	0	0	0	0	87

The results indicate that, despite not employing a mutation operator, PSO was able to obtain better solutions in terms of both objectives. In contrast, although GA generated greater dispersion among solutions, it may still be an appropriate option for larger-scale problems or more complex objective functions requiring greater population diversity. Furthermore, the high standard deviation of GA indicates that its performance is strongly dependent on initialization and stochastic parameters, whereas PSO demonstrates considerably more stable performance. Both algorithms were independently executed 30 times using identical general parameter settings, except for algorithm-specific parameters, on the same problem instance. All runs were performed on identical hardware. Table 8 summarizes the descriptive statistics of the fitness function, including penalties, across the 30 runs.

Table 8. Comparison of PSO and GA Results Across 30 Runs

Criterion	PSO	GA
Best fitness value	1,000,209,139.23	610,322,937.69
Worst fitness value	1,000,210,127.80	2,867,318,291.17
Mean fitness value	1,000,209,596.01	1,561,633,526.69
Standard deviation	324.22	557,578,748.14
Median fitness value	1,000,209,676.04	1,525,180,919.79

As can be observed, the PSO fitness-function values are considerably larger than those obtained by GA, which is primarily attributable to the large penalty coefficient and the manner in which constraints are handled. Therefore, for a fair comparison, the actual values of the objective functions, excluding penalties, in the best run of each algorithm should be considered, as shown in Table 9.

Table 9. Actual Objective-Function Values in the Best Run

Algorithm	Total Cost (Z_1)	Total Time (Z_2)	Composite Objective
GA	171,973.43	47,218.27	122,071.36
PSO	132,645.98	35,411.48	93,752.18

PSO reduced total cost by approximately 23% and total time by approximately 25% relative to GA. Moreover, the substantially lower standard deviation of PSO, 324 compared with 557 million for GA, indicates the exceptional repeatability and stability of this algorithm for the problem under investigation.

Examination of the execution stages indicates that GA initially exhibits considerable fluctuations and, in some instances, continues to generate substantial improvements even up to Generations 300 and 400. For example, in Run 3, the fitness value decreased from approximately 2.8 billion to 610 million. This finding indicates GA's strong capability for exploring the solution space, although its convergence time is longer. In contrast, PSO reaches values close to the final solution during the early iterations, approximately by Iteration 50, and subsequently improves gradually through a slow decreasing trend. Nevertheless, the PSO fitness value consistently remains higher than that of GA, suggesting that despite its rapid convergence, PSO may be more successful in identifying solutions with lower penalties and, consequently, lower actual costs.

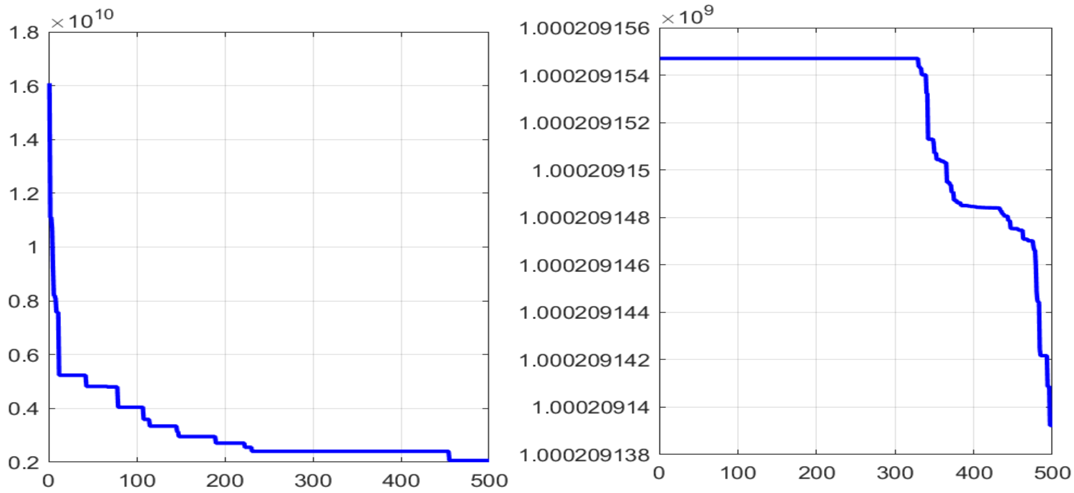

Figure 2. Convergence Curves of PSO and GA, Respectively

4. Discussion and Conclusion

The present study developed and evaluated a multi-objective reverse supply chain network model for the plastic recycling industry and compared the performance of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in solving the resulting location-allocation problem. The model simultaneously considered total network cost and transportation time and incorporated facility-selection decisions for collection–inspection, recycling, and disposal centers as well as product-flow allocation among the network echelons. The numerical results showed that PSO outperformed GA in terms of the actual values of both objective functions. In the best solution obtained by PSO, total cost was reduced from 171,973.43 under GA to 132,645.98, corresponding to an improvement of approximately 23%, while total transportation time declined from 47,218.27 to 35,411.48, representing an improvement of approximately 25%. The composite objective value was also lower for PSO, decreasing from 122,071.36 to 93,752.18. These findings indicate that, for the problem structure investigated in this study, PSO was more effective in identifying economically and operationally efficient reverse supply chain configurations.

The superior performance of PSO can first be interpreted in light of the structure of reverse logistics network design problems. Such problems require simultaneous optimization of strategic facility-location decisions and operational product-flow decisions, which creates a high-dimensional and combinatorial search space. Previous studies have similarly shown that integrated reverse logistics models become computationally challenging when facility location, capacity, routing, and material-flow variables must be optimized jointly [15, 16]. In this context, the relatively rapid information-sharing mechanism of PSO appears to have enabled particles to converge toward promising regions of the solution space more efficiently than the evolutionary operators used in GA. This result is consistent with the broader literature emphasizing the usefulness of metaheuristic and intelligent optimization approaches for complex reverse and closed-loop supply chain problems where exact methods may become computationally demanding [19, 20, 26].

The finding that PSO achieved lower total cost is also aligned with previous research demonstrating that appropriate reverse supply chain network configuration can significantly reduce fixed facility and transportation costs. Reverse logistics network design for plastic waste management has shown that careful selection of collection and processing facilities, together with appropriate assignment of waste flows, can materially improve economic performance [5]. Similarly, optimization models for local and distributed plastic recycling indicate that facility configuration and transportation linkages are central determinants of overall recycling-system cost [7]. The present results extend this evidence by showing that the choice of optimization algorithm itself can substantially influence the economic quality of the resulting network configuration. In particular, PSO selected fewer recycling and disposal facilities than GA while maintaining feasible product flows, thereby avoiding unnecessary fixed establishment costs and contributing to a more efficient network structure.

The observed reduction in transportation time under PSO is equally important from a supply chain management perspective. Reverse logistics performance depends not only on minimizing monetary expenditure but also on ensuring timely and efficient movement of returned products through collection, inspection, recycling, and disposal stages. Multi-objective reverse supply chain research increasingly recognizes that delay and responsiveness must be considered alongside cost [8, 11]. The approximately 25% reduction in total transportation time obtained by PSO suggests that the algorithm was better able to identify allocation structures with shorter or more efficient transportation paths. This result is compatible with studies showing that simultaneous optimization of location and routing can improve both economic and operational performance in reverse logistics systems [15, 16]. It is also consistent with the logic of eco-efficient reverse logistics models, in which reduced transportation requirements may simultaneously improve service efficiency and reduce resource consumption [10].

Another important result concerns the allocation pattern generated by the two algorithms. The best GA solution distributed the flow from each customer among multiple collection centers, producing a relatively dispersed network structure. In contrast, PSO generated a much more concentrated allocation pattern in which each customer was effectively assigned to a single collection center. In practical terms, such concentration can simplify routing, reduce coordination complexity, and facilitate operational control. The result is consistent with the general principle that unnecessary fragmentation of reverse flows can increase handling, transportation, and coordination burdens. Research on collaborative reverse logistics routing has demonstrated that consolidation and coordinated allocation can improve the efficiency of recyclable collection systems [13]. Similarly, integrated forward and reverse logistics studies have emphasized that coordinated network and routing decisions can reduce redundant movements and improve system-wide efficiency [4]. The concentrated PSO solution therefore appears to reflect a more coherent allocation strategy that reduces unnecessary dispersion of return flows.

The lower number of active recycling and disposal centers in the PSO solution is also relevant from the perspective of facility utilization. While GA activated all six recycling centers and five disposal centers, PSO selected only four recycling centers and four disposal centers. This outcome indicates that PSO was more successful in balancing facility-opening costs against available capacity and transportation requirements. Such a result is theoretically consistent with network design studies showing that opening more facilities does not necessarily improve total system performance because additional facilities generate fixed costs and may lead to inefficient capacity utilization [2, 9]. Sustainable closed-loop supply chain design therefore requires selecting a network configuration that is sufficiently dense to satisfy demand and capacity restrictions but not so extensive that fixed costs outweigh transportation advantages. The present findings suggest that PSO identified such a balance more effectively.

The environmental implications of the results are also noteworthy, even though the numerical comparison focused mainly on cost and transportation time. In reverse logistics systems, transportation intensity is closely related to fuel consumption, emissions, and environmental burden. Therefore, shorter and more concentrated transportation patterns may indirectly support environmental improvement. Previous research has explicitly incorporated emission reduction into sustainable reverse logistics network design and has shown that routing and facility-allocation decisions can substantially affect environmental performance [12]. Likewise, routing optimization for recyclable collection has demonstrated that transportation configuration plays a major role in both circular-economy performance and environmental outcomes [13]. Research on energy-efficient logistics also supports the argument that transportation decisions should be evaluated not only on cost grounds but also in terms of energy consumption and sustainability [14]. Thus, the lower transportation time and more concentrated flows obtained by PSO may be interpreted as potentially favorable from an environmental perspective as well.

The results also revealed a substantial difference between the two algorithms in terms of stability across repeated runs. The standard deviation of the PSO fitness values was only 324.22, whereas the GA standard deviation was 557,578,748.14 in the main comparative analysis. This exceptionally large difference indicates that PSO produced highly repeatable outcomes under the specified parameter settings, while GA was much more sensitive to initialization and stochastic evolutionary operations. This result is consistent with the underlying mechanisms of the two methods. GA relies heavily on selection, crossover, and mutation, which can generate considerable population diversity but may also result in greater variation across independent runs. PSO, by contrast, updates each particle based on both its own best experience and the global best solution, which can promote more coordinated convergence. The literature on artificial intelligence and metaheuristic optimization in reverse logistics increasingly emphasizes solution robustness and repeatability in addition to objective quality [20, 21]. The present findings provide empirical support for the view that PSO may offer particularly stable performance for medium-sized reverse supply chain location-allocation problems.

However, the higher penalized fitness values reported for PSO require careful interpretation. In the descriptive statistics, PSO showed fitness values of approximately 1.0 billion, while GA achieved lower best penalized fitness values. This apparent contradiction results from the use of a large quadratic penalty coefficient for constraint violations and differences in the way the algorithms interacted with the penalty structure. Therefore, the penalized fitness value alone did not provide a fair basis for comparing actual operational performance. When the penalty was excluded and the true objective values were examined, PSO clearly outperformed GA in both total cost and transportation time. This finding highlights an important methodological issue in metaheuristic supply chain optimization: penalty design can strongly affect algorithm ranking, convergence trajectories, and the apparent quality of solutions. Studies using multi-objective and uncertainty-based models similarly demonstrate that objective scaling, constraint handling, and solution representation are critical to achieving reliable comparisons between algorithms [8, 26]. Consequently, researchers should distinguish carefully between penalized fitness values used internally for search guidance and actual objective-function values used for managerial evaluation.

The convergence behavior of the two algorithms further supports this interpretation. GA showed more pronounced fluctuations during early generations and, in some runs, continued to improve substantially even after 300 or 400 generations. This pattern indicates a strong exploratory capacity and the ability to escape certain local regions of the search space. Such behavior is consistent with the evolutionary structure of GA, in which crossover and mutation maintain population diversity. Previous research applying genetic and fuzzy genetic methods to reverse supply chain design has similarly emphasized the flexibility of evolutionary approaches in complex and uncertain search spaces [23]. Hybrid developments, such as reinforcement-learning-based genetic algorithms, further indicate that genetic search remains a powerful approach for green reverse logistics problems when adaptive exploration is required [24]. Accordingly, although GA performed less favorably in the present problem, its exploratory characteristics may still be advantageous for larger or more irregular solution spaces.

By contrast, PSO reached values close to its final solution after approximately 50 iterations and then improved gradually. This faster convergence is consistent with the collective-learning mechanism of swarm intelligence, in which information about successful regions of the search space is rapidly disseminated among particles. Such performance is particularly valuable in managerial settings where solution time and computational efficiency matter. Artificial intelligence applications in closed-loop and reverse supply chains increasingly seek not only higher-quality solutions but also faster and more adaptive decision support [19, 22]. The present results therefore suggest that PSO may be especially appropriate for reverse supply chain planning contexts in which repeated scenario analysis or relatively rapid re-optimization is needed.

The study also supports the broader trend toward using intelligent optimization in circular economy and waste-management systems. Reverse supply chains are becoming increasingly dependent on computational methods that can coordinate collection, recovery, recycling, and disposal decisions under multiple economic and environmental objectives [3, 27]. Sustainable plastic waste management particularly requires integrated decisions regarding collection points, recycling facilities, disposal capacities, and material flows [5, 6]. The superior PSO configuration identified in the present study demonstrates how metaheuristic optimization can support this transition by generating network structures that reduce cost and transportation requirements while maintaining feasibility. Such results are also consistent with the increasing use of digital and intelligent technologies in reverse logistics and closed-loop supply chains, including artificial intelligence, the Internet of Things, and blockchain-enabled decision systems [25, 26].

From a strategic perspective, the findings indicate that reverse supply chain design should not be limited to minimizing the number of facilities or transportation distance independently. Rather, facility-selection and flow-allocation decisions must be solved jointly because they interact strongly. A center with a low fixed establishment cost may create excessive transportation requirements, whereas a strategically located but somewhat more expensive facility may reduce total system cost when transportation is considered. The same logic applies to recycling and disposal facilities. This conclusion is in line with integrated supply chain network studies emphasizing the importance of coordinating strategic and operational decisions [4, 18]. The present study demonstrates that PSO was able to exploit these interactions effectively, resulting in a network with fewer active downstream facilities and more concentrated customer allocations without sacrificing feasibility.

Overall, the findings indicate that PSO was the more appropriate algorithm for the specific reverse supply chain network examined in this study. It produced lower total cost, shorter transportation time, a simpler allocation structure, fewer active recycling and disposal facilities, more rapid convergence, and substantially greater stability across repeated runs. Nevertheless, the comparative results do not imply that PSO is universally superior to GA. Algorithm performance is highly dependent on problem size, representation, parameterization, constraint-handling strategy, and objective structure. The review literature on reverse logistics and circular supply chain optimization similarly emphasizes that no single solution approach can be considered universally optimal across all problem classes [1, 2]. Thus, the main contribution of the present comparison lies in identifying the relative strengths of the two algorithms for a specific multi-stage plastic recycling network and demonstrating the managerial value of metaheuristic optimization in reverse supply chain design.

The present study has several limitations that should be considered when interpreting its findings. First, the case study was based on a relatively small and stylized network consisting of five customers and six candidate locations for each facility type, and the results may differ in larger industrial networks with hundreds of customers and facilities. Second, several parameters, including transportation costs, times, facility capacities, and the disposal ratio, were treated as deterministic, whereas real plastic recycling systems are characterized by uncertainty in returned quantities, product quality, transportation conditions, processing yields, and market demand for recycled material. Third, environmental performance was represented indirectly through transportation-related considerations rather than through explicit measures such as carbon emissions, energy consumption, water use, or landfill impacts. Fourth, the weighted-sum approach used fixed weights for the two objectives, and different weight combinations could generate different preferred network configurations. Fifth, the comparison was limited to GA and PSO and was conducted under a particular set of parameter values; alternative tuning strategies could affect their relative performance. Finally, the penalty-based constraint-handling mechanism generated penalized fitness values that were difficult to interpret directly and may have influenced convergence behavior.

Future studies should extend the proposed framework to larger and more realistic reverse supply chain networks with multiple product categories, heterogeneous facility capacities, and geographically detailed transportation links. Uncertainty in return volumes, quality levels, transportation times, processing capacities, and recycling yields could be incorporated using stochastic, robust, fuzzy, or scenario-based optimization. Future models should also include explicit environmental indicators such as greenhouse-gas emissions, energy consumption, fuel use, and landfill diversion, together with social sustainability indicators where data are available. Rather than relying solely on weighted-sum scalarization, multi-objective approaches such as NSGA-II, MOPSO, MOEA/D, or hybrid Pareto-based algorithms could be used to generate complete nondominated solution sets for decision-makers. Comparative studies could also include additional algorithms such as differential evolution, ant colony optimization, simulated annealing, grey wolf optimization, and hybrid machine-learning-assisted metaheuristics. Further research should investigate alternative constraint-handling methods, adaptive penalty coefficients, repair operators, and decomposition approaches. Finally, sensitivity analyses should be conducted for objective weights, disposal ratios, facility capacities, and cost parameters to determine the robustness of network decisions under changing operational conditions.

Managers in plastic recycling companies should use integrated location-allocation models when deciding where to establish collection, recycling, and disposal facilities rather than making these decisions separately. The findings suggest that minimizing the number of active facilities while maintaining adequate capacity can reduce fixed investment and simplify operations, but such decisions should always be evaluated jointly with transportation requirements. Managers should also prioritize concentrated allocation patterns where operationally feasible because assigning customers to fewer collection centers can simplify routing, monitoring, scheduling, and coordination. PSO can be considered a practical decision-support tool for medium-scale network planning when rapid convergence and consistent solutions are important, while GA may remain useful where greater exploration of highly complex search spaces is required. Organizations should conduct multiple independent algorithm runs and evaluate actual objective values rather than relying solely on penalized fitness measures. In addition, companies should periodically re-optimize the network as return volumes, fuel prices, facility capacities, and recycling conditions change, and should integrate optimization models with operational information systems so that strategic network decisions can be updated using current data.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] R. Aryee and E. Adaku, "A Review of Current Trends and Future Directions in Reverse Logistics Research," *Flexible Services and Manufacturing Journal,* vol. 36, no. 2, pp. 379-408, 2024, doi: 10.1007/s10696-023-09493-y.

[2] I. Shahsavani and A. Goli, "A Systematic Literature Review of Circular Supply Chain Network Design: Application of Optimization Models," *Environment, Development and Sustainability,* vol. 27, no. 10, pp. 23483-23514, 2025, doi: 10.1007/s10668-023-03362-2.

[3] S. A. Khan, "Connecting Reverse Logistics with Circular Economy in the Context of Industry 4.0," *Kybernetes,* vol. 52, no. 12, pp. 6279-6320, 2023, doi: 10.1108/K-03-2022-0468.

[4] Ding, "Integrated Design of Forward and Reverse Logistics Networks," *Computers & Industrial Engineering,* vol. 175, p. 108876, 2023.

[5] R. Ardi, S. Nurkamila, D. L. Citraningrum, and T. N. Zahari, "Reverse Logistics Network Design for Plastic Waste Management in Jakarta: Robust Optimization Method," *International Journal of Technology,* vol. 14, no. 7, pp. 1560-1569, 2023, doi: 10.14716/ijtech.v14i7.6681.

[6] D. Sengupta, A. Das, U. K. Bera, and L. Chen, "A Sustainable Green Reverse Logistics Plan for Plastic Solid Waste Management Using TOPSIS Method," *Environmental Science and Pollution Research,* vol. 30, no. 43, pp. 97734-97753, 2023, doi: 10.1007/s11356-023-29067-7.

[7] P. Santander, F. A. C. Sanchez, H. Boudaoud, and M. Camargo, "Closed Loop Supply Chain Network for Local and Distributed Plastic Recycling for 3D Printing: A MILP-Based Optimization Approach," *Resources, Conservation and*

Recycling, vol. 154, p. 104531, 2020, doi: 10.1016/j.resconrec.2019.104531.
[8] M. A. Momeni and A. Mostofi, "A Novel Multi-Objective Optimization Model for Designing a Reverse Supply Chain Network," *Journal of Cleaner Production,* p. 145249, 2025, doi: 10.1016/j.jclepro.2025.145249.
[9] J. N. Rodríguez-Escoto, E. Olivares-Benitez, S. Nucamendi-Guillén, and J. Drzymalski, "A Multi-Objective Sustainable Closed-Loop Supply Chain Network Problem with Hybrid Facilities," *International Transactions in Operational Research,* vol. 32, no. 6, pp. 3497-3527, 2025, doi: 10.1111/itor.13523.
[10] D. Kannan, R. Solanki, and J. D. Darbari, "A Novel Bi-Objective Optimization Model for an Eco-Efficient Reverse Logistics Network Design Configuration," *Journal of Cleaner Production,* vol. 394, p. 136357, 2023, doi: 10.1016/j.jclepro.2023.136357.
[11] M. Ghahremani, R. Ehtesham Rasi, and S. Abedi, "Optimization Multi-Objective Cost and Delay Rate in Delivering Orders in the Three-Echelon Reverse Supply Chain Based on Cost Management," *International Journal of Finance & Managerial Accounting,* vol. 9, no. 33, pp. 43-58, 2024.
[12] S. E. Hashemi, "A Fuzzy Multi-Objective Optimization Model for a Sustainable Reverse Logistics Network Design of Municipal Waste-Collecting Considering the Reduction of Emissions," *Journal of Cleaner Production,* vol. 318, p. 128577, 2021, doi: 10.1016/j.jclepro.2021.128577.
[13] S. Cao, W. Liao, and Y. Huang, "Heterogeneous Fleet Recyclables Collection Routing Optimization in a Two-Echelon Collaborative Reverse Logistics Network from Circular Economic and Environmental Perspective," *Science of the Total Environment,* vol. 758, p. 144062, 2021, doi: 10.1016/j.scitotenv.2020.144062.
[14] A. Ghobadi, M. Fallah, and R. Tavakkoli-Moghaddam, "A Fuzzy Two-Echelon Model to Optimize Energy Consumption in an Urban Logistics Network with Electric Vehicles," *Sustainability,* vol. 14, p. 14075, 2022, doi: 10.3390/su142114075.
[15] X. Xu, W. Liu, and M. Jiang, "A Multi-Cycle and Multi-Echelon Location-Routing Problem for Integrated Reverse Logistics," *Industrial Management & Data Systems,* vol. 122, pp. 2237-2260, 2022, doi: 10.1108/IMDS-01-2022-0015.
[16] F. Kangi, S. H. R. Pasandideh, E. Mehdizadeh, and H. Soleimani, "The Optimization of an Integrated Forward and Reverse Logistics Network Based on Routing and Cross-Docking Strategy," *Journal of Applied Research on Industrial Engineering,* vol. 11, no. 2, pp. 251-282, 2024.
[17] R. Li and X. Chen, "Reverse Logistics Network Design under Disruption Risk for Third-Party Logistics Providers," *Sustainability,* vol. 14, p. 14936, 2022, doi: 10.3390/su142214936.
[18] B. Naderi, K. Govindan, and H. Soleimani, "A Benders Decomposition Approach for a Real Case Supply Chain Network Design with Capacity Acquisition and Transporter Planning: Wheat Distribution Network," *Annals of Operations Research,* vol. 291, pp. 685-705, 2020, doi: 10.1007/s10479-019-03137-x.
[19] S. Bhattacharya, K. Govindan, S. G. Dastidar, and P. Sharma, "Applications of Artificial Intelligence in Closed-Loop Supply Chains: Systematic Literature Review and Future Research Agenda," *Transportation Research Part E: Logistics and Transportation Review,* vol. 184, p. 103455, 2024, doi: 10.1016/j.tre.2024.103455.
[20] O. Bhowmik, S. Chowdhury, J. H. Ashik, G. I. Mahmud, M. M. Khan, and N. U. I. Hossain, "Application of Artificial Intelligence in Reverse Logistics: A Bibliometric and Network Analysis," *Supply Chain Analytics,* vol. 7, p. 100076, 2024, doi: 10.1016/j.sca.2024.100076.
[21] P. Cortés-Pellicer, F. Alarcón, and D. Pérez-Perales, "Artificial Intelligence in Reverse Logistics Process: Recent Theory and Applications," 2024, doi: 10.1007/978-3-031-82334-3_14.
[22] S. Mukherjee, R. Nagariya, K. Mathiyazhagan, M. M. Baral, M. Pavithra, and A. Appolloni, "Artificial Intelligence-Based Reverse Logistics for Improving Circular Economy Performance: A Developing Country Perspective," *The International Journal of Logistics Management,* vol. 35, no. 6, pp. 1779-1806, 2024, doi: 10.1108/IJLM-03-2023-0102.
[23] P. Barzegar Keliji, H. A. Aghajani, and S. A. Shayan Nia, "Presenting a Model Based on Artificial Intelligence in the Reverse Supply Chain of the Home Appliance Industry in Tehran Province by Fuzzy Genetic Algorithm," *Journal of Industrial Strategic Management,* vol. 6, no. 1, pp. 58-61, 2021.
[24] M. Y. Li and F. Y. Shih, "Solving the Green Reverse Logistics Problem in E-Commerce Using a Reinforcement Learning Based Genetic Algorithm," *Electronic Commerce Research and Applications,* vol. 68, p. 101455, 2024, doi: 10.1016/j.elerap.2024.101455.
[25] A. Babaei, M. Khedmati, M. R. Akbari Jokar, and E. B. Tirkolaee, "Designing an Integrated Blockchain-Enabled Supply Chain Network under Uncertainty," *Scientific Reports,* vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-30439-9.
[26] Z. Madani, F. Goodarzian, A. Navaei, and I. Ali, "Optimization Modelling for a Sustainable Closed-Loop Supply Chain Network Using IoT: Multiobjective Metaheuristic Algorithms," *Central European Journal of Operations Research,* 2024, doi: 10.1007/s10100-024-00942-z.
[27] J. J. d. S. Filho, A. d. Paço, and P. D. Gaspar, "Artificial Intelligence and MCDA in Circular Economy: Governance Strategies and Optimization for Reverse Supply Chains of Solid Waste," *Applied Sciences,* vol. 15, no. 9, p. 4758, 2025, doi: 10.3390/app15094758.
[28] B. Banoor, "Factors Affecting Rice Processors' Participation in Supply Chains," *Journal of Supply Chain Management,* vol. 59, no. 3, pp. 112-128, 2023, doi: 10.4324/9781003145783-3.
[29] A. Pooya, A. Mansoori, and M. Eshaghnezhad, "Neural Network for a Novel Disturbance Optimal Control Model for Inventory and Production Planning in a Four-Echelon Supply Chain with Reverse Logistic," *Neural Processing Letters,* vol. 53, pp. 4549-4570, 2021, doi: 10.1007/s11063-021-10612-9.
[30] X. Zhou, M. Farivar, and Z. Liu, "Reverse and Forward Engineering of Local Voltage Control in Distribution Networks," *IEEE Transactions on Automatic Control,* vol. 66, pp. 1116-1128, 2020, doi: 10.1109/TAC.2020.2994184.