Review

Optimization Approaches for Multiple Conflicting Objectives in Sustainable Green Supply Chain Management

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Abstract: Over the years, the global supply chain has evolved into a more extensive interconnected complex network with multiple suppliers, manufacturers, and customers. Since environmental issues have become a burning question in recent years, the focus has shifted to attaining sustainability in supply chain management. The green supply chain or sustainable network is a concept to reduce environmental impacts in the life cycle of a product. However, green supply chain management is often challenged with additional operating costs and difficulty monitoring the implications within the complex network system. Additionally, many stakeholders are unaware of the importance of sustainability analysis, which eventually complicates adopting green cultures in actual applications. Since green supply chain management deals with multiple aspects, such as cost and carbon emission, the multiobjective optimization method is widely used to evaluate supply chain performance. This paper intensively reviews the state-of-the-art literature on applying multiobjective optimization techniques in green supply chain management. The study highlights aspects of green supply chain structures, model formulation techniques considering multiple objectives simultaneously, and solution methods for multiobjective optimization problems. Finally, a conclusion is drawn with the scope of the potential research opportunities for integrating economic and environmental considerations in sustainable supply chain management practice.

Keywords: green supply chain management; multiobjective optimization; mathematical model

1. Introduction

The notion of supply chain management (SCM) was introduced in the early 1980s [1]. However, it received immense attention from researchers and industries in the mid-1990s [1]. SCM consists of a network or organizations that involve upstream and downstream relations in various operations, producing value in the form of products and services with less expenditure [2]. Supply chain management integrates design, planning, and procurement with logistics activities to maximize profit and increase customer satisfaction. Today, environmental issues are receiving attention along with economic concerns to protect the Earth from global warming, maintain ecological balance, and reduce severe health problems. Therefore, SCM not only evolves around financial circumstances but also includes sustainability in the primary decision-making processes. SCM coupled with environmental factors is also known as the green supply chain management (GSCM) concept [3]. Ensuring green culture is the key for an organization to sustain itself in the competitive global market.

GSCM involves environmental concerns in supply chain activities to minimize ecological impacts [3]. The aim of GSCM is to find a balance between economic and

environmental activities. GSCM deals with the concept of sustainability of the entire supply chain network along with providing green products or services to customers [4]. GSCM has been established as an essential discipline in the academic world and a separate branch of sustainability [5]. Maditati et al. (2018) presented the most cited definitions of GSCM and sustainable supply chain management (SSCM) [6]. The concept of GSCM evolved in the early 1990s when environmental issues became a burning question around the globe [7]. Several aspects, including waste management, natural resources, and efficient network systems of green supply chain management, have become potential research interests in academia. Over the past few years, the literature review in this area has expanded around green design, green operations, green manufacturing, reverse logistics, and waste management [5–9].

Some of the critical environmental aspects of the green supply chain are noticeable in the green design (engineering and marketing), green procurement practices (environment-friendly raw material, recycled material), and transportation (CO_2 reduction and minimization of fuel consumption). However, implementing the green concept is one of the biggest challenges for enterprises since it often requires additional investment. A supply chain structure becomes more complex when the economic, social, and environmental aspects are incorporated into supply chain performance analysis. Thus, finding the right balance between the economic, social, and environmental issues during decision making is the top priority for many organizations.

To overcome the challenges mentioned, employing multiobjective optimization (MOO) techniques is suitable to formulate and analyze supply chain network design. The MOO problem deals with multiple conflicting objectives simultaneously. Usually, there is no single optimum solution for MOO problems. Instead, a set of non-dominated solutions, known as Pareto optimal solutions, are generated by solving the MOO problems [10]. A trade-off between social, economic, and environmental issues can be analyzed through MOO. Based on the decisionmaker's preference, the optimal solution is chosen from the Pareto solution sets. Thus, the decisionmakers (DM) need expertise in the problem domain.

There are tremendous opportunities to apply MOO approaches in green supply chain applications to analyze economic, social, and environmental aspects. Current research has shown significant applications of MOO techniques in decision-making phases such as green supply chain network design in the agricultural [11], packaging [12], biofuel [13], or biodiesel [14] industries. Jayamartha et al. [15] reviewed MOO for sustainable supply chain and logistics applications from 1999 to 2019. This paper serves as an extension of their review and discusses in more detail how several MOO approaches are formulated and solved. Different types of MOO techniques, such as classical [16–23], evolutionary [16,24–28], and interactive [29,30] methods, have been applied in GSCM application depending on the size and complexity of the problem or the attributions from the decisionmakers. Moreover, some researchers have incorporated uncertain parameters in the decision-making phases. In short, this literature provides an overview of the present studies for the applications of MOO techniques in GSCM.

The structure of this review paper is as follows: Section 2 includes an overview of green supply chain management and structures. Section 3 highlights the mathematical model formulation techniques. Section 4 discusses different MOO problem-solving techniques utilized in the green supply chain. Section 5 summarizes the application of MOO techniques in green supply chain network design. Section 6 includes a discussion and provides potential research direction for the future, and the concluding remarks are given in Section 7.

2. Green Supply Chain Management

Green supply chain management integrates environmental factors into different supply chain activities, including product design, material sourcing and selection, manufacturing procedures, transportation to the end users, and management of the green

product's end of life [31,32]. Green design involves designing products with minimum material or energy consumption [33]. The green design also incorporates the reuse, recovery, or recycling of products or parts [34]. In addition, the green design also considers the negative impacts on the environment in a product's life cycle. Green manufacturing minimizes waste and pollution during production activities [35,36]. Green logistics includes environment-friendly transportation, distribution, and alternative fuel options [37,38]. In short, environmental, social, and economic aspects are considered the objectives in measuring the performance of GSCM [4,39,40], as shown in Figure 1.
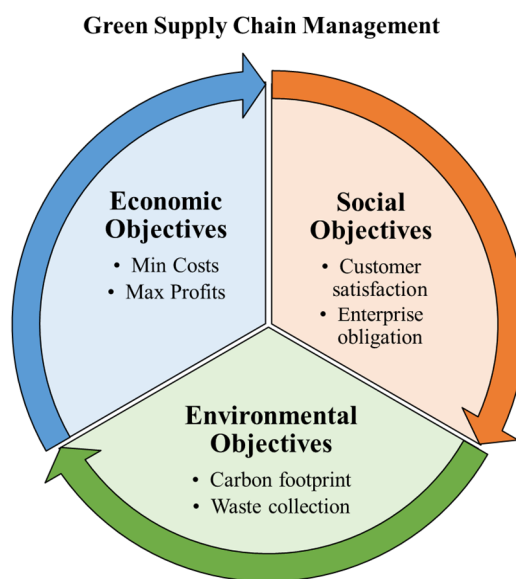

Figure 1. Three objectives of green supply chain management.

Green supply chain management can improve environmental performance, although the relationship depends on organizational capacity [41]. However, the relationship between environmental and economic performance is often conflicting in nature [42,43]. In many cases, enterprises would often like to maximize profits and minimize carbon emissions. However, maximizing profits by increasing supply chain activities often produces higher carbon emissions. It is essential to understand the relationship between social aspects, green dolphin choir management, and operational performance [44]. Enterprises often struggle to understand the direct link between green supply chain management adoption and the subsequent enhanced performance in operational, economic, or environmental areas. Thus, adopting green culture on a broad scale is often challenging to implement efficiently.

Before discussing MOO model development, different structures of the green supply chain are described. The model formulation includes certain model assumptions, notations regarding parameters, and decision variables. The mathematical model formulation is carried out considering several factors, including the conditions of the parameters. Generally, the entire model is formulated based on a deterministic assumption of parameters. However, in many cases, the parameters may be uncertain. The structure of the model formulation differs depending on the nature of the parameters. Finally, solution methods are implied to solve MOO problems to improve green supply chain performance. The solution methods may vary, considering the complexity of the problem and the decisionmakers' preferences. The classical, evolutionary, and interactive methods are three broad categories of solution approaches. The different MOO approaches and their solution techniques applied in GSCM are intensively discussed in this article. The framework presented in this literature review for the applications of MOO in GSCM is shown in Figure 2.
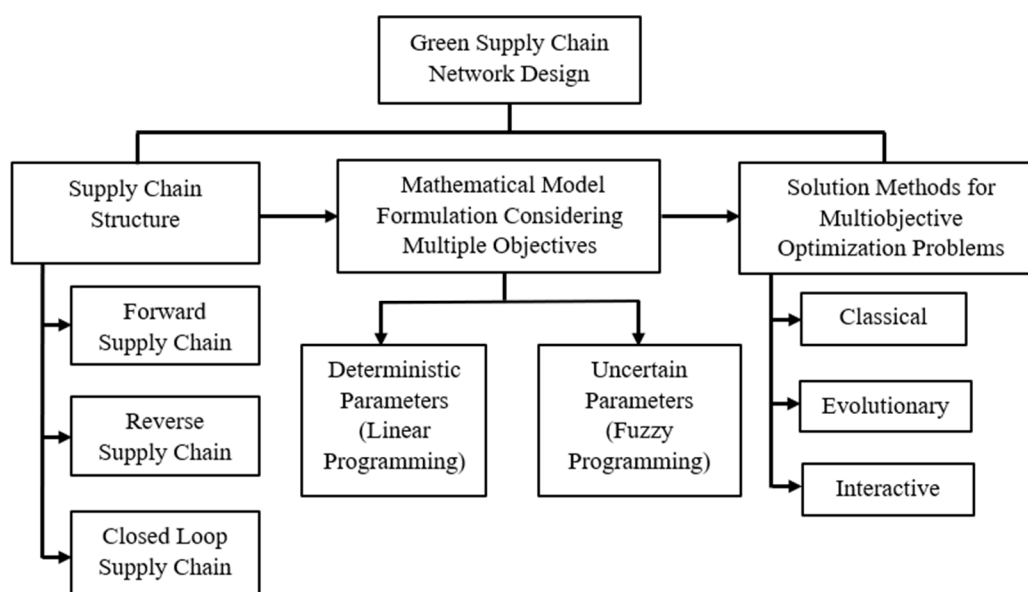
Figure 2. A GSCM framework with MOO approaches.

In order to design a green supply chain network, the first step is to choose a specific supply chain structure. Material and information flow between different domains of a supply chain network is required to be identified for multiobjective model formulation. Various supply chain structures are introduced in this section that are generally considered during the green model formulation. Figure 3 represents the overall structure of the forward, reverse, and closed-loop supply chain in one frame. Three types of supply chain structures are described in the following subsections.

2.1. Forward Supply Chain

The forward supply chain starts with delivering raw materials for manufacturing goods in a factory and ends with delivering goods to the end users. It is rather straight-forward and encompasses all possible entities to satisfy customer requirements, such as suppliers, manufacturers, warehouses, retailers, and customers [45,46]. In a typical forward supply chain structure, customers are the final entity of the process. Over the past few decades, the facility allocation problem in forward logistics has been considered a well-recognized topic by many researchers. A comprehensive summary of the modeling approaches in the forward supply chain over the past 15 years, where sustainability has been incorporated into the value chain, can be found in Refs. [47,48]. Thus, the modeling approaches for the forward supply chains are not elaborated further.
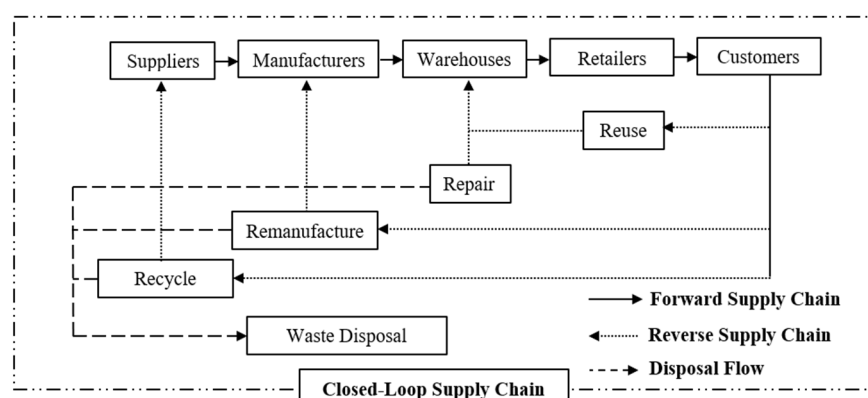

Figure 3. Three supply chain structures in one frame [46,49].

2.2. Reverse Supply Chain

The reverse supply chain deals with the practices and operations necessary to process the reuse of materials [50,51]. The prime objective of reverse logistics is to manage the backward flow in the current supply chain network. The reverse supply chain begins with collecting the used products from the customers and managing end-of-life products through decisions such as recycling, remanufacturing, repairing, and disposal [52]. Based on the American Reverse Logistics Executive Council's definition, reverse logistics is *''The process of planning, implementing, and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods, and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal''* [52,53]. The reverse logistics ensure an efficient reverse flow of the material from the point of consumption to the point of origin [46].

Reverse logistics are used in diverse fields, including the electronics, chemical, and medical industries [54]. While reverse logistics provide an excellent opportunity for remanufacturing the returned products, the entire process of recovering the product is extremely challenging. Collecting the product from the customer to the recovery center is highly expensive for companies. As a result, efficient network design is vital in reverse logistics. The reverse logistics starts with product return from the consumer end. Once the product condition is identified, the product is sent to the return collection centers. Ideally, products are inspected to categorize into fix, resell, repair, and recycle types. In the repair area, either the product is repaired or the sellable parts are sold. Similarly, the product is sent to the recycling area if any components or products are not fixable. The spare parts are collected either for reselling or waste material. Figure 4 highlights the major steps in a general reverse logistics flowchart.

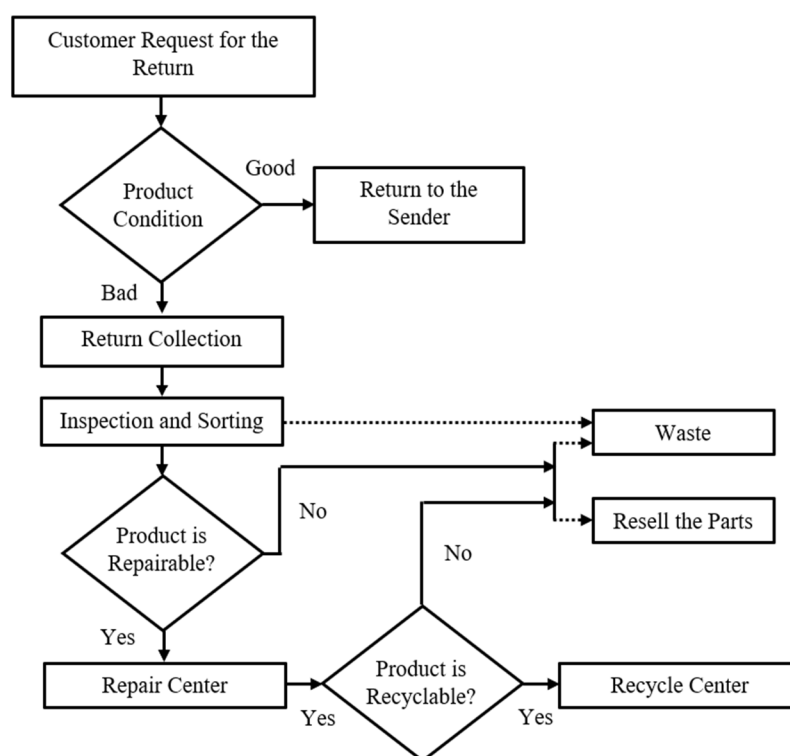**Figure 4.** A flowchart of major steps in reverse logistics.

Several literature sources have addressed various supply chain aspects while discussing the concept of reverse logistics. Linton et al. [55] highlighted the interaction between sustainability and the supply chain by handling product design, product end of life, and the recovery process of end-of-life products. The review paper by Rubio et al. [56]

summarized the literature on reverse logistics published between 1995 and 2005 and covered areas such as recovery, distribution of end-of-life products, production, and inventory management. Additionally, Pokharel and Mutha [57] reviewed major features of reverse logistics such as product acquisition, pricing, and collection of the used product.

2.3. Closed-Loop Supply Chain

Closed-loop supply chain combines both forward and reverse networks. The closed-loop supply chain deals with recovering the final product from the customers and creates added value by reusing the entire product or some parts of the product [58]. According to Kumar et al. [59], a closed-loop supply chain deals with the customer demand in the forward supply chain and manages the product's end of life in reverse logistics. The closed-loop supply chain prioritizes efficient supply chain management aiming at reuse, remanufacture, recycling, and disposal. Figure 3 provides a collective overview of a closed-loop supply chain where forward and reverse supply flow are combined.

Several aspects of the closed-loop supply chain are still under observation. Researchers such as Schenkel et al. [60] showed ways to create values using a closed-loop supply chain. The value creation for the environment includes creating green products, processes, and markets, whereas the economic perspective provides cost and risk minimization. Customer value includes serving the customer better via return practices and services [61]. Finally, information value ensures the overall improvement of the forward and reverse supply chain, life cycle information, and product performance [62,63]. Additionally, researchers have also addressed the industrial challenges and uncertainties related to the remanufacturing system [64]. Therefore, studies are conducted regarding the performance improvement methods of the closed-loop supply chain. Asif et al. [65] highlighted that the performance of the closed-loop supply chain can be improved using a resource-conservative manufacturing approach.

3. Model Formulation Techniques

Once the supply chain structure is defined, the next step is to proceed with the model formulation. The green supply model primarily deals with multiple conflicting objectives with a set of constraints. Assumptions, decision variables, and model parameters are required to be well-defined before the model formulation. Based on the nature of the parameters, the model formulation structure can be different. Some of the literature addressed deterministic parameters during the model formulation, whereas a few studies considered uncertain parameters. In this section, research on model formulation with deterministic and uncertain parameters is highlighted briefly.

3.1. Deterministic Parameters

Model formulation using deterministic parameters means all the necessary data related to the parameters are available in the supply chain system for predicting the future result. The biggest motivation for using deterministic parameters is to reduce the model complexity. The deterministic parameters are often simple, straightforward, and easy to understand. Therefore, most of the literature on green supply chains utilizes deterministic parameters during the model formulation. The parameters can be segregated into economic and environmental parameters. Economic parameters include several types of costs related to production and transportation. Expected economic parameters include fixed costs, processing costs, inventory costs, holding costs, transportation costs, and investment costs for reducing carbon dioxide (CO_2) emissions. On the other hand, environmental parameters include carbon emission quantity during production and transportation activities within the supply network.

Other general deterministic parameters, such as the capacity of the facilities and customer demands, are essential parameters during the model formulation. However, sometimes, model parameters are difficult to determine due to insufficient data availability. In

deterministic assumptions, the parameter uncertainty is ignored for mathematical model formulation. Therefore, the firm is often exposed to a higher risk in the performance evaluation since uncertain parameters are not incorporated correctly in the decision-making phase. The results obtained may be infeasible or inconsistent with other decisions.

3.2. Uncertain Parameters

In order to establish a robust approach, researchers focus on including uncertain parameters during the model formulation of the decision-making phase. As a result, the complexity of mathematical model formulation increases with the involvement of uncertain parameters. Thus, the fuzzy mathematical model is an excellent medium for dealing with uncertain parameters when the decisionmakers do not have the exact value of those parameters [30]. In a fuzzy model, the uncertain parameters are expressed using a form of fuzzy numbers. The mathematical model formulation is carried out considering the multiple objective functions and constraints. Later, the defuzzification method converts the fuzzy mathematical model into a crisp equivalent linear programming model. Finally, multiobjective solution methods are applied to determine the optimum solution. The general steps of the mathematical model formulation for fuzzy-based MOO are highlighted in Figure 5.

Figure 5. Steps for fuzzy-based multiobjective model formulation.

Uncertain parameters are expressed in the form of fuzzy numbers. The fuzzy number F is expressed as an interval $[f_l, f_u]$, where f_l and f_u denote the lower and upper bounds of F, respectively [66]. Triangular fuzzy number F can be defined as $F = [f_a, f_b, f_c]$, where f_a, f_b and f_c are real numbers. Thus, the membership function can be expressed as Equation (1) [67].

$$\mu_f(x) = \begin{cases} \frac{x - f_a}{f_b - f_a} & for\ f_a \leq x \leq f_b \\ \frac{f_c - x}{f_c - f_b} & for\ f_b \leq x \leq f_c \\ 0 & otherwise \end{cases} \tag{1}$$

Similarly, trapezoidal Fuzzy number F can be defined as $F = [f_a, f_b, f_c, f_d]$, where f_a, f_b, f_c, and f_d are real numbers and $f_a \leq f_b \leq f_c \leq f_d$. The membership function is given below in Equation (2) [67].

$$\mu_f(x) = \begin{cases} 0 & for \ x < f_a \\ \frac{x - f_a}{f_b - f_a} & for \ f_a \leq x \leq f_b \\ 1 & for \ f_b \leq x \leq f_c \\ \frac{f_d - x}{f_d - f_c} & for \ f_c \leq x \leq f_d \\ 0 & for \ x > f_d \end{cases} \qquad (2)$$

From the definition of a fuzzy number, it is observed that the triangular fuzzy number has one most likely value f_b if f_a and f_b are considered the lowest and highest value, respectively. Similarly, the trapezoidal fuzzy number has two most likely values f_b and f_c if f_a and f_d are considered the lowest and highest value, respectively. Several past works have implemented fuzzy-based mathematical models for designing green supply chain networks considering uncertain situations. Pishvaee et al. [30], Talaei et al. [18], and Midya et al. [22] considered the trapezoid fuzzy numbers, while Saffar et al. [17] and Yu and Khan [23] utilized triangle fuzzy numbers during the model formulation. A summary of the uncertain parameters related to the fuzzy-based multiobjective model formulation in the green supply chain is highlighted in Table 1.

Table 1. Uncertain parameters related to the fuzzy-based multiobjective model formulation in the green supply chain.

References	Fuzzy Number	Uncertain Parameters
Pishvaee et al., 2012 [30]	Trapezoidal fuzzy number	Demands of the customers, capacities, fixed opening costs, transportation costs, production costs, and carbon dioxide CO_2 emission factors
Saffar et al., 2015 [17]	Data triangular fuzzy number	Fixed cost, production cost, maintenance cost, transportation cost, CO_2 emission rate in different activity levels, return and recovery rates
Talaei et al., 2016 [18]	Trapezoidal fuzzy number	Variable costs and demands
Midya et al., 2021 [22]	Trapezoidal fuzzy number	Fixed and transportation cost, transportation time, carbon emission quantity, capacity, and demand
Yu and Khan, 2022 [23]	Triangular fuzzy number	Costs (transportation, distribution, processing, shortage), space occupied by processing products, carbon emissions during processing products and demand

4. Solution Methods for Multiobjective Optimization Problems

There are many solution methods depending on how the supply chain MOO problem is formulated. Additionally, the advantages and disadvantages of these MOO methods are discussed briefly to help practitioners to decide on the suitable MOO method to be adopted in their scenario. Before diving deeper into the MOO solution method, some basics of MOO problem formulation are detailed briefly.

Let $S \subset R^n$ be a dimensional search space with $f_i(x)$. Where, $f_i(x)$ is the ith objective functions defined by x and $i = 1, \cdots, I$. A general MOO problem with constraints is shown in Equation (3).

$$minimize \ f_i(x) = f_1(x), f_2(x), f_3(x) \dots, f_I(x) \qquad (3)$$

subject to (s.t.),

$$g_j(x) \leq 0, j = 1, \dots, p$$
$$h_k(x) = 0, k = 1, \dots, q$$
$$x_l^L \leq x_l \leq x_l^U, l = 1, \dots, n$$

where $x_l = x_1, x_2, \cdots, x_n$ is a vector with n decision variables. $g_j(x)$ *and* $h_k(x)$ indicates the jth inequality and k^{th} equality constraints, respectively. p and q are the numbers of inequality and equality constraints. x_l^L and x_l^U are the lower and upper bounds of x_l. The goal is to find out the optimum solution vector x^* that satisfies the constraints and minimizes objective functions. It is often impossible to find an optimum solution that simultaneously minimizes or maximizes all the objective functions due to the inherent conflicting properties of the objective functions. Thus, finding out the Pareto optimal solution is essential. Pareto optimal solution indicates a solution set where none of the objective functions can be improved further without degrading at least one of the other objective functions.

Several solution methods are available to solve MOO problems. Generally, the solution methods can be classified into three categories: classical, evolutionary, and interactive [15]. In the classical method, decisionmakers play a vital role as final solutions are evaluated based on the decisionmaker's preferences. Evolutionary methods are population-based metaheuristic algorithms using fitness scores to find optimal solutions. On the other hand, in the interactive method, decisionmakers utilize preference information interactively in each iteration. The Pareto optimal solutions generated in each iteration are observed and improved in the next iteration by changing the preference information. Three categories of MOO problem-solving methods are discussed in this section.

4.1. Classical Methods

Classical methods can be both a priori and a posteriori. In the a priori method, the decisionmaker provides the preference information for different objectives to generate Pareto optimal solutions. On the other hand, in the a posteriori method, Pareto optimal solutions are generated first, and a decisionmaker then selects the most desired solution considering other requirements. In this section, some popular classical MOO techniques are described briefly.

4.1.1. Weighted Sum Method

The weighted sum method is considered one of the most common approaches and is widely adopted for solving MOO problems due to its simplicity. The method can be expressed as Equation (4) [68,69].

$$minimize \sum_{i=1}^{I} w_i f_i(x) \tag{4}$$

$$s.t., g_j(x) \leq 0, j = 1, \ldots, p$$
$$h_k(x) = 0, k = 1, \ldots, q$$
$$x_l^L \leq x_l \leq x_l^U, l = 1, \ldots, n$$

where $w_i \geq 0$ and $\sum_{i=1}^{t} w_i = 1$. w_i denotes the weight of the ith objective function. In this method, multiple objectives are converted into a single objective by using weights. The weighted sum method is simple and easy to implement. The decisionmakers can utilize different weights for each objective function, which would then convert the MOO problem into a single objective problem. Pareto optimal solutions are generated accordingly, following the new weighted objective function. Although the method is widely popular because of its simplicity, it is not always adequate for solving non-convex problems [70]. Apart from that, sometimes, the decisionmaker faces difficulties in choosing the right weight for the objective functions, which is one of the vital concerns in the weighted sum method.

4.1.2. ε-constraint method

In the ε-constraint method, one of the objective functions is optimized, while the rest of the objective functions are converted to constraints [71,72]. A general representation of MOO formulation for the ε-constraint method is given in Equation (5).

$$minimize\ f_m(x) \tag{5}$$

$$s.t., f_i(x) \le \varepsilon_i, i = 1, \dots, I\ and\ i \ne m$$
$$g_j(x) \le 0, j = 1, \dots, p$$
$$h_k(x) = 0, k = 1, \dots, q$$
$$x_l^L \le x_l \le x_l^U, l = 1, \dots, n$$

where ε_i indicates the upper bound of ith objective function. In Equation (5), only $f_m(x)$ objective is optimized, and the remaining $(I - 1)$ objectives are used as constraints. Like the weighted sum method, the ε-constraint method does not require providing any weights to the objective functions reducing the unnecessary operations with different combinations of weights [73]. It is considered a suitable approach for solving both convex and non-convex optimization problems [70].

4.1.3. Weighted Metrics Method

The weighted metrics method considers combining multiple objectives by introducing a reference point or the ideal point z*. This reference point is assumed to be an ideal solution for the decisionmaker. The optimization solution is then found based on minimizing the distance between the reference point and the feasible solution region. Different solutions can be generated by weighing the metrics. Duckstein [74] and Zeleny [75] introduced the weighted metrics method as compromised programming. The mathematical formulation for the weighted metrics method can be expressed as Equation (6).

$$minimize\ L_s(x) = \left(\sum_{i=1}^{I} w_i |f_i(x) - z_i^*)|^s \right)^{\frac{1}{s}} \tag{6}$$

$$s.t.,\ g_j(x) \le 0, j = 1, \dots, p$$
$$h_k(x) = 0, k = 1, \dots, q$$
$$x_l^L \le x_l \le x_l^U, l = 1, \dots, n$$

where w_i denotes the non-negative weight of the ith objective function. In Equation (6), $1 \le s \le \infty$. Here, z_i^* is called the reference point. When $s = 1$, the problem becomes equivalent to the weighted sum method detailed in Section 4.1.1. The problem becomes the weighted Tchebycheff problem when $s = \infty$, which can be expressed as Equation (7)

$$minimize\ L_\infty(x) = \max_{i=1,\dots,I} w_i |f_i(x) - z_i^*)| \tag{7}$$

$$s.t.,\ g_j(x) \le 0, j = 1, \dots, p$$
$$h_k(x) = 0, k = 1, \dots, q$$
$$x_l^L \le x_l \le x_l^U, l = 1, \dots, n$$

For weighted Tchebycheff metrics, each Pareto optimal solution can be found. However, the weighted metrics method suggests using a normalized objective function. Implementing this requires information on each objective function's minimum and maximum values, which is sometimes difficult to identify. Moreover, the reference point z_i^* has to be calculated before finding out the L_s metrics. As such, each of the objective functions needs to be optimized. This method can find all the Pareto optimal solutions when the s value is small. However, as the s value increases, the problem becomes non-differentiable.

4.2. Evolutionary Methods

Evolutionary methods are biology-inspired techniques that often comprise reproduction, mutation, crossover, and selection [10]. During natural selection, the fittest individual from the population is selected. The offspring from the population possesses the characteristics of the parents. Later, the offspring will be added to the future generation. The offspring will have a better chance to survive if they inherit better qualities from the parents. The process keeps continuing until the fittest individual is found. This section highlights some popular evolutionary algorithms used to solve MOO problems.

4.2.1. Genetic Algorithm (GA)

The genetic algorithm (GA) was first introduced by Holland and his colleagues in the 1960s [10]. The GA is inspired by evolutionary theory, where the fittest species receive the opportunity to pass genes down to the future generation. The genetic algorithm includes five major phases. The initialization starts with generating a set of random populations. The fitness function indicates the ability of one individual to survive over others. Survival of the best individual depends on the fitness score. An individual with the highest score is selected for the subsequent evaluation. In the selection phase, the fittest individual is selected and thus passes genes down to future generations. During the mutation period, the crossover point is chosen randomly within genes. The offspring from the crossover is also added to the population for evaluation. In the mutation phase, some of the genes of the new offspring can often be deformed to bring diversity to the population. Figure 6a highlights the general steps that the GA follows [76,77]. Over the years, variations and advancements have been made to the general GA approach for solving MOO problems, such as Pareto-based GA, decomposition-based GA, parallel GA, chaotic GA, and hybrid GA. More detail on each of these GA variations can be found in Ref. [78].

4.2.2. Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II is one of the most popular MOO approaches by Deb et al. [79], and it is an upgraded version of NSGA developed by Srinivas et al. [80]. Figure 6b provides an overview of the phases of NSGA-II [81,82]. Similar to the GA, this process also starts with generating a random population. Once the initialization is carried out, each individual's fitness value is identified based on non-dominated sorting and crowding distance. Thus, parents are selected from the population based on rank and crowding distance. After that, offspring is generated from the parent using crossover and mutation. Finally, the selection process is completed based on the rank after combining parents and offspring populations. The prime difference between the GA and NSGA-II is selecting the parents. Non-dominated sorting and crowding distance are two additions to the NSGA-II compared to the GA.
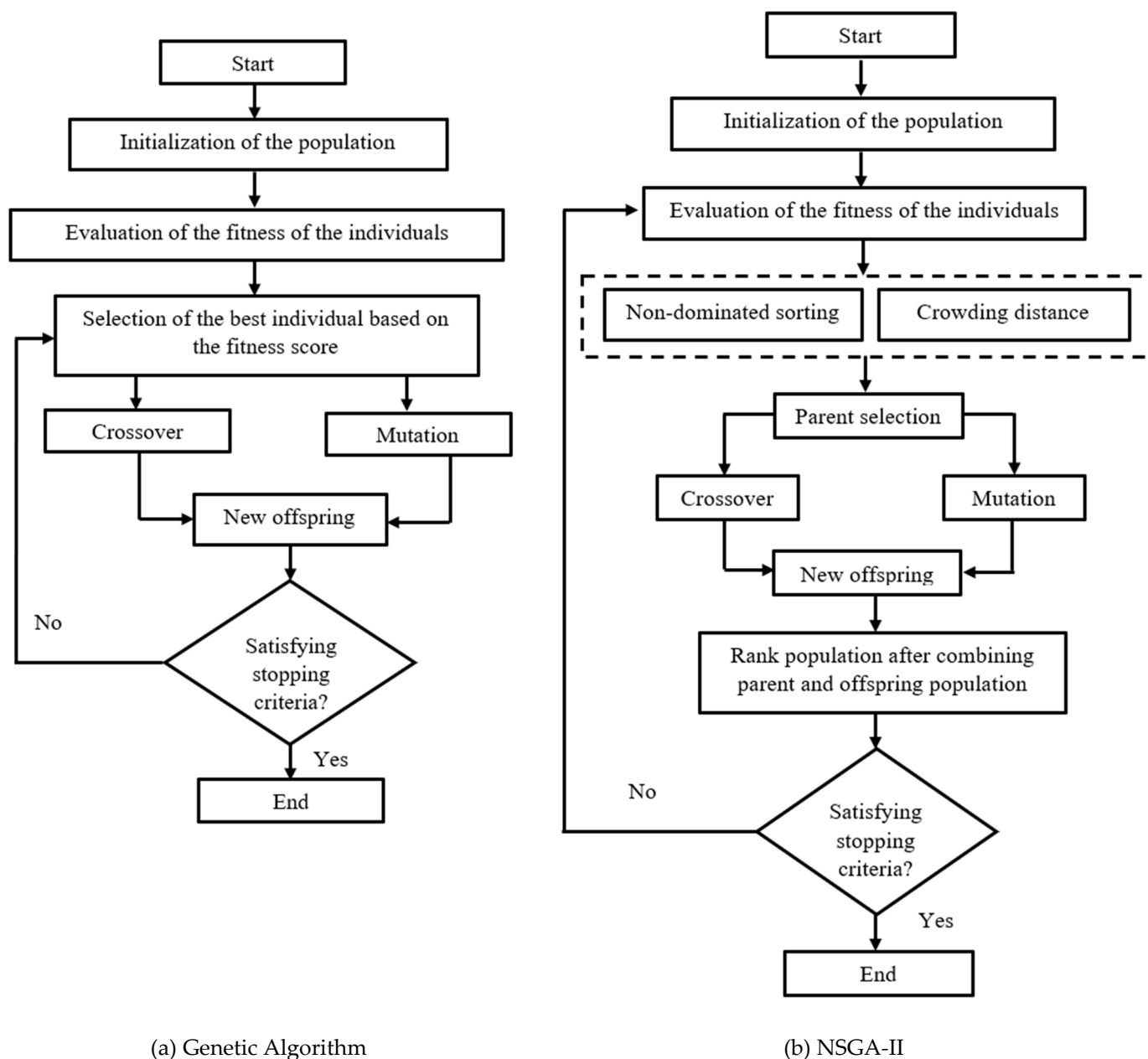
(a) Genetic Algorithm   (b) NSGA-II

Figure 6. Flowchart of GA and NSGA-II. (**a**) Genetic Algorithm; (**b**) NSGA-II.

4.2.3. Multiobjective Particle Swarm Optimization (MOPSO)

Particle swarm optimization (PSO) is inspired by stimulating social behavior from the movement of living entities in a bird flock or fish school. MOPSO has the potential to offer higher convergence speeds to solve multiobjective problems [83,84]. It was initially introduced by Kennedy and Eberhart [85], and several researchers later improved it. Coello et al. [86] applied particle swarm optimization in solving multiple objective problems. The study compared MOPSO with other multiobjective evolutionary algorithms. Tripathi et al. [87] introduced a new approach to MOPSO, called time variant multiobjective particle swarm optimization (TV-MOPSO), by allowing specific parameters such as inertia weight and acceleration coefficients to change with iteration. A competitive and cooperative co-evolutionary approach is adapted with MOPSO by Goh et al. [88] to solve complex optimization problems. This method can improve the efficiency and effectiveness of MOPSO. Meza et al. [89] introduced a multiobjective vortex particle swarm

optimization (MOVPSO), which is dependent on a swarm's rotational and translational motions.

The general steps of MOPSO are summarized as follows.

Step 1: Initiate the population $p(t)$ with random position and velocity. Here, t is the generation counter.

Step 2: Evaluate the population and assign the fitness of the swarm.

Step 3: *If $t \leq T$*, update the local best of each particle and find the global best of the swarm. Here, T is the maximum allowed generation. Otherwise, terminate the process.

Step 4: *If $i \leq N$*, update the velocity and position of the particle. Here, N is the number of particles in the swarm and i is the ith particle in t generation.

Step 5: Evaluate the position of the particle and assign the fitness. Repeat Steps 4 and 5 unless all the particles' fitness values are checked.

Step 6: Go to Step 3 for the next generation and continue the rest of the steps until the termination condition is satisfied.

4.2.4. Ant Colony Optimization (ACO)

Ant colony optimization (ACO) is one of the most effective metaheuristic algorithms in the field of multiobjective optimization [90]. It is inspired by the shortest path searching behavior of different ant species. In ACO, the shortest path is found by identifying the pheromone trails. The ants deposit these pheromone trails whenever they travel as a form of communication. The general steps followed by ACO are pictured in Figure 7(a). Several researchers have applied ACO to solve MOO problems in supply chain issues such as scheduling [91–93], vehicle routing [94,95], and portfolio selection [96]. García-Martínez et al. [97] proposed a taxonomy of multiobjective ant colony optimization (MOACO) algorithms. Later, performance analysis is carried out considering the multiobjective traveling salesman problem. McMullen [98] used ACO to deal with production sequencing problems, such as minimizing the setup cost and material use rate. Later, the solution generated from ACO is compared with other heuristics techniques.

4.3. Iterative Methods

Unlike classical and evolutionary methods, in interactive methods, the decisionmaker (DM) provides preference information at every step in the solution process [70]. According to Miettinen et al. [70], the first step of an iterative method is initialization. In this step, the ideal and nadir values are calculated, and the information is shared with the decisionmaker. The components of the ideal and nadir value define the lower and upper bounds of the objective function, respectively. A Pareto optimal starting point is generated in the next step. This Pareto optimal solution is either neutral or selected by the decisionmaker. Before the next iteration, the decisionmaker is asked to share preference information for generating new solutions. Otherwise, preference information is again shared with the decisionmaker, and a set of new solutions are generated at the next step. Figure 7b represents the flowchart of the general iterative method. Some iterative methods for solving MOO problems are discussed in the following subsections.
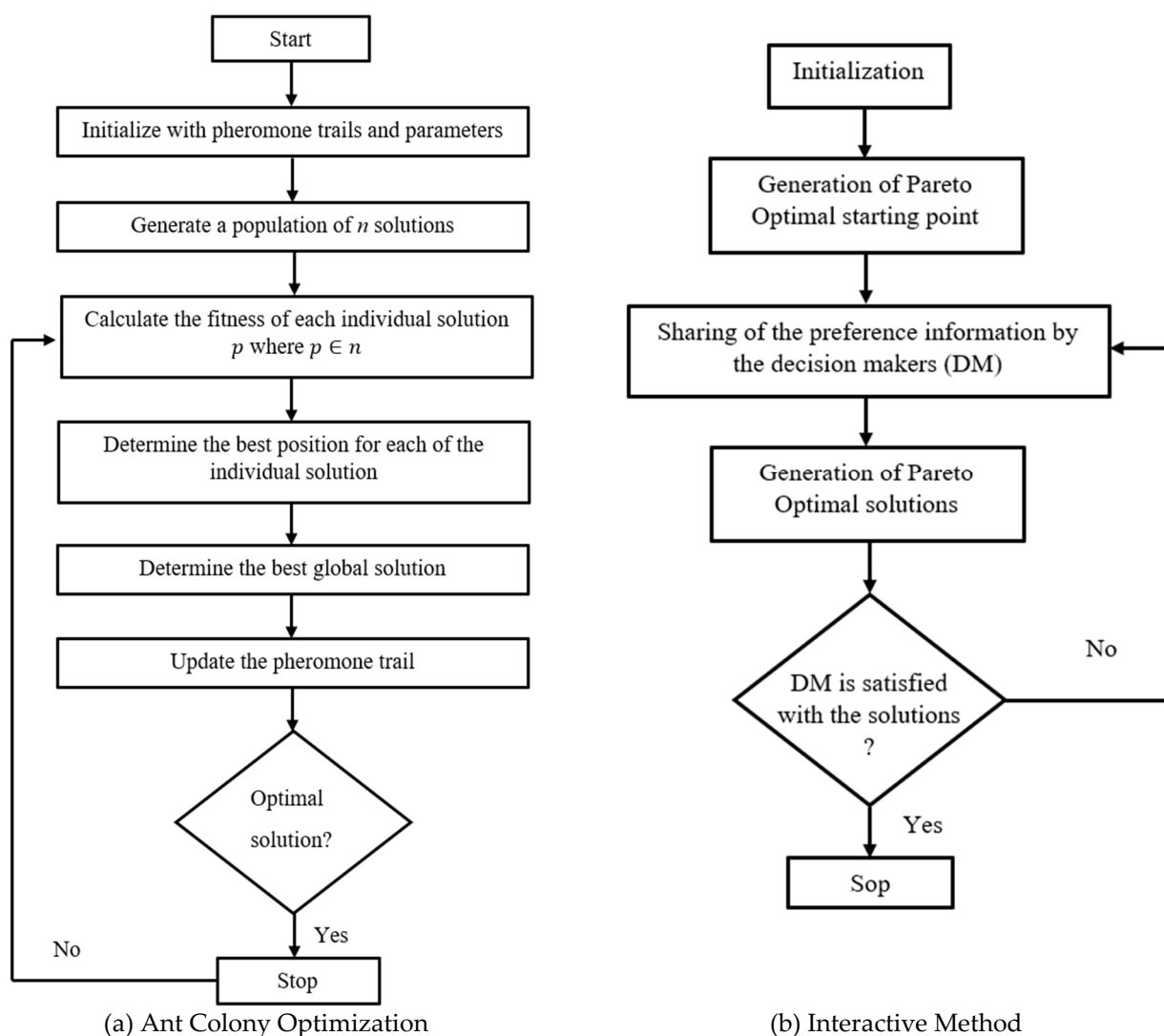
(a) Ant Colony Optimization

(b) Interactive Method

Figure 7. General flowcharts of (**a**) ant colony optimization and (**b**) interactive method.

4.3.1. Method of Geoffrion–Dyer–Feinberg (GDF)

The method was proposed by Geoffrion, Dyer, and Feinberg [99]. The decisionmaker provides the subjective trade-off information that GDF applies to perform a line search to determine the search direction. It utilizes the Frank–Wolfe algorithm [100] to solve the intermediate problem. In GDF, the decisionmaker wishes to maximize the value function (utility function) [101]. GDF is based on certain assumptions [70], such as that the feasible region is compact and convex. The objective functions are continuously differentiable and convex. The value function is implicitly known and assumed to be continuously differentiable, concave, and decreasing. The decisionmaker has to provide a marginal substitution rate that helps to identify the value function's rising direction.

The general steps of GDF are highlighted here [102].

Step 1: Initiate by providing a feasible starting point z^q. Set iteration *i=1*. The decisionmaker (DM) needs to select the reference function f_q where q is the qth objective function in *p* number of the objective function and $q \neq p$.

Step 2: DM must provide a marginal rate of substitution between the reference objective and the other objective at the current solution point z^i.

Step 3: Find the optimum solution. Set the search direction d_i. If $d_i = 0$, stop.

Step 4: DM must provide the appropriate step size in the direction d_i. Thus, identify the current solution z^{i+1}.

Step 5: Set *i=i+1*. Unless DM wants to continue, stop. Otherwise, go to Step 2.

4.3.2. Reference Point Method

The reference point method was proposed by Wierzbicki [103,104]. This iterative MOO technique is based on the scalarization achievement function. Here, the decisionmaker provides a reference point representing each objective function's aspiration level. Now, using the achievement scalarization function, the solutions that can better satisfy the aspiration level are obtained. The iteration stops if the decisionmaker is satisfied with the current solution. Otherwise, the decisionmaker is obliged to share a new reference point. The problem can be expressed as Equation (8) [105,106].

$$minimize\ max_{i=1,....,I}[w_i f_i(x) - \bar{z}_i] + p\sum_{i=1}^{I}(f_i(x) - \bar{z}_i) \tag{8}$$

$$s.t, x \in S$$

where w is a fixed normalizing factor and $w_i = \frac{1}{z_i^{max} - z_i^{min}}$

For each criterion, z_i^{max} and z_i^{min} are the maximum and minimum values of $f_i(x)$, respectively. $\bar{z}$ is the reference point where $\bar{z}_i = (\bar{z}_1, ..., \bar{z}_I)$. p is an augmented multiplier, and $p > 0$. The reference point is created based on the preference information of the decisionmaker. In the scenario where the decisionmaker is not satisfied with the solution approach, the preference information might be changed and eventually generate a new solution. In short, regardless of the method used to choose the reference point, Pareto optimum solutions are generated.

5. Research Findings of MOO Techniques in Green Supply Chain

The application of MOO techniques in the green supply chain is mainly related to the optimum network design. MOO techniques help to design the optimum network considering economic and environmental aspects. The network design includes the optimum number of facilities for each of the domains, the amount of material flow between the domains, transportation mode, technology type, and carbon emission quantity during different activities. The following subsections summarize some of the past literature that applied various MOO techniques in model formulation for green supply chain applications.

5.1. Classic Techniques

One of the most used MOO techniques for solving green supply chain problems is the ε-constraint method [15]. Van der Plas et al. [16] applied both weighted sum and ε-constraint methods along with two evolutionary algorithms and highlighted a comparison among them for reverse supply chain network design. Saffar et al. [17] and Talaei et al. [18] proposed a fuzzy-based closed-loop supply network considering the economic and environmental objectives. Both research groups used the ε-constraint method for triangular and trapezoidal fuzzy-based model formulation. Franco et al. [13] designed a sustainable supply chain network for biofuels considering economic, environmental, and social objectives simultaneously. This problem was also solved using the ε-constraint method.

Multiple classical methods were applied by Zhao et al. [19]. They highlighted three separate scenarios considering the risk, carbon emission, and economic cost and used different methods for each of the scenarios. In the first scenario, the risk was optimized first, then the carbon emission, and later the economic cost. For this, the minimum value of the risk was considered the constraint of the problem to obtain the minimum value for the carbon emission, which was later substituted by the economic cost. In the second scenario, the risk and carbon emission were optimized first, and the financial cost was minimized using the ε-constraint method. Finally, in the last scenario, the ideal point method simultaneously optimized risk, carbon emission, and cost functions.

Nurjanni et al. [20] constructed a green supply chain network considering economic and environmental objectives using the weighted sum method. The study highlighted scenarios considering optimal structures of the supply chain facilities and narrated each of the cases. A multiproduct, multiperiod, multiobjective closed-loop green supply chain model was formulated by Rad and Nahavandi [21], considering the quantity discount.

They determined the optimum network, transportation mode, technology type, carbon dioxide emissions, and inventory levels. For multiobjective problem solving, L_p-metrics was implemented in this case to obtain the final solution. Midya et al. [22] modeled a multistage, multiobjective fixed-charge solid transportation problem for a green supply chain considering an intuitionistic fuzzy environment. Both weighted Tchebycheff metrics programming and min–max goal programming were utilized for the result, and a comparison was performed between the Pareto optimal solutions.

In a recent publication, a fuzzy-based mathematical model was proposed by Yu and Khan [23]. The model utilized an integrated hierarchical method combined with the ε-constraint and weighted ideal point method. Table 2 summarizes the applications of several classical techniques in multiobjective green supply chain network design from past years. Please note that the references listed in Table 2 are not exhaustive. Table 2 is meant to show that the classic methods are still implemented to date with some deteriorations in the green supply chain network optimization application.

Table 2. Summary of several classical model formulations for multiobjective green supply chain.

References	Optimization Objectives	Solving Techniques	Supply Chain Network
Van der Plas et al., 2012 [16]	Minimization of total cost and total emission	Weighted sum method, ε-constraint method	Reverse supply chain network design
Saffar et al., 2015 [17]	Minimization of cost and CO_2 emission	ε-constraint method	Closed-loop supply chain network design
Talaei et al., 2016 [18]	Minimization of cost and CO_2 emission	ε-constraint method	Closed-loop supply chain network design
Zhao et al., 2017 [19]	Minimization of risk, CO_2 emission, and cost	ε-constraint method and ideal point method	Forward supply chain network design
Nurjanni et al., 2017 [20]	Minimization of cost and CO_2 emission	Weighted sum method	Closed-loop supply chain network design
Rad and Nahavandi, 2018 [21]	Minimization of cost and CO_2 emission	L_p-metrics method	Closed-loop supply chain network design using quantity discount
Midya et al., 2021 [22]	Minimization of the transportation cost, time, and CO_2 emission	Weighted Tchebycheff Min–max goal programming	Forward supply chain network design
Franco et al., 2021 [13]	Maximization of the overall profit, employment generation, and minimizing carbon emission	ε-constraint method	Sustainable supply chain network for biofuel generation from the forest waste
Yu and Khan, 2022 [23]	Minimization of the total cost, variance model of the cost, risk function, and carbon emission	Integrated hierarchical method with ε-constraint method and weighted ideal point method	Forward supply chain network design

5.2. Evolutionary Methods

Various studies have embraced evolutionary algorithms for multiobjective green supply chain model formulation. Table 3 demonstrates several examples of the adoptions of the evolutionary methods in multiobjective green supply chain design. Harris et al. [24] utilized NSGA-II to solve the incapacitated facility location problem. The paper assumed

that the environmental cost of transportation is higher than the CO_2 emission impact of operating the facilities. Another application of NSGA-II is noticeable in multiobjective biodiesel supply chain network design by Geng and Sun [14].

Yeh and Chuang [96] addressed some of the important concerns in green supply chains, such as partner selection. Since several conflicting factors are related during partner selection, MOO approaches are used to design the planning model. The authors considered cost, time, product quality, and green appraisal score in the model formulation for the partner selection. Types of multiobjective genetic algorithms (MOGA) were applied to find out the Pareto optimal solutions. Both algorithms utilized the weighted sum approach for the objective functions during the selection procedure. The key difference in the algorithms is that the latter one used a segment-based crossover and mutation during the solution procedure. The authors evaluated the solutions of the algorithms considering indicators such as the average number of Pareto optimal solutions and CPU (or processing) time and identified that the first algorithm provides the best solution result.

Table 3. Examples of various evolutionary methods in multiobjective green supply chain.

References	Optimization Objectives	Solving Techniques	Supply Chain Network
Harris et al., 2009 [24]	Minimization of cost uncovered demand, and environmental impact from transport and depots	NSGA-II	Incapacitated facility location problem in logistics network design
Yeh and Chuang, 2011 [25]	Minimization of cost and time, maximization of average product quality, green appraisal score	GA	Green supplier selection
Van der Plas et al., 2012 [16]	Minimization of total cost and total emission	NSGA-II	Reverse supply chain network design
Harris et al., 2014 [26]	Minimization of cost and CO_2 emission from transport and depots	SEAMO2	Capacitated facility location-allocation problem
Tang and Zhang, 2015 [27]	Minimization of economic cost and CO_2 emission, maximization of minimal service reliability	Hybrid Evolutionary	Capacitated facility location problem in logistics network design
Soleimani et al., 2017 [28]	Maximization of the chain profit and the customer demand, minimization of the number of missed working days due to occupational accidents	GA	Closed-loop supply chain network design
Geng ang Sun, 2021 [14]	Minimization of total cost, carbon emission, and unused kitchen waste	NSGA-II	Biodiesel supply chain network design

Both classical and evolutionary techniques were implemented by van der Plas et al. [16] for green supply chain network design. Further, a comparison between different optimization techniques was presented in the paper. A capacitated facility location model was presented by Tang and Zhang [27], and a hybrid evolutionary approach was implemented to identify the optimum solutions. The hybrid method was a combination of NSGA-II and the greedy algorithm. The result indicated that the hybrid method could effectively solve facility location problems in the green supply chain.

Similarly, for the multiobjective capacity facility location problem, simple evolutionary multiobjective optimization 2 (SEAMO2) was implemented by Harris et al. [26]. The paper hybridized the evolutionary multiobjective optimization algorithm through Lagrangian relaxation, where two constraints are relaxed to find the best allocation. Soleimani et al. [93] designed a fuzzy-based multiobjective closed-loop supply network using a genetic algorithm. Here, fuzzy logic was implemented to maximize the customer demand and minimize the total missed days in the entire system.

5.3. Iterative Methods

Although not as popular as classical and evolutionary methods, interactive methods have been adopted in multiobjective green supply chain network design. Table 4 highlights the applications of the interactive methods in multiobjective green supply chain network design. Pishvaee et al. [30] proposed a multiobjective credibility-based fuzzy mathematical model to design a green supply chain network under uncertainties. Here, the uncertain parameters were considered independent trapezoid fuzzy numbers, and a hybrid credibility-based chance constraint programming model was proposed. Since the model had bi-objective functions, an interactive method was utilized to find the optimum solution. Similarly, Garg et al. [29] proposed a closed-loop supply chain network minimizing the environmental impact on transportation activities and maximizing profit. An interactive method was utilized here to identify the Pareto optimal solutions.

Table 4. Some adoptions of interactive methods in multiobjective green supply chain model.

References	Optimization Objectives	Solving Techniques	Supply Chain Network
Pishvaee et al., 2012 [30]	Minimize cost and CO_2 emission	Fuzzy interactive solution method	Forward supply chain network design
Garg et al., 2015 [29]	Maximize the total profit and CO_2 emissions by reducing transporting vehicles in the forward supply chain	Interactive multiobjective optimization	Closed-loop supply chain network design

Different researchers have developed and explored various optimization techniques to solve the multiple objective problems in supply chain activities. From the similarity of all the presented methods, it is evident that the application of MOO techniques in green supply chain activities is mainly related to decision making in network design and supplier selections. Further, the concept of adapting green applications adds a new dimension to defining organizations' objectives. The solution techniques offered here will help to find the right balance between an organization's economic and environmental objectives.

6. Potential Research Opportunities and Future Work

The literature review shows that multiple objectives are integrated in developing a complex supply chain network. Due to global concern, environmental issues and economic stability have become top priorities for organizations. The green supply chain facilitates the goal of merging economic and environmental perspectives in the organizational network. However, methods to solve these problems are often complex since they deal with numerous parameters and decision variables. In the previous section, current research work on MOO in the green supply chain was highlighted, and different solution methods were explored. This section addresses the potential research opportunities for multiobjective model formulation in green supply chain network design. Apart from that, this section highlights future work opportunities in the field of the green supply chain.

6.1. Exploring Different Multiobjective Optimization Techniques

The popular approach to solving multiple objective optimization problems is to use the weight coefficient or convert the MOO problem into a single objective optimization problem that can eventually be solved using numerical or heuristic methods. Applying suitable MOO model formulation and solver algorithms is essential to achieve dynamic and simultaneous optimization processes between conflicting objectives and decision-making methods. MOO often results in a solution set instead of one optimal solution. These variations are based on many factors, such as the relative importance of different objective functions during optimization steps, the algorithm implemented, the model formulations, and the parameters considered. Depending on the model context and scenario, variables utilized in the model formulation can significantly vary between different models. For example, models having multiplication of two binary variables result in bringing nonlinear terms in the objective functions [107]. Therefore, these variables often need linearization techniques to simplify the process. Thus, scenarios incorporating different types of variables in the model formulation can be a future research direction in this field.

It should be noted that the complexity of the solution procedure increases with the increase in the number of objective functions considered. Therefore, exploring an appropriate optimization algorithm suitable for the problem is essential. Approaches such as convexification, problem decomposition, constraint handling, and similar methods can be implemented to simplify complex optimization issues [108]. Green supply chain management has utilized a few MOO techniques. Some studies embraced classical methods, while others applied evolutionary and interactive ways. A constructive comparison between different solution techniques is also addressed by some of the literature [16]. Thus, exploring different types of MOO techniques in combination with machine learning and data-driven methods in the green supply chain field can be one of the future research opportunities for many.

6.2. Addressing the Uncertain Parameters

One of the prime research opportunities in the green supply chain is addressing the uncertainties of the parameters and including them in the robust decision-making process. In most cases, supply parameters are complicated to measure. Thus, incorporating uncertainties in model formulation involves identifying the uncertain parameters in the network. It is observed that customer demand [18,22,30] and associated variable costs [17,18,22,30] are difficult to measure in several cases for multiobjective model formulation. Some research work verified that demands [103] and costs [104] uncertainties impact strategic and tactical decision-making processes. Moreover, in many cases, suppliers' capacities [45,105] are uncertain due to the circumstances, including labor shortages, sudden accidents, and pandemic outbreaks. There is also a need for the green supply chain to be resilient against all environmental uncertainties [109]. The quantification of environmental parameters such as carbon emission is another uncertain factor that should be considered [22,30]. Thus, another research direction is identifying the uncertain parameters and incorporating them in a multiobjective model formulation. Further, green supply chain network design can include different uncertainty quantification techniques and robust optimization techniques.

6.3. Understanding the Environmental and Social Aspects

Understanding the environmental objectives associated with a green supply chain is essential. The prime sources of environmental impact are greenhouse gas emissions from energy use, waste generation and disposal on- and off-site, water utilization, and emission of organic compounds during manufacturing [110]. From the literature review, it is clear that reducing carbon emissions is considered the prime environmental objective that also has social impacts on the green supply chain network design. However, environmental

and social aspects' interaction is often hard to quantify and incorporate into MOO formulations.

Most of the literature worked only on one aspect, mainly minimizing carbon emissions during production and transportation activities. In most cases, it includes additional investment costs [93,107] to reduce carbon emissions during production. On the other hand, a few references have addressed optimizing carbon emissions during transportation [111]. Other social aspects, for example, minimizing water and soil pollution during supply chain activities, can also be another research dimension to be incorporated into green supply chain operation management. One performance measure can be optimizing the supply chain consumption and waste discharge during various production stages [112]. More emphasis should be given to these environmental and social implications while minimizing the economic cost. Thus, understanding the ultimate purpose of the green supply chain is for environmental and social benefits, while exploring different objectives with minimum economic impact can be a potential research area.

7. Conclusions and Implications

Environmental issues are often complex and challenging to comprehend to achieve sustainability within limited economic resources. That is why significant research is needed in this field to overcome the obstacles of dealing with multiple aspects, primarily environmental and social factors, simultaneously towards the entire supply chain network. The decisionmakers should choose the best course of action depending on the complexity of the green supply chain problem and the availability of resource constraints. Thus, MOO may be a promising approach to optimizing this green supply chain application's social, environmental, and economic aspects. This section presents some of the theoretical and practical implications of MOO approaches in the green supply chain, along with the concluding remarks.

7.1. Theoretical and Practical Implications

Theoretical implications of MOO have resulted in the development of advanced and complex supply chain optimization models and algorithms. These MOO supply chains are able to simultaneously consider economic, environmental, and social objectives during strategic and operational decision making, which is fundamental to the concept of a green and sustainable supply chain. MOO techniques have been applied to various practical applications of green supply chain implementations. Some of these examples that are noticeable are in packaging companies, biodiesel enterprises, biofuel, and other agriculture industries. Resat and Unsal [12] designed a two-stage hybrid optimization technique and applied it to actual data from a packaging manufacturing company to create a sustainable supply chain network. Similarly, a multiobjective biodiesel supply chain model was constructed by Geng and Sun [14] concerning economic, environmental, and social objectives. Franco et al. [13] designed a multiobjective sustainable supply chain model for biofuel generation from forest waste. Seydanlou et al. [11] applied hybrid metaheuristic algorithms to create a closed-loop supply chain network in agriculture, namely in the olive industry. These practical applications of MOO examples are not exhaustive. MOO approaches are becoming well-adopted now more than ever before along with technology advancements. MOO has been applied in diverse industries and agricultural complex network design to promote the concept of sustainability in supply chain management.

7.2. Conclusions

The MOO approach helps decisionmakers to solve multiple and often conflicting objectives. Both conventional and novel metaheuristic MOO techniques are viable approaches to optimizing green supply chain network designs and operations. However, the applications of these techniques can be complicated since they deal with numerous parameters, alternatives, objective functions, and constraints during the model

formulation of a large-scale supply chain application. Possible combinations of mixing multiple methods might help to resolve such complicated problems. In this study, several aspects of modeling green supply chain management have been addressed. Moreover, the importance and advances of MOO in this field are described. The paper also elaborates on the green supply chain structures, model formulation techniques, and solution methods for MOO problems. The detailed approaches, mathematical formulations, flowcharts, and advantages and disadvantages between the presented model formulation and solving techniques are also addressed. Three major solution approaches, namely classical, evolutionary, and iterative, to solving MOO in the green supply chain are detailed with examples from the published literature. Some of the potential future research directions discussed are exploring more advanced MOO-solving techniques, addressing the uncertain parameters in MOO model formulation, and understanding the environmental and social aspects associated with the green supply chain. The current applications regarding MOO techniques in the green supply chain are provided. Finally, future research directions are suggested to aggregate the green supply chain concept with the entire value chain.

Author Contributions: Conceptualization, L.N.A., A.D, and N.Y.; methodology, L.N.A. and A.D.; validation, A.D., N.Y., and L.G.A.; formal analysis, L.N.A.; investigation, L.N.A.; resources, N.Y.; writing—original draft preparation, L.N.A. and A.D.; writing—review and editing, N.Y. and L.G.A.; visualization, L.N.A.; supervision, N.Y.; project administration, N.Y.; funding acquisition, N.Y. All authors have read and agreed to the published version of the manuscript.

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

Abbreviations

ACO	Ant colony optimization
CO_2	Carbon dioxide
DM	Decisionmakers
GA	Genetic algorithm
GDF	Method of Geoffrion–Dyer–Feinberg
GSCM	Green supply chain management
MOACO	Multiobjective ant colony optimization
MOGA	Multiobjective genetic algorithm
MOO	Multiobjective optimization
MOPSO	Multiobjective particle swarm optimization
MOVPSO	Multiobjective vortex particle swarm optimization
NSGA-II	Non-dominated sorting genetic algorithm II
PSO	Particle swarm optimization
SCM	Supply chain management
SEAMO2	Simple evolutionary multiobjective optimization 2
SSCM	Sustainable supply chain management
TV-MOPSO	Time variant multiobjective particle swarm optimization

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