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Stochastic Multi-Objective Sustainable Supply Chain Network Design with Solar Energy and Water Footprint Integration: A Hybrid NSGA-II Approach

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Abstract

This study addresses the sustainable supply chain network design (SSCND) problem by integrating economic and environmental dimensions through a multi-objective, multi-echelon stochastic mathematical model. The proposed model focuses on simultaneously optimizing total cost, carbon emissions, water footprint, and renewable energy utilization. Strategic solar energy investment alongside facility location and sizing decisions are considered under uncertain conditions. Initially, a multi-product stochastic model is developed and solved utilizing the augmented epsilon constraint (AUGMECON2) method to obtain Pareto-optimal solutions for small-scale instances. For validation purposes, the exact solutions obtained using AUGMECON2 were used as the benchmark for the small-scale instance, while the proposed hybrid NSGA-II algorithm generated near-optimal solutions with deviations of 0.30%, 1.53%, 0.03%, and 0.0006% for total cost, carbon emissions, renewable energy use, and water footprint, respectively. Compared with the cost-oriented solution, the renewable energy-focused solution increased total cost by 76.33% while reducing the water footprint by 6.36% and carbon emissions by 3.57%. For medium- and large-scale instances, where exact solutions became computationally impractical, the hybrid NSGA-II algorithm remained applicable and generated feasible Pareto solutions within 59.05 s and 309.62 s, respectively. Overall, the presented framework provides a scalable decision-support tool for sustainable supply chain planning under uncertainty.

Keywords: sustainable supply chain network design; hybrid NSGA-II; meta-heuristic algorithms; stochastic programming; mathematical modeling; optimization; SDG 7

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1. Introduction

In today's world, supply chain management is undergoing a paradigm shift, transitioning from a traditional cost-focused framework to a sustainable approach that simultaneously integrates economic, environmental, and social dimensions. Aligned with this transformation, this study addresses the multi-objective, two-stage sustainable supply chain network design (SSCND) problem. The proposed model is designed to optimize facility location, capacity (facility type), and technology selection at the strategic level, as well as production quantities and distribution processes at the operational level.

According to recent studies, using renewable energy sources (especially solar energy) in production can significantly reduce energy-related carbon emissions, and these invest-

ments can be economically competitive in the long term [1,2]. The integration of clean energy sources aligns with the United Nations Sustainable Development Goal 7 (Affordable and Clean Energy), which targets increasing the share of renewable energy use as a key determinant of environmental sustainability [3]. Therefore, it has become a necessity to expand supply chain design models to incorporate energy mix decisions, such as on-site renewable energy or fossil fuels, in addition to transportation and production decisions [1,4].

In the literature, environmental performance is generally addressed through the minimization of carbon emissions. However, energy-use metrics, such as the "renewable energy use rate," which are influenced by green building and facility certification systems, including LEED and GRESB, have gained growing attention in recent years [5,6]. Based on the "on-site generation and self-consumption" approach, the model proposed in this study has a unique structure aiming to maximize independence from grid electricity in manufacturing operations.

Furthermore, energy production and supply chain operations cause not only carbon emissions but also significant water consumption. While earlier models in the literature, such as the one by Wang et al. (2011), primarily focused on the trade-off between costs and carbon emissions, our study aims to provide a more comprehensive environmental performance evaluation by integrating the water–energy–carbon nexus [7]. The approach referred to in the literature as the "water–energy–carbon nexus" perspective argues that environmental sustainability should be managed from an integrated perspective that includes the water footprint in addition to emissions and the energy mix [8]. By incorporating water consumption along with cost and carbon emission levels into energy source selection (grid electricity or on-site renewable energy), the model's real-world relevance and environmental inclusivity are increased.

The integration of sustainability and clean energy goals through stochastic parameters and multiple objective functions has accelerated the development of advanced solution methodologies. Especially in complex problems with conflicting objectives, comparing the performance of exact solution methods with meta-heuristic algorithms is a common research area. For instance, Talaei et al. (2016) constructed a structure that integrated demand and cost uncertainties and designed a closed-loop supply chain network that included carbon emission reduction policies [9]. Due to the complexity of their model, they presented NSGA-II (non-dominated sorting genetic algorithm II) and MOPSO (multi-objective particle swarm optimization) methods to solve large-scale problems and compared the results with exact solutions obtained via GAMS 50.2.0 software. Pishvaee et al. (2012) proposed a multi-objective fuzzy programming model to design an integrated forward-and-reverse supply chain network design under uncertainty, where they employed a life cycle assessment (LCA)-based method, specifically Eco-indicator 99, to quantify environmental impacts [10]. In their research, they developed a hybrid interactive fuzzy solution approach based on the ε-constraint method with possibilistic programming to address the inherent uncertainty in the decision environment.

Govindan et al. (2014) developed a multi-objective mixed-integer linear programming (MILP) model for the two-echelon location-routing problem with time windows (2E-LRPTW) that incorporated carbon emissions into the objective function [11]. The aim of the study was to formulate a sustainable perishable food supply chain network design model that minimized logistics costs and the environmental impact of carbon emissions. To solve the model, they introduced a hybrid meta-heuristic solution method named MHPV, which combined the multi-objective particle swarm optimization (MOPSO) and adapted multi-objective variable neighborhood search (AMOVNS) algorithms, demonstrating better

results than traditional genetic algorithms such as NSGA-II (non-dominated sorting genetic algorithm II) and NRGA (non-dominated ranking genetic algorithm).

Similarly, Zhalechian et al. (2016) proposed a sustainable closed-loop supply chain model that simultaneously addressed economic, environmental, and social sustainability dimensions [12]. In the study, they developed NSGA-II- and SA (simulated annealing)-based algorithms to solve large-scale instances and validated the performance of their developed algorithm on small-scale examples using GAMS software. In a similar context, Setiawan et al. (2021) developed a fuzzy multi-objective closed-loop supply chain network model for medical mask distribution that maximized profit and social responsibility while simultaneously minimizing environmental impact [13]. The inherent trade-offs between sustainability dimensions were highlighted by evaluating the results with sensitivity analysis for demand. Vahdani et al. (2012) proposed a bi-objective model aiming to minimize total cost and optimize the expected transportation time by considering the risk of plant failures [14]. The Pareto solutions of their problem were found by using the epsilon constraint method for small-scale problems, and for large-size problems they developed the NSGA-II and NRGA meta-heuristic algorithms. The diversity of Pareto solutions obtained and metrics measuring the success of convergence were compared.

Recent contributions to the field have further refined these approaches. Wang et al. (2021) presented a multi-objective sustainable supply chain network design model that explicitly considered the carbon footprint and highlighted the trade-offs between environmental and economic objectives [15]. More recently, Pakdel et al. (2024) introduced a multi-objective green closed-loop supply chain model incorporating a product bundling strategy for perishable goods [16]. The study presented a mathematical model aimed at minimizing the total cost, emissions, and operational risks caused by equipment failure and labor shortages. Their model was developed under uncertain demand turnover rates and validated using meta-heuristic algorithms such as NSGA-II and MOPSO for both small-scale and large-scale problems. These studies underline the increasing importance of advanced mathematical modeling and optimization techniques in handling the challenges in sustainable supply chains.

In parallel with these developments in SSCND, the broader multi-objective optimization literature has increasingly explored hybrid evolutionary algorithms that combine swarm-based and genetic search mechanisms to improve convergence, diversity, and Pareto front approximation quality. For instance, Akopov (2024) introduced the MORCGA-MOPSO-II algorithm, which integrated a real-coded genetic algorithm with MOPSO and clustering-based selection to enhance bi-objective Pareto front generation [17]. Likewise, Leung et al. (2015) presented a MOPSO variant enhanced with a crossover operator and a leader selection mechanism to accelerate the expansion of the solution space [18]. These studies reflect the growing methodological interest in hybrid evolutionary search strategies for complex multi-objective problems. Motivated by this methodological trend, this study employs a problem-specific hybrid NSGA-II algorithm tailored to the proposed stochastic SSCND model.

The literature indicates that sustainable supply chain network design is generally addressed through exact methods for small-scale problems or meta-heuristic algorithms for large-scale instances [19,20]. However, approaches based only on exact solution methods are limited by computational load in circumstances where complexity levels are high due to the combination of various factors, such as uncertainty, multiple objective structures, and renewable energy integration; thus, the need for hybrid approaches increases.

The structural modeling and methodological characteristics of the examined studies are comparatively illustrated in Table 1.

Table 1. Structural and methodological characteristics of representative SSCND studies.

Reference	Network Type	Objective Function	Uncertainty Modeling	Sustainability Pillars	Solution Approach
Melo et al. (2009) [19]	SCND (Rev.)	-	-	-	Review
Wang et al. (2011) [7]	Green SCND	C-E	Deterministic	Eco., Env.	MILP
Vahdani et al. (2012) [14]	Forward SC	C-R	Plant Failure Risk	Eco.	ε-Constraint, NSGA-II, NRGA
Govindan et al. (2014) [11]	SSCND	C-E	Deterministic	Eco., Env.	MILP, MHPV (MOPSO + AMOVNS)
Talaei et al. (2016) [9]	CL-SSCND	C-E	Demand, Cost	Eco., Env.	MILP + NSGA-II, MOPSO
Pishvaee et al. (2012) [10]	CL-SSCND	C-E	Fuzzy/Possibilistic	Eco., Env.	Fuzzy Programming + ε-Constraint
Zhalechian et al. (2016) [12]	CL-SSCND	C-E-S	Deterministic	Eco., Env., Soc.	MILP + NSGA-II, SA
Govindan et al. (2017) [20]	SSCND (Rev.)	-	-	Eco., Env.	Review
Wang et al. (2021) [15]	SSCND	C-E-T-TW	Deterministic	Eco., Env.	MIP
Setiawan et al. (2021) [13]	CL-SSCND	P-E-S	Fuzzy	Eco., Env., Soc.	Fuzzy MOO
Pakdel et al. (2024) [16]	Green CL-SSCND	C-E-R	Demand	Eco., Env.	NSGA-II, MOPSO
This Study	Two-Stage SSCND	C-E-WF-RE	Demand, Solar efficiency	Eco., Env.	AUGMECON2, Hybrid NSGA-II

C: Cost, E: Emission, S: Social, R: Risk, WF: Water Footprint, RE: Renewable Energy Use, P: Profit, Eco.: Economic, Env.: Environmental, Soc.: Social, CL: Closed-Loop, T: Delivery Time, TW: Time window, MOO: Multi-objective optimization.

Despite extensive research on sustainable network optimization, a significant gap remains in the integrated modeling of the water–energy–carbon nexus within a stochastic environment. The majority of recent studies address environmental impact primarily from a transportation perspective, frequently overlooking the complex interdependencies between production processes and resource-specific energy sources.

To bridge the gap in the existing literature, this study introduces an integrated stochastic framework for sustainable supply chain network design (SSCND). Specifically, the study examines how demand and solar efficiency uncertainties influence strategic supply chain network design decisions; what quantitative trade-offs emerge among total cost, carbon emissions, renewable energy use, and water footprint; and whether the proposed hybrid NSGA-II algorithm can generate scalable, high-quality solutions across different problem scales. The novelty of this study lies in adopting a water–energy–carbon (WEC) nexus perspective by incorporating rooftop PV investment and water footprint considerations into the SSCND problem under concurrent uncertainties in demand and solar efficiency, and in developing a problem-specific hybrid NSGA-II algorithm.

The main objectives and contributions are as follows:

1. A stochastic, scenario-based integrated multi-objective sustainable supply chain network design (SSCND) model is proposed, considering not only demand uncertainty but also fluctuations in solar energy efficiency, which are rarely addressed together in the existing literature.

2. Rooftop photovoltaic (PV) investment is explicitly integrated with facility location and capacity planning decisions, placing energy transition considerations at the center of supply chain network design.
3. By incorporating the water footprint associated with production and energy processes into a multi-objective optimization framework, sustainability assessment is extended beyond traditional SSCND models, which mainly include carbon emissions.
4. The exact Pareto front is obtained using exact solvers (GAMS/CPLEX) for small-scale problems, providing a benchmark for solution quality.
5. A meta-heuristic approach based on the NSGA-II algorithm is developed and validated through comprehensive comparisons with exact Pareto-optimal solutions and established performance metrics from the literature.
6. The proposed hybrid NSGA-II algorithm is further modified and extended to efficiently generate high-quality solutions for medium- and large-scale complex NP-hard problems within a reasonable computational time.

This study goes beyond existing sustainable supply chain models by integrating energy investment, water consumption, and operational logistics decisions within a stochastic framework. To solve this complex structure, a hybrid solution framework that integrates exact solution methods with meta-heuristic algorithms is presented. The proposed methodological approach is validated using exact solutions for small-scale problems and subsequently extended to address medium- and large-scale problems through a hybrid NSGA-II algorithm. Consequently, the results are expected to provide a unique contribution to the sustainable supply chain network design literature, both methodologically and practically, by advancing theoretical modeling and offering a viable roadmap for industrial practitioners toward sustainable transformation.

2. Materials and Methods

This study proposes a multi-objective supply chain network design model that includes uncertain parameters and is aligned with the SDGs, especially SDG 7 (Affordable and Clean Energy). The problem is formulated using a two-stage stochastic programming approach to address uncertainties in demand and renewable energy production.

The first-stage decisions (here-and-now) involve strategic facility location choices and investment decisions in on-site photovoltaic (PV) solar capacity, which are made before the uncertainty is realized. The second-stage decisions (wait-and-see) focus on optimizing production quantities, logistic flows, and the allocation of energy sources (grid electricity versus renewable energy) based on actual scenarios (low/medium/high demand and solar efficiency).

Considering the real-life uncertainties in supply chains, a scenario-based stochastic programming approach is adopted in the model. The fundamental factors containing the uncertainty in the study are defined as follows:

- Demand uncertainty: Demand for each product from distribution centers and retailers is modeled under three different scenarios: low, normal, and high.
- Renewable energy production uncertainty: Renewable energy production is represented by a scenario-based solar efficiency parameter.
- Energy usage and operational load uncertainty: The energy consumption per unit produced is defined within a specified range to capture operational volatility.

The scenarios are weighted with predetermined probability values, and the objective functions are defined using an expected value minimization/maximization approach. Investment decisions (facility location and facility type selection and solar energy capacity) are formulated as scenario-independent first-stage decisions, whereas produc-

tion, transportation, and energy usage decisions are determined as scenario-dependent second-stage decisions.

The model simultaneously addresses four conflicting objectives: (1) minimizing the total expected cost, (2) minimizing the total emissions, (3) maximizing the renewable energy use, and (4) minimizing the total water footprint. To obtain the trade-off solutions from this multi-objective structure and to construct the Pareto-optimal set, the enhanced augmented epsilon constraint method (AUGMECON2), a well-established and effective method in the literature, is used [21]. Unlike traditional weighted sum methods, this approach can generate efficient solutions even in non-convex solution spaces and offers the decision-maker a comprehensive set of alternatives. Additionally, to address the computational challenges of larger problems, a hybrid NSGA-II-based meta-heuristic algorithm is employed to ensure scalability.

2.1. Problem Definition

This study addresses the sustainable supply chain network design problem with a two-stage stochastic programming approach. The model encompasses a supply chain network containing 5 candidate facilities ($i = 1, \ldots, 5$), 4 retailers ($r = 1, \ldots, 4$), 3 distributors ($j = 1, \ldots, 3$), and 3 products ($p = 1, \ldots, 3$). This configuration constitutes the small-scale benchmark problem used in this study for numerical illustration and comparative analysis, serving as a common test problem for both exact and meta-heuristic solution approaches.

The primary aim is to develop an integrated decision support model that simultaneously considers economic, environmental, and energy-related sustainability goals. In the model, uncertainty is represented through three different scenarios (s) defined based on demand level and solar energy efficiency. These scenarios, defined as low, normal, and high, are weighted with probability values of $\pi_s = \{0.25, 0.50, 0.25\}$, respectively. Therefore, the model can examine the effects of various demand and renewable energy production conditions on supply chain performance. To ensure the practical feasibility of the supply chain network, the associated decision structure is evaluated under constraints related to facility configuration, solar capacity, energy balance, production and transportation capacities, flow balance, and demand satisfaction. The network structure of the small-scale benchmark problem is illustrated in Figure 1.

The first stage of the two-stage stochastic structure includes strategic investment decisions made before the realization of uncertainty. These decisions include the selection of the facility location to be opened, facility capacity level, and the solar panel investment ratios. In the second stage, operational production and distribution decisions are determined based on the first-stage decisions for each scenario.

The effectiveness criteria prioritized in this study align with the strategic sustainability focus of network design. Accordingly, total cost, carbon emissions, renewable energy utilization, and water footprint are considered the primary evaluation dimensions since they directly reflect the economic and environmental trade-offs associated with facility configuration, production, transportation, and energy-sourcing decisions. While operational metrics, such as delivery speed, reliability, and service accuracy, are also important in supply chain management, they fall outside the strategic scope of the model. This delimitation helps the model maintain its concentration on long-term resource efficiency and overall system configurations.

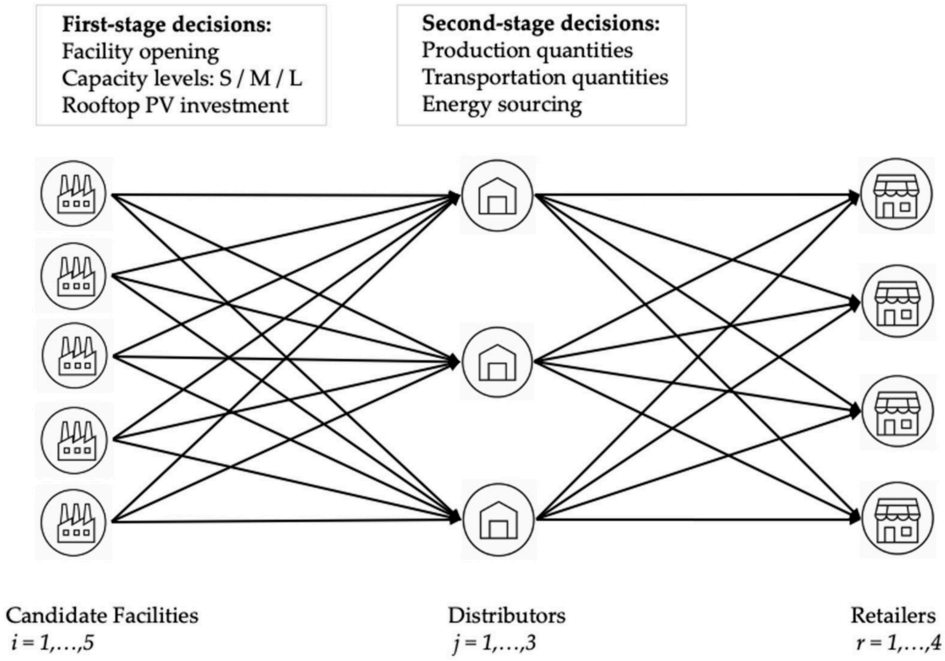


Figure 1. Illustrative network structure of the small-scale benchmark problem. Arrows indicate the direction of material flow between echelons; symbols represent candidate facility locations, distributors, and retailers, respectively.

2.2. Mathematical Model

The proposed problem is formulated as a two-stage stochastic multi-objective mixed-integer linear programming model. In the first stage, facility location, facility size selection, and solar panel investment decisions are determined. In the second stage, production, transportation, and energy-sourcing decisions are optimized under scenario-dependent demand levels. The formulation presented below corresponds to the benchmark problem defined in Section 2.1. The indices, parameters, and decision variables used in the model are defined as follows:

2.2.1. Sets

$i \in \mathcal{I}$: Potential facility locations (suppliers)
$j \in \mathcal{J}$: Distribution centers (DC)
$r \in \mathcal{R}$: Retailers
$l \in \mathcal{L}$: Facility type (small, medium, large)
$p \in \mathcal{P}$: Product type
$t \in \mathcal{T}$: Set of available trucks
$s \in \mathcal{S}$: Scenario

2.2.2. Parameters

F_l: Fixed cost of opening a facility of type l
SC : Unit investment cost of photovoltaic (PV) capacity
A_l: Maximum available rooftop area for facility type l
α : Rooftop area required per unit of photovoltaic capacity (m^2/kW)
$\overline{Q_l}$: Maximum production capacity of a facility of type l
$\overline{N}$: Maximum number of facilities that can be opened
π_s : Probability of occurrence of scenario s
D^{DC}_{jps} : Demand of product p at distribution center j under scenario s
D^{R}_{rps} : Demand of product p at retailer r under scenario s

c_{ij} : Unit transportation cost from facility i to distribution center j
c_{jr} : Unit transportation cost from distribution center j to retailer r
dis_{ij} : Distance between facility i and distribution center j
dis_{jr} : Distance between distribution center j and retailer r
c_{ip} : Unit production cost of product p at facility i
P : Unit price of electricity from the grid
γ : Carbon emission factor of grid electricity (kg CO_2e/kWh)
e : Energy requirement per unit of production
η_s : Solar energy efficiency under scenario s
$\overline{C}$: Capacity of a truck
β : Emission factor for transportation
m_p : Material-related emissions associated with producing one unit of product p
W_p : Water footprint coefficient of producing one unit of product p
G : Water footprint coefficient of grid electricity consumption
H : Water footprint coefficient of photovoltaic (PV) electricity generation

2.2.3. Decision Variables

y_{il} : 1 if a facility of type l is opened at location i, 0 otherwise
K_{il} : Installed solar capacity of a type l facility opened at location i
xf_{ilj}^{pts} : Quantity of product p transported from facility l at i to DC j by truck t in scenario s
xd_{jrp}^{ts} : Quantity of product p transported from DC j to retailer r by truck t in scenario s
xp_{ilps} : Amount of product p produced at the type l facility at location i under scenario
EG_{ils} : Electricity drawn from the grid at the type l facility at location i in scenario s (kWh)
EP_{ils} : Electricity generated by panels at the type l facility at location i in scenario s (kWh)

2.2.4. Objective Functions

In the proposed mathematical model, four objectives are denoted as Z_1, Z_2, Z_3, and Z_4, representing total expected cost, total carbon emissions, total expected renewable energy use, and total expected water footprint, respectively. Within this structure, y_{il} and K_{il} denote first-stage decision variables for facility opening and solar panel investment, while xf_{ilj}^{pts}, xd_{jrp}^{ts}, xp_{ilps}, EG_{ils}, and EP_{ils} are scenario-dependent second-stage variables for transportation quantities, production levels, and electricity consumption from the grid and the panels. All four objective functions are linear with respect to the decision variables, while uncertainty is incorporated through probability-weighted second-stage terms.

The first objective, Equation (1), represents the total cost of the supply chain network design problem and consists of two components: strategic investment decision and operational expenditures. In the first stage, facility installation and photovoltaic (PV) panel investment costs (CI) are determined independently of the scenario, based on the facility-opening decision (y_{il}) and solar panel installation capacities (K_{il}), as formulated in Equation (2). In the second stage, the expected costs of transportation, production, and grid electricity purchase are minimized depending on demand and solar efficiency uncertainties. The total transportation cost (CT) is estimated by Equation (3), where the quantities of the products transported from supplier i to distributor j and from distributor j to retailer r are denoted by xf_{ilj}^{pts} and xd_{jrp}^{ts}, respectively. Equation (4) represents the total production cost incurred by the total production amount, xp_{ilps}. Equation (5) estimates the total cost of electricity usage (CGE) arising from grid electricity consumption, EG_{ils}.

$$Min\ Z_1 = CI + CT + CP + CGE \tag{1}$$

$$CI = \sum_{i\in I}\sum_{l\in L} F_l \cdot y_{il} + \sum_{i\in I} SC \cdot K_{il} \tag{2}$$

$$CT = \sum_{s\in S} \pi_s \left[\sum_{i\in I}\sum_{l\in L}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} c_{ij} x f_{ilj}^{pts} + \sum_{j\in J}\sum_{r\in R}\sum_{p\in P}\sum_{t\in T} c_{jr} x d_{jrp}^{ts} \right] \tag{3}$$

$$CP = \sum_{s\in S}\sum_{i\in I}\sum_{l\in L}\sum_{p\in P} \pi_s c_{ip} x p_{ilps} \tag{4}$$

$$CGE = \sum_{s\in S}\sum_{i\in I}\sum_{l\in L} \pi_s \cdot P \cdot EG_{ils} \tag{5}$$

The second objective, Equation (6), aims to minimize the total expected carbon emissions of the supply chain operations across all scenarios. This function captures emissions originating from transportation (*ET*), production activities (*EP*), and indirect grid electricity usage (*EG*). Specifically, using Equations (7)–(9), the emissions are estimated based on the transported quantities (from supplier *i* to distributor *j* and from distributor *j* to retailer *r*), production volumes, and grid electricity consumption, denoted by xf_{ilj}^{pts}, xd_{jrp}^{ts}, xp_{ilps}, and EG_{ils}, respectively.

$$Min\ Z_2 = ET + EP + EG \tag{6}$$

$$ET = \sum_{s\in S} \pi_s \left[\sum_{i\in I}\sum_{l\in L}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} dis_{ij} \cdot \beta \cdot x f_{ilj}^{pts} + \sum_{j\in J}\sum_{r\in R}\sum_{p\in P}\sum_{t\in T} dis_{jr} \cdot \beta \cdot x d_{\mathrm{jrp}}^{\mathrm{ts}} \right] \tag{7}$$

$$EP = \sum_{s\in S}\sum_{i\in I}\sum_{l\in L}\sum_{p\in P} \pi_s m_p x p_{ilps} \tag{8}$$

$$EG = \sum_{s\in S}\sum_{i\in I}\sum_{l\in L} \pi_s \cdot \gamma \cdot EG_{ils} \tag{9}$$

The third objective, Equation (10), focuses on maximizing the utilization of renewable energy use (*RE*) within the network, quantified by the total expected solar energy generated by the PV panels installed at the selected facilities (EP_{ils}), depending on the probability-based solar efficiency. This objective function encourages the model to select facility locations and sizes that provide greater solar efficiency and larger roof areas, thereby improving the supply chain's overall energy sustainability.

$$Max\ Z_3 = RE \tag{10}$$

$$RE = \sum_{s\in S}\sum_{i\in I}\sum_{l\in L} \pi_s \cdot EP_{ils} \tag{11}$$

The fourth objective, Equation (12), is dedicated to minimizing the total water footprint of the network. This objective accounts for both the direct water consumption in production (*WP*) and the indirect water usage related to the energy mix (grid vs. solar), (*WE*). Equation (13) calculates the expected water footprint caused by the amount of product p produced (xp_{ilps}). The water footprint produced by the electricity usage sources from the grid (EG_{ils}) and solar panels (EP_{ils}) are estimated by Equation (14). The model addresses the crucial need for water resource management in modern industrial systems by prioritizing water-efficient decisions.

$$Min\ Z_4 = WP + WE \tag{12}$$

$$WP = \sum_{s\in S} \pi_s \left[\sum_{i\in I}\sum_{l\in L}\sum_{p\in P} W_p \cdot x p_{ilps} \right] \tag{13}$$

$$WE = \sum_{s\in S}\sum_{i\in I}\sum_{l\in L} \pi_s (G \cdot EG_{ils} + H \cdot EP_{ils}) \tag{14}$$

The integrated multi-objective optimization problem, which simultaneously addresses the four conflicting goals is formulated as follows:

$$Min\ Z = \{Z_1, Z_2, -Z_3, Z_4\} \tag{15}$$

Subject to:

$$\sum_{l \in L} y_{il} \leq 1 \quad \forall i \in I \tag{16}$$

$$\sum_{i \in I} \sum_{l \in L} y_{il} \leq \overline{N} \tag{17}$$

$$K_{il} \cdot \alpha \leq A_l \cdot y_{il} \quad \forall i \in I, l \in L \tag{18}$$

$$\sum_{p \in P} (xp_{ilps} \cdot e) = EG_{ils} + EP_{ils} \quad \forall i \in I, l \in L, s \in S \tag{19}$$

$$EP_{ils} \leq K_{il} \cdot \eta_s \quad \forall i \in I, l \in L, s \in S \tag{20}$$

$$xp_{ilps} \leq y_{il} \cdot \overline{Q_l} \quad \forall i \in I, l \in L, p \in P, s \in S \tag{21}$$

$$\sum_{p \in P} xf_{ilj}^{pts} \leq \overline{C} \quad \forall i \in I, j \in J, l \in L, t \in T, s \in S \tag{22}$$

$$\sum_{p \in P} xd_{jrp}^{ts} \leq \overline{C} \quad \forall j \in J, r \in R, t \in T, s \in S \tag{23}$$

$$\sum_{j \in J} \sum_{t \in T} xf_{ilj}^{pts} = xp_{ilps} \quad \forall i \in I, l \in L, p \in P, \mathrm{s} \in S \tag{24}$$

$$\sum_{i \in I} \sum_{l \in L} \sum_{t \in T} xf_{ilj}^{pts} = \sum_{r \in R} \sum_{t \in T} xd_{jrp}^{ts} + D_{jps}^{DC} \quad \forall j \in J, p \in P, s \in S \tag{25}$$

$$\sum_{j \in J} \sum_{t \in T} xd_{jrp}^{ts} = D_{rps}^{R} \quad \forall r \in R, p \in P, s \in S \tag{26}$$

$$xf_{ilj}^{pts}, xd_{jrp}^{ts},\ xp_{ilps}, K_{il}, EG_{ils}, EP_{ils} \geq 0 \quad \forall i \in I, j \in J, l \in L, p \in P, r \in R, s \in S, t \in T \tag{27}$$

$$y_{il} \in \{0, 1\} \quad \forall i \in I, l \in L \tag{28}$$

The constraint system can be grouped into seven main categories: facility opening and type selection, facility number and solar capacity, energy balance and solar generation, production capacity, transportation capacity, flow balance, and demand satisfaction. Equation (16) guarantees that, at most, one type of facility is established at each candidate location, while Equation (17) ensures that the total number of facilities does not exceed the specified limit. Equation (18) restricts the solar energy capacity based on the available roof area of the selected facility type. Equation (19) represents the energy balance that ensures the total energy requirement for production is equal to the sum of solar panels and grid electricity. Here, e denotes the average unit energy requirement per unit of production and is assumed to be product-independent for tractability. Equation (20) limits the actual solar energy production by the installed capacity and the scenario-dependent solar efficiency. Equation (21) states that the production amount cannot exceed the capacity of the selected facility. Equations (22) and (23) impose vehicle capacity limits on transportation between the supplier and distributor and between the distributor and retailer, respectively. Equation (24) ensures the facility-level flow balance, where the total shipments from facility type l at i are equal to the corresponding production quantity in each scenario. Equation (25) maintains the flow balance at the distribution center, ensuring that the total amount of product received from facilities first satisfies the distribution center's local demand, and the remaining quantity is shipped to retailers. Equation (26) guarantees that retailer demands are satisfied in each scenario. Finally, Equations (27) and (28) define the decision variables,

specifying that flow quantities, production quantities, and solar installation capacities are non-negative continuous variables, while facility location decisions are binary values.

2.3. Data and Parameters

The environmental and operational parameters used in the study are based on internationally accepted standards and current sectoral reports. The emission factors and fundamental calculation methodology for greenhouse gas (GHG) emission were obtained from the Intergovernmental Panel on Climate Change (IPCC) 2006 guidelines [22]. Diesel fuel consumption rates in logistics activities were obtained from Dekker et al. (2012) and SHURA (2023) data, while the data on renewable energy were obtained from the REN21 (2024) report [4,23,24]. Current diesel prices used in economic analysis were obtained from the Global Petrol Prices (2025) database [25].

Solar energy efficiency parameters (kWh/kW) were defined based on the predictions in the SHURA (2023) report, considering Turkey's regional solar potential and grid transformation scenarios [4]. The total investment cost of the solar energy system was determined as \$800/kW, which is consistent with the global average installation costs (~691\$/kW) presented in the IRENA (2025) report and the cost range projected (\$600–1000/kW) by SHURA (2020) for commercial rooftop implementations in Turkey [26,27].

In the proposed model, the parameter e is defined as an average unit energy consumption coefficient and is assumed to be independent of product type. This simplification was adopted to maintain model tractability and to represent aggregate production energy usage at the strategic planning level, where facility configuration and energy sourcing decisions are prioritized over product-specific operational detail.

Water footprint parameters, which strengthen the sustainability dimension of the model, were also determined through studies in the literature. In the presented model, the water footprint is associated with both production and energy use. It includes direct water use in production as well as indirect water use arising from the selected energy source, specifically grid electricity and on-site generated solar energy. The corresponding coefficients were calibrated using the relevant literature, including the study by Gerbens-Leenes et al. (2009) [28]. This criterion is particularly relevant in sustainability-oriented supply chain design since energy-related decisions may reduce emissions while still creating significant pressure on water resources. For this reason, water consumption is evaluated together with cost, carbon emissions, and renewable energy use within an integrated framework. The main numerical settings of the benchmark instance used in the small-scale analysis are summarized in Table 2. The same benchmark structure, parameter values, and mathematical formulation were adopted in both the exact and meta-heuristic solution approaches to ensure consistency in the comparative analysis.

To provide a numerical illustration of the model's logic, consider the energy balance (Equation (19)) for a large-capacity facility under the normal scenario. For a production volume of 500 units, the energy demand is calculated as 293 kWh (500 $\times$ 0.586 kWh/unit). If the first-stage decision results in 50 kW of installed solar capacity (K_{il}), the facility generates 250 kWh (50 $\times$ 5.0 solar efficiency). Consequently, the balance in Equation (19) is satisfied by drawing the remaining 43 kWh from the grid (EG_{ils}), which directly influences the operational outcomes of the objective functions. Within the calculation procedure, this calculated grid dependency (43 kWh) is multiplied by the electricity price (P), grid emission factor (γ), and water coefficient (G) to determine its specific contribution to the total cost (Z_1), carbon emission (Z_2), and water footprint (Z_4) objectives, respectively.

The effective implementation of the proposed model requires an initial dataset covering the network configuration, technical and financial specifications, and stochastic variables associated with operational, environmental, and economic dimensions. Key

inputs include facility locations, production capacities, emission factors, demand levels, solar investment costs, and scenario probabilities. In this study, these data were calibrated using current global reports and established literature. However, the model can be readily updated by incorporating firm-specific operational data in practical industrial applications.

Table 2. Main numerical setting of the benchmark instance.

Category	Value
Network structure	5 candidate facilities, 3 distribution centers, 4 retailers, 3 products
Scenarios	3 scenarios (low, normal, high) with probabilities of 0.25, 0.50, and 0.25
Maximum number of open facilities	3
Facility capacities	500, 1000, 2000
Facility opening costs ($)	200,000, 350,000, 600,000
Available rooftop area (m^2)	500, 1200, 3000
Solar panel investment cost ($/kW)	800
Rooftop area requirement (m^2/kW)	6
Grid electricity price ($/kWh)	0.15
Unit energy requirement (kWh/unit)	0.586
Grid emission factor ($kgCO_2$/kWh)	0.44
Grid and solar water coefficients (L/kWh)	2.5 and 0.1
Product water coefficients (L/unit)	23.433, 20.504, 18.011
Material-related emission coefficients	2.024, 1.978, 1.972
Solar efficiency coefficient	3.5, 5.0, 6.5
Truck capacity and available fleet	1000 units, 4 trucks

2.4. Solution Methodology

The overall solution methodology of the study is illustrated in Figure 2. The framework follows a multi-phase structure that begins with input data and stochastic problem definition, proceeds with exact Pareto solution generation for the small-scale benchmark using the AUGMECON2 method implemented in GAMS 50.2.0 with CPLEX 22.1.2.0 as the MIP solver, and continues with the proposed hybrid NSGA-II algorithm coded in Python 3.10 using the pymoo 0.6.1.6 library for the analysis of larger-scale instances. It also incorporates model verification, RPD-based validation, and comparative performance assessment against standard evolutionary algorithms.

2.4.1. Augmented Epsilon Constraint Method (AUGMECON2)

An improved version of the augmented ε-constraint method, AUGMECON2, was employed to obtain the exact Pareto-optimal solutions for the small-scale instance of the proposed stochastic SSCND model. In this study, total cost was selected as the primary objective, whereas total emissions, renewable energy use, and total water footprint were formulated as ε-constrained secondary objectives. The method combines an augmented objective term with a bypass mechanism, thereby improving the efficiency of Pareto front generation by avoiding redundant and infeasible grid evaluations [21].

Let z_i denote the primary objective and z_k ($k = 2, \ldots, m$) denote the remaining objectives. The augmented ε-constraint formulation is given as follows:

$$max\ a_{obj} = d_1 z_1 + \rho \sum_{k=2}^{m} \frac{s_k}{z_k^{max} - z_k^{min}} \tag{29}$$

subject to:

$$z_k - d_k s_k = \varepsilon_k, \quad k = 2, \ldots, m \tag{30}$$

$$s_k \geq 0, \quad k = k, \ldots, m \tag{31}$$

Here, d_k denotes the direction parameter of objective k, taking the values of +1 for maximization and -1 for minimization, s_k is the nonnegative slack variable, ε_k is the right-hand-side value of the corresponding ε constraint, and ρ is a small positive value. In the present model, the objective directions were defined according to the original problem structure: total cost, total emissions, and total water footprint were minimized, whereas renewable energy use was maximized.

The payoff table was first constructed to determine the lower and upper bounds of each objective. Based on these bounds, the ε-ranges of the secondary objectives were divided into 10 equal intervals, yielding 11 grid points ($g_0 \ldots, g_{10}$). The augmented coefficient was set to $\rho = 10^{-3}$. During the iterative search, the bypass mechanism was used to skip redundant grid regions, which reduced the computational effort while preserving the exact efficient solutions. The resulting solution set obtained from GAMS/CPLEX was then used as the exact benchmark for validation of the proposed hybrid NSGA-II algorithm.

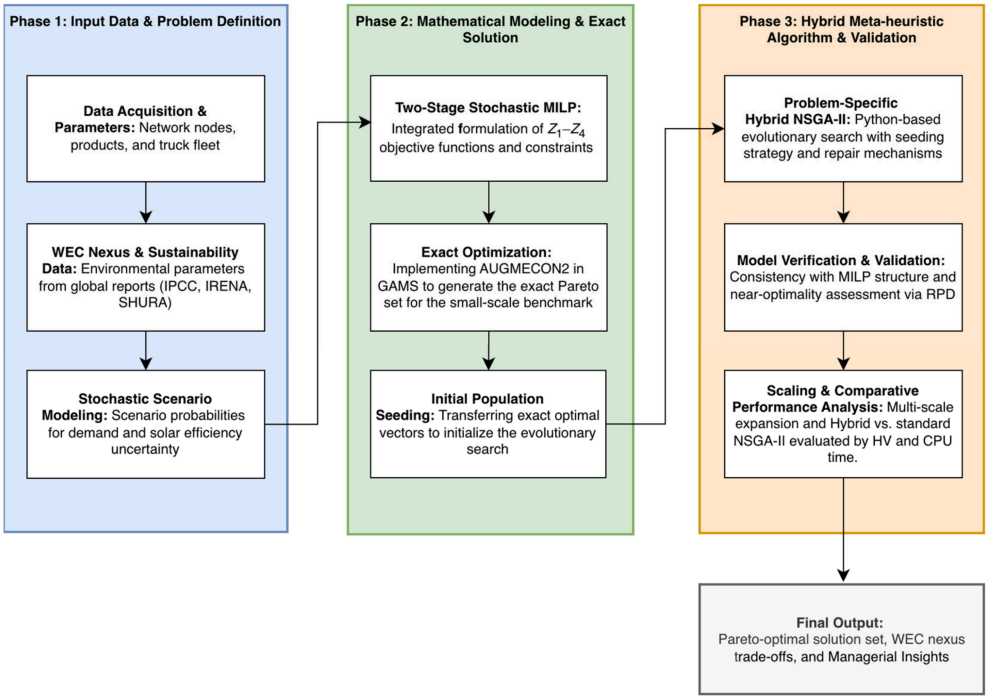


Figure 2. Overall methodological framework of the study.

2.4.2. Hybrid NSGA-II Algorithm

The non-dominated sorting genetic algorithm II (NSGA-II) is a population-based meta-heuristic evolutionary algorithm used for problems that aim to simultaneously optimize multiple objectives [29]. The primary goal of this methodology is not to generate a single "best" solution but rather to obtain a Pareto-optimal set of solutions that represent various trade-offs between objectives.

In two-stage stochastic programming, decisions are separated into two groups: those made prior to and following the occurrence of uncertainty. In the NSGA-II algorithm, which maintains this structure, each chromosome represents the first-stage decisions, while the second-stage decisions are determined based on the scenario and reflected in the objective functions.

The multi-objective stochastic supply chain network design problem addressed in this work is classified as NP-Hard because of the multi-objective nature (cost minimization, emission minimization, and renewable energy use maximization) and the strict constraints

(maximum number of facilities, demand fulfillment, and product flow constraints) it contains. Due to the inadequacy of classical optimization methods for large-scale problems, a hybrid approach based on NSGA-II was developed to efficiently search the solution space and generate Pareto-optimal solutions. The hybrid NSGA-II algorithm's chromosome structure, genetic operators, and constraint management strategy are detailed below.

Chromosome Structure and Encoding Strategy: Given the complex nature of the solution space, a mixed-integer and real-value encoding strategy is employed. Each individual chromosome consists of 10 genes, each representing the solution vector:

- Location and capacity genes (X1–5): Discrete integers {0, 1, 2, 3} representing facilities that are close or have a specific capacity (small, medium, large).
- Renewable energy investment (X6–10): Continuous values [0.0, 1.0] for solar panel utilization ratios.

Hybrid Initialization: The study employs the NSGA-II algorithm, enhanced with a population seeding strategy to accelerate convergence. Specifically, optimal solution vectors for cost, emissions, and renewable energy use (calculated via GAMS/CPLEX) are integrated into the initial population. By incorporating these global optimal solutions as initial input (seeding), the algorithm starts from high-quality regions of the search space rather than random points, thereby facilitating faster convergence and more reliable Pareto solutions.

Constraints and Repair Procedure: Adopting the approach proposed by Gen and Syarif (2005), a repair mechanism is applied to map solutions back to the feasible region instead of eliminating infeasible individuals [30].

The main parameter settings of the developed hybrid NSGA-II algorithm are summarized in Table 3 for the small-, medium-, and large-scale instances. Population size represents the number of candidate solutions maintained in each generation, whereas the maximum number of generations defines the stopping limit of the evolutionary search. These settings were adjusted according to the problem size to balance diversification and computational effort.

Table 3. Parameter settings of the developed hybrid NSGA-II algorithm.

Parameter	Small-Scale	Medium-Scale	Large-Scale
Population size	200	250	400
Max. generation	300	400	500
Crossover operator	SBX (η_c = 15, p = 0.9)	SBX (η_c = 15, p = 0.9)	SBX (η_c = 15, p = 0.9)
Mutation operator	PM (η_m = 20, p = 0.25)	PM (η_m = 20, p = 0.1)	PM (η_m = 20, p = 0.1)
Termination criterion	N_{gen} reached	N_{gen} reached	N_{gen} reached

In this configuration, simulated binary crossover (SBX) and polynomial mutation (PM) are employed as the primary stochastic search operators for offspring generation. These operators utilize distribution indices (η_c and η_m) of 15 and 20, respectively, to control the spread of new solutions. The crossover probability (p) is maintained at 0.9, while the mutation probability is strategically reduced from 0.25 to 0.1 as the problem scale increases to balance diversification and convergence stability across different problem sizes.

The algorithm proposed to solve the multi-objective stochastic supply chain network design problem was coded in Python 3.10 programming language using the open source pymoo 0.6.1.6 (multi-objective optimization in Python) library, which is developed for evolutionary algorithms. The pseudocode of the developed hybrid NSGA-II algorithm is presented in Algorithm 1.

Algorithm 1. Pseudocode of hybrid NSGA-II

1. Define input data, model parameters, and scenario sets.
2. Define chromosome structure for facility type and solar panel investment decisions.
3. Generate the initial population using random and seeded solutions.
Repeat
4. Decode each chromosome and apply the repair procedure.
5. Initialize expected objective values.
For each scenario
6. Perform demand allocation and shipment assignments.
7. Compute production volume, energy requirement, solar energy use, and grid electricity purchase.
8. Update scenario-based cost, emission, renewable energy use, and water footprint values.
End for
9. Compute expected objective values over all scenarios.
10. Check feasibility for unsatisfied demand and limit for facility-opening
11. Apply non-dominated sorting and crowding distance ranking
12. Generate offspring through selection, crossover, and mutation.
13. Update the population.
Until the stopping criterion is satisfied.
14. Extract feasible Pareto-optimal solutions and report results.

2.4.3. Model Verification and Validation

The relationship between the model formulation, constraint system, calculation procedure, and solution process is explicitly outlined as follows. The mathematical model defines the decision variables, objective functions, and overall system structure, while the constraint set restricts the feasible solution space. Within this framework, the calculation process is carried out by assigning numerical values to the parameters and evaluating the constraints step by step under the defined scenarios. As illustrated by the energy balance example in Section 2.3, this process demonstrates the interdependency between production quantities, solar energy generation, and grid electricity use under the same parameter settings. The optimization model is then solved through the exact and meta-heuristic approaches, thereby ensuring that the reported results are derived from the same model formulation and constraint enforcement.

Model verification was conducted to ensure the structural and logical consistency between the exact MILP formulation and the proposed meta-heuristic implementation. The process focused primarily on the alignment of common model inputs, scenario probabilities, and the structure of the objective functions. Additionally, key constraints related to facility-opening decisions, capacity conditions, demand satisfaction, solar energy generation limits, and energy balance were examined within the evaluation procedure. Although the proposed hybrid NSGA-II algorithm is based on a decoding-and-repair mechanism with heuristic scenario evaluation, the verification indicated that the implemented search logic remains consistent with the mathematical structure and feasibility boundaries of the problem.

For validation and quantitative assessment of solution quality, the relative percentage deviation (RPD) metric, which is frequently used in the literature to evaluate the outcomes of meta-heuristic algorithms against optimal or best solutions, was employed to quantitatively compare the two solution approaches [31,32]. The mathematical representation of this performance evaluation metric is provided in Equation (32). Specifically, RPD was used as the main numerical indicator to measure the gap between the exact solutions obtained

by solving the developed mathematical model with the AUGMECON2 method and the near-optimal results generated by the proposed hybrid NSGA-II algorithm.

$$RPD = \frac{|Sol_{AUGMECON2} - Sol_{NSGAII}|}{Sol_{AUGMECON2}} \times 100 \quad (32)$$

The proposed hybrid NSGA-II model demonstrated high computational consistency with the exact mathematical framework, yielding objective function deviations of 0.30%, 1.53%, 0.03%, and 0.0006% for total cost, carbon emissions, renewable energy use, and water footprint, respectively. These results fell within the 1–3% threshold established in the literature for meta-heuristic validation [33]. Consequently, the proposed algorithm can be considered both verified in terms of implementation consistency and validated for small-scale benchmark instances, confirming its reliability for large-scale problems.

2.4.4. Model Scaling and Parametric Extension

To verify the applicability of the developed mathematical model and the performance of the algorithm under more realistic conditions, the NSGA-II algorithm was scaled to medium-size and large-size models. The problem space was broadened in terms of both parametric quantities and topological structure as follows:

- Scaling and dynamic dataset: The network was systematically expanded from a small-scale problem of 5 candidate facilities, 3 distributors, and 4 retailers to a mid-scale of 20–12–16 nodes, and finally to a large-scale of 40–24–32 nodes. To maintain a constant node density at expanded scales, a dynamic geographic structure was used in a coordinate plane expanding from 150 km (mid-scale) to 212 km (large-scale). Euclidean distance calculations for these expanded coordinate sets were executed using the scipy (Scientific Python) library to ensure computational efficiency and high-speed vectorization for larger data sets.
- Capacity and demand parameters: Total demand and capacities were proportionally calibrated. The number of trucks was increased from 4 to 16 (medium-scale) and 32 (large-scale) and the facility capacities were conserved as 500, 1000, and 2000, aligned with economies of scale.
- Configuration: The hybrid NSGA-II algorithm's search parameters were modified due to the increasing difficulty of exploring the solution space effectively in larger-scale instances. By increasing the population size from 200 to 250 (mid-scale) and to 400 (large-scale) and the number of iterations from 300 to 400 (mid-scale) and to 500 (large-scale), the algorithm's ability to search the solution space and refine best solutions was strengthened.

Table 4 summarizes how the problem dimension was expanded across small-, medium-, and large-scale instances. The scaling process involved enlarging the network size, maximum number of facilities to be opened, and available truck fleet size while preserving the same modeling structure and objective functions. Therefore, the proposed hybrid NSGA-II was evaluated under increasingly complex decision environments.

Table 4. Scaling parameters and algorithm configurations.

Parameter	Small-Scale	Medium-Scale	Large-Scale
Network nodes (S–D–R) [1]	5-3-4	20-12-16	40-24-32
Max. facilities to open (N)	3	12	15
Truck fleet size	4	16	32
Capacity levels	500, 1000, 2000	500, 1000, 2000	500, 1000, 2000

[1] S: Supplier, D: Distributor, R: Retailer.

2.4.5. Comparative Performance of Hybrid NSGA-II and Standard NSGA-II

To further assess the effectiveness of the developed hybrid NSGA-II algorithm, its performance was compared with that of standard NSGA-II over five independent runs by using the hypervolume (HV) indicator and CPU time. Originally introduced by Zitzler and Thiele [34], the HV metric measures the size of the objective-space region dominated by the non-dominated solution set with respect to a predefined reference point. A larger HV value indicates a better Pareto set approximation, as this metric jointly reflects both convergence toward favorable objective values and diversity of the solution set. In the present study, HV was computed after transforming the renewable energy use objective into minimization form and normalizing all runs using common ideal and nadir points within each problem size. To maintain a computationally manageable benchmark for these repeated runs, the population and generation settings were specifically adjusted for each scale, as detailed in Table 5.

Table 5. Comparative performance of hybrid and standard NSGA-II across different problem scales.

Scale	Algorithm	Pop.	Gen.	Mean HV	Std. HV	Mean CPU (s)	Std. CPU (s)
Small	Hybrid	120	200	1.101622	0.012846	4.180169	0.035158
Small	Standard	120	200	1.104637	0.007915	4.016922	0.023479
Medium	Hybrid	150	250	1.045971	0.001502	22.813830	0.360585
Medium	Standard	150	250	1.037991	0.004238	19.382000	0.179976
Large	Hybrid	200	250	0.924412	0.018480	77.526741	0.183444
Large	Standard	200	250	0.849447	0.052277	57.810952	0.931895

Pop.: Population, Gen.: Generation, HV: Hypervolume, CPU: Mean Central Processing Unit (seconds), Mean/Std.: Mean/Standard Deviation.

The comparison results indicate that the effectiveness of the hybrid NSGA-II algorithm is scale-dependent. For the small-scale instance, standard NSGA-II produced a slightly higher mean HV (1.104637) than hybrid NSGA-II (1.101622), with an advantage of approximately 0.27%. By contrast, hybrid NSGA-II outperformed the standard baseline for the medium- and large-scale instances, yielding mean HV values of 1.045971 and 0.924412, respectively, compared with 1.037991 and 0.849447 for standard NSGA-II. These results correspond to HV improvements of 0.77% for the medium-scale and 8.83% for the large-scale instance.

In terms of computational effort, hybrid NSGA-II required approximately 4.06%, 26.76%, and 34.10% more time for the small-, medium-, and large-scale problems, respectively. Standard deviation values for both HV and CPU time are also included in Table 5 to reflect the stability of the algorithms across repeated runs. Overall, these findings indicate that the proposed hybrid algorithm does not uniformly improve computational speed but becomes increasingly beneficial as problem size grows when Pareto-front quality is prioritized over runtime.

3. Results

This section conducts a comparative analysis of findings from the proposed sustainable supply chain network design model using different solution approaches. Initially, the exact solutions obtained through the AUGMECON2 method, implemented in GAMS, are presented for the small-scale instance. Then, the results generated by the developed hybrid NSGA-II algorithm are reported for the same small-scale instance and compared with the exact solutions to assess solution quality. The low RPD values obtained from this comparison support the validity of the proposed algorithm, which is subsequently applied to the medium- and large-scale problem instances. This comparison enables a comprehensive assessment of the trade-offs between exact mathematical optimization and

meta-heuristic solution methods, particularly in terms of objective function values, solution quality, and computational applicability.

Additionally, the computational performance of the proposed solution approaches is analyzed across different problem sizes. For the small-scale instance, the exact Pareto solutions were obtained within a reasonable computational time of 55.36 s. By contrast, the hybrid NSGA-II algorithm generated solutions for the same problem in significantly shorter time, requiring 10.26 s. However, the limitations of exact solution methodologies become evident as the problem size increases. For the medium- and large-scale instances, exact solutions could not be obtained due to rapid growth in model size and complexity. Conversely, the proposed hybrid NSGA-II algorithm demonstrated strong scalability and consistent performance, successfully producing solutions within 59.05 s for medium-scale and 309.62 s for large-scale problems. Despite the increased population size to preserve solution diversity for larger instances, the algorithm maintained high computational efficiency, delivering operationally reasonable solution times. The computational efficiency and scalability of both methodologies are summarized in Table 6, which provides a comparative overview of execution times associated with problem scales.

Table 6. Computational performance comparison between exact and meta-heuristic methods.

Problem Scale	Model Nodes (S–D–R) [1]	AUGMECON2 (Exact) Solution Time (s)	Hybrid NSGA-II (Meta-Heuristic) Solution Time (s)
Small	5–3–4	55.36	10.26
Medium	20–12–16	Exact solution not obtained	59.05
Large	40–24–32	Exact solution not obtained	309.62

[1] S: Supplier, D: Distributor, R: Retailer.

To ensure a fair and consistent comparison, both solution approaches are applied to the same benchmark problem instance. The model structure, constraint set (capacity, flow balance, energy balance, and demand satisfaction), and all parameter settings are kept identical across the AUGMECON2 method implemented in GAMS and the hybrid NSGA-II algorithm developed in the Python environment. No modifications are made to the problem definition between the two solution methods. Therefore, the observed differences in results are solely due to the solution techniques rather than any variation in the problem definition or input data.

As presented in Table 6, the computational results indicate that the proposed hybrid NSGA-II algorithm provides a practical and efficient solution methodology for large-scale, NP-hard sustainable supply chain network design problems, where exact methods become computationally impractical. The following sections present the detailed results obtained from the exact solution of the small-scale problem, the hybrid NSGA-II results for the same instance, and its solution behavior across different problem scales.

3.1. Exact Solutions for the Small-Scale Benchmark Problem

To further illustrate the solution process, the optimal configuration obtained by GAMS/CPLEX for the cost-minimizing case is presented. The model selects Facility 2 (small-capacity) and Facility 4 (large-capacity). Under the normal demand scenario, product quantities reach the capacity limit of 500 units per product at Facility 2, while all constraints are fully met, yielding a cost of $1,226,122, carbon emissions of 192,337 kg CO_2, a renewable energy use of 0 kWh, and a water footprint of 123,715 L, consistent with Table 7. The same benchmark instance solved by the hybrid NSGA-II algorithm produces a total cost of $1,229,755—a deviation of 0.30% from the exact solution—confirming the consistency of both approaches under the identical problem structure.

Table 7. Multi-objective optimization problem results (AUGMECON2).

Optimization Goal	Total Cost ($)	Total Emission (kg CO_2)	Renewable Energy Use (kWh)	Total Water Footprint (L)
1. Best cost value	1,226,121.528	192,336.547	0	123,714.527
2. Best emission value	2,546,569.041	178,771.486	3280.076	115,842.346
3. Best renewable energy use value	2,161,977.217	185,472.237	3280.076	115,842.346
4. Best water footprint value	2,161,977.217	185,472.237	3280.076	115,842.346

In the exact solution of the small-scale benchmark problem, a total of 442 candidate solutions are evaluated, yielding 23 distinct Pareto-optimal points. Each of these points represents a unique balance between conflicting objectives, providing a comprehensive map of the solution space. The computational analysis using the GAMS/CPLEX solver reveals a significant trade-off between economic and environmental objectives within the multi-objective supply chain network structure. The cost-oriented scenario minimizes total costs to $1.23M by eliminating solar energy investments and operating only two facilities (small and large) to maximize efficiency.

Conversely, prioritizing sustainability goals leads to a radical reconfiguration of the network. The renewable energy-focused scenario results in a maximum solar energy utilization of 3280.08 kWh through partial solar panel investment in one large size facility and full solar integration in two medium-size facilities, resulting in a 76.33% cost increase ($2.16M). Similarly, the emission-oriented objective yields the lowest carbon footprint (178,771 kg CO_2) by adopting a decentralized network to minimize logistics activities, although it increases total cost by 107.69% ($2.55M) compared to cost-oriented results. All scenarios were solved within 55.36 s. Table 7 shows the objective values of the optimized model, based on the optimization goal.

The quantitative analysis reveals a positive correlation between environmental objectives yet a strong conflict between economic and environmental goals. Notably, the maximum renewable usage and minimum water footprint objectives converge on an identical network configuration, yielding the same objective values with a total cost of $2,161,977 and water footprint of 115,842 L. This result indicates that a strategic focus on renewable energy implementation inherently satisfies the water conservation requirements. This interdependency arises from the substantially higher water intensity of grid electricity (2.5 L/kWh) compared to solar energy generation (0.1 L/kWh). Logistics improvement and energy optimization strategies implemented to reduce carbon emissions indirectly contribute to conservation of water resources. The solution space of the problem is visualized in Figure 3.

The outlier point observed in Figure 3 is mainly associated with the discrete nature of the first-stage decisions. Since the facility-opening, facility size, and solar panel investment decisions are modeled as mixed-integer variables, certain alternative network configurations generate stepwise changes in cost and environmental performance. As a result, an isolated Pareto solution may emerge instead of a smooth frontier.

Although these results provide a reliable benchmark for small-scale problems within an acceptable computational time, the observed trade-offs and structural complexity imply that meta-heuristic approaches will be necessary to maintain computational effectiveness as the network size increases.

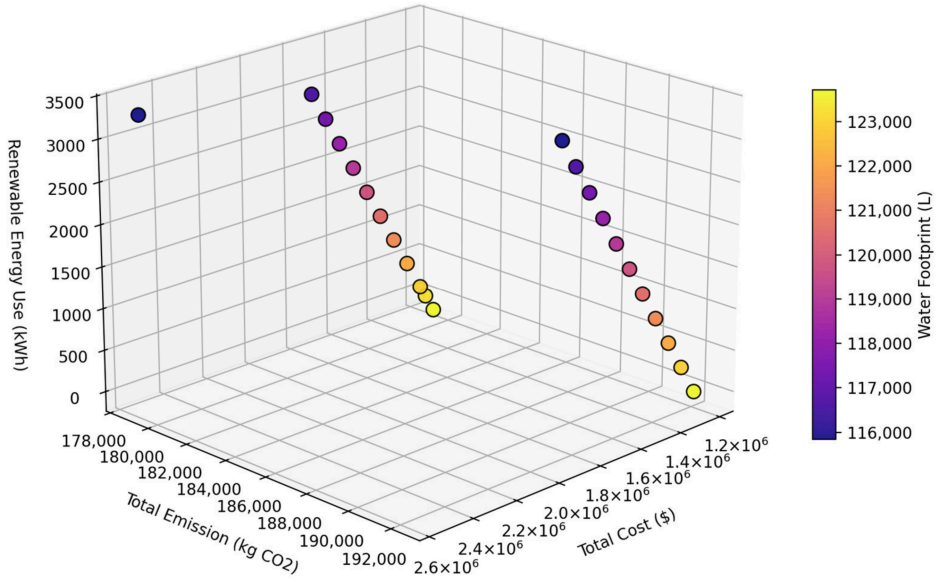


Figure 3. Exact Pareto solution space for small-scale SSCND problem.

3.2. Hybrid NSGA-II Results for the Small-Scale Problem

The small-scale problem was also solved using the proposed hybrid NSGA-II algorithm in order to compare its results with the exact Pareto-optimal solutions under the same benchmark setting. The corresponding objective values obtained for this instance are presented in Table 8. A comparative analysis shows that prioritizing the best cost value minimizes the total cost ($1,229,755) but maximizes the environmental impact due to grid reliance and the absence of renewable energy integration (0 kWh). Conversely, the best emission and best water footprint objectives converge at a higher cost level ($2,553,982), while the renewable energy use solution is obtained at a slightly lower cost ($2,553,501). These solutions yield the same total emission (181,503 kg CO_2), renewable energy use (3281 kWh), and water footprint (115,843 L), indicating that greater renewable energy integration requires higher capital investment to support a more sustainable resource-consumption strategy.

Table 8. Multi-objective optimization problem results (hybrid NSGA-II).

Optimization Goal	Total Cost ($)	Total Emission (kg CO_2)	Renewable Energy Use (kWh)	Total Water Footprint (L)
1. Best cost value	1,229,755	193,916	0	123,717
2. Best emission value	2,553,982	181,503	3281	115,843
3. Best renewable energy use value	2,553,501	181,503	3281	115,843
4. Best water footprint value	2,553,982	181,503	3281	115,843

The geometric structure of the Pareto solution space obtained at small-scale using the hybrid NSGA-II algorithm and the distribution of the solution space is presented in Figure 4. The Pareto curve clearly visualizes the cost–sustainability trade-off, where achieving the lowest emission values maximizes investment costs. Furthermore, the striped structure observed in the solution space reflects the discrete nature of the problem, indicating that each cluster corresponds to a distinct facility decision.

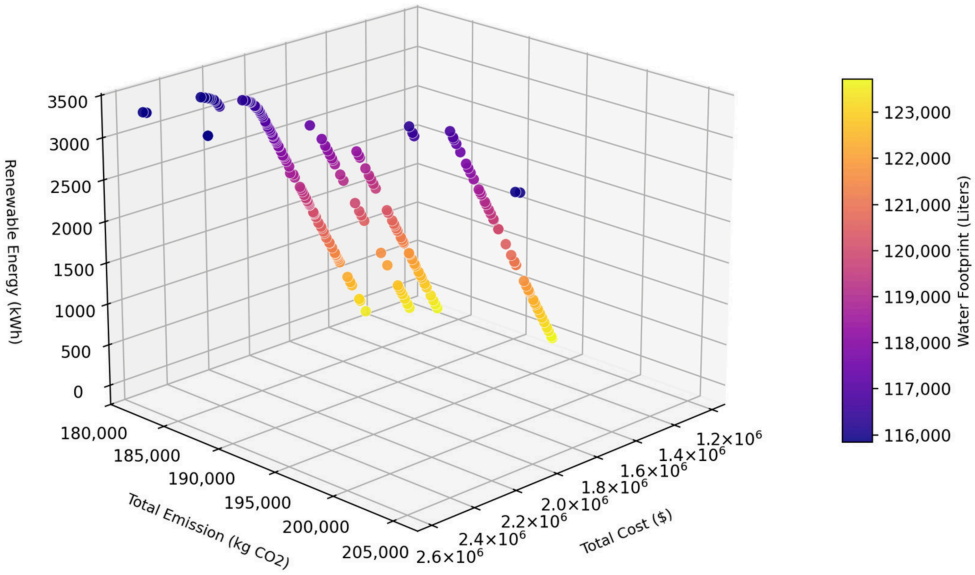


Figure 4. Pareto solution space for small-scale SSCND problem (hybrid NSGA-II).

3.3. Medium-Scale and Large-Scale Problem Application with Hybrid NSGA-II

As the problem complexity increases to medium- and large-scale, the NP-hard nature of the supply chain network design problem becomes more pronounced, resulting in significantly stronger trade-offs among economic, environmental, and resource-related objectives. The obtained feasible solution spaces show enhanced multi-dimensional trade-off surfaces with increasing dispersion and complexity. This reflects the exponential increase in the marginal cost of further reducing emissions or the water footprint, as well as the rapid growth in decision variables. The Pareto solution space for the medium- and large-scale instances is presented in Figures 5 and 6.

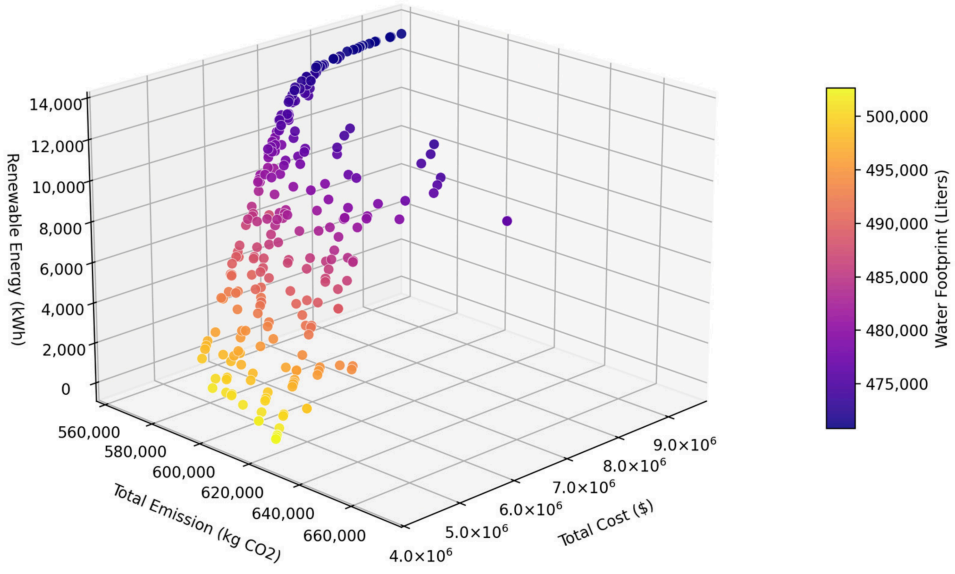


Figure 5. Pareto solution space for mid-scale SSCND problem (hybrid NSGA-II).

When the problem is expanded to the large-scale instance, the points are grouped into distinct clusters, in contrast to the more regular trend observed in the small-scale problem. These results indicate that at larger scales, achieving environmental benefits becomes significantly more costly. Furthermore, carbon emission outcomes show a strong correlation with total cost, where achieving the lowest emission levels requires significant capital investment in renewable technologies. The graphs clearly demonstrate the positive

correlation between renewable energy use (kWh) and total cost ($), indicating the economic burden of renewable energy investment. Additionally, the transition of the water footprint color scale from yellow to purple denotes that the total water footprint tends to stabilize where emissions are minimized, suggesting a balance between carbon reduction and water conservation at a certain threshold.

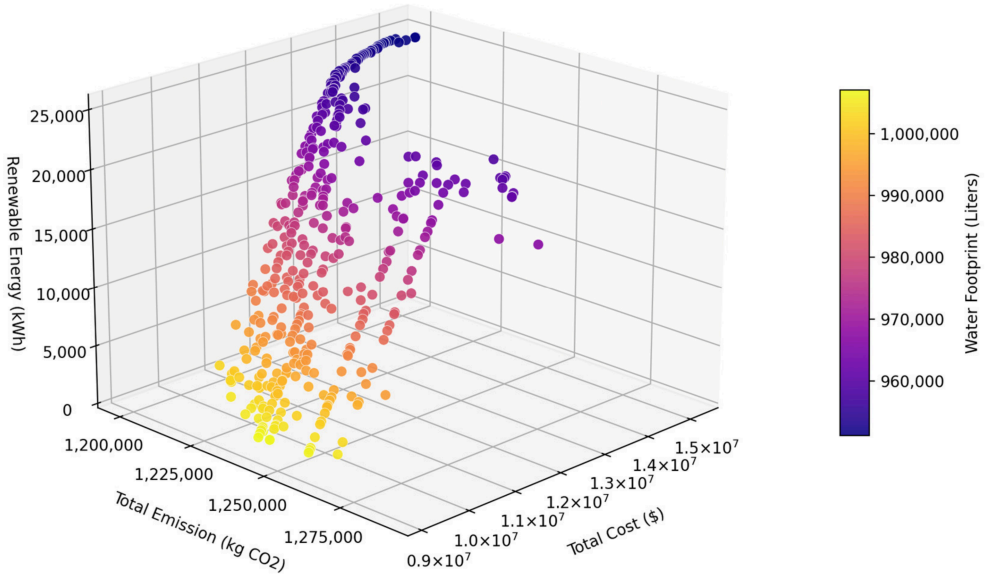


Figure 6. Pareto solution space for large-scale SSCND problem (hybrid NSGA-II).

These findings demonstrate that at larger scales, sustainable supply chain planning requires more strategic and well-balanced decisions, reinforcing the necessity of multi-objective optimization approaches for providing effective decision support.

4. Discussion

The multi-objective sustainable supply chain network design model developed in this study was analyzed using two different methodological approaches. In the first approach, the model was constructed as a mixed-integer linear programming (MILP) model and solved using GAMS. The Pareto-optimal solutions, which define the theoretical limits of the problem, were obtained utilizing the augmented ε-constraint (AUGMECON2) solution method. In the second approach, the model was implemented in Python and solved using hybrid NSGA-II, a meta-heuristic multi-objective optimization algorithm. The findings of the multi-objective optimization reveal significant trade-offs between economic and environmental goals. In particular, the "best green case" and "best water footprint case" were found to be highly aligned, indicating that prioritizing renewable energy utilization not only reduces carbon emissions but also drastically lowers the total water footprint compared to systems with intense grid usage.

These improvements in renewable energy utilization and water footprint reduction are associated with a substantial increase in total cost. The findings of the research underscore the critical trade-offs between economic efficiency and environmental performance in sustainable supply chain design. This result aligns with the literature showing that environmental objectives, such as carbon emission reduction, require significant initial investment, especially where renewable energy integration is prioritized [13,35]. In this context, the study by Naveed et al. (2022) supports these findings by demonstrating that optimizing integrated energy-water systems for carbon reduction requires substantial structural modifications and increased source usage, which leads to higher investment costs and complex economic trade-offs [36].

Furthermore, as highlighted in recent studies on the water–energy–carbon (WEC) nexus, the interdependency between carbon reduction and water conservation in this research shows the integrated nature of environmental performance metrics [8,37]. This result is consistent with the findings of Zhou and Zhu (2024), who illustrated that integrating water-saving measures directly correlate with energy demand reduction and lower carbon footprints [38]. As Tan and Yao (2023) suggest, identifying the WEC nexus is vital for sustainability, where the integration of technological advancements and ecological conservation strategies enables the simultaneous optimization of resource efficiency and environmental protection without compromising economic growth [39].

From a methodological perspective, the hybrid approach utilized in this study suggests a strong balance between accuracy and scalability, in accordance with established multi-objective mathematical programming frameworks [10,19]. By leveraging the augmented ε-constraint method in GAMS to effectively define the theoretical limits of the Pareto-optimal front for small-scale problems, the model establishes a reliable baseline for performance. To handle the increased complexity of larger scale problems, the hybrid NSGA-II-based algorithm was employed with an initial seeding strategy, which enhanced the generation of high-quality Pareto solutions, particularly for medium- and large-scale instances. Consequently, while the AUGMECON2 method offers highly accurate solutions, the hybrid NSGA-II-based algorithm can be considered an effective alternative, providing a wide variety of solutions to the decision-maker, especially in large-scale and multi-dimensional problems. In this context, the hybrid use of both approaches provides significant contributions in terms of both accuracy and flexibility in supply chain design problems.

In terms of implementation, the proposed methodology can be automated as a decision-support tool by integrating data input, scenario generation, and optimization modules within a unified software environment. This structure could assist decision-makers in evaluating alternative facility configurations, renewable energy investment levels, and energy-sourcing strategies under uncertainty. Therefore, the study has potential value for both analytical assessment and managerial planning in supply chains.

Although the study offers useful methodological and practical insights, certain limitations should be acknowledged. First, uncertainty is represented through demand and solar efficiency scenarios, while other potentially important sources of uncertainty, such as energy price fluctuations, transportation disruptions, regulatory changes, and technology transitions related to transport systems with low emissions, are not incorporated into the model. Second, the numerical analysis is conducted on an illustrative network structure and relies on scenario-based data to represent uncertainty rather than firm-specific operational data, which may limit the practical applicability of the results. Third, the proposed approach focuses on long-term strategic and tactical planning decisions and does not explicitly incorporate detailed operational-level decisions, such as vehicle routing or scheduling decisions. In addition, the model is limited to a forward supply chain structure and does not extend to reverse logistics or closed-loop supply chains. While the study provides a detailed assessment of the economic and environmental dimensions of sustainability, the current formulation does not incorporate the social sustainability pillar. Finally, from a computational perspective, exact Pareto solutions were computationally feasible only for small-scale problems, whereas medium- and large-scale problems required a meta-heuristic solution approach.

Despite these limitations, several future research directions can be identified. The proposed model could be extended to a closed-loop supply chain network design (CLSCND) framework by incorporating reverse logistics, thereby enabling the analysis of circular economy strategies. To effectively manage the long-term complexities of these expanded

networks, future formulations could transition from scenario-based modeling toward robust optimization or dynamic programming. These approaches would allow for better management of volatile market conditions and time-dependent investment decisions. Furthermore, the model may be adapted to investigate the impacts of fleet electrification by integrating electric vehicles into distribution operations to facilitate the assessment of decarbonization approaches and their alignment with related Sustainable Development Goals.

Future studies might also consider the integration of social sustainability aspects, which would allow for a comprehensive evaluation of sustainable supply chain design decisions from a triple bottom line (TBL) perspective involving economic, environmental, and social goals. Due to the subjective nature of social indicators, fuzzy programming could be utilized to transform qualitative social metrics into a quantifiable mathematical formulation, thereby enhancing the integrated assessment of the network. Finally, even though this study concentrates on a specific network configuration, the modeling methodology presented here provides decision-makers a scalable foundation to evaluate complex environmental trade-offs for more resilient and resource-efficient industrial ecosystems.

5. Conclusions

This study contributes to sustainable supply chain research by presenting a quantitative framework that connects strategic logistics decisions with decarbonization and resource management objectives. By simultaneously optimizing strategic solar capacity investments, operational carbon emissions, and water consumption, the proposed approach aligns supply chain network design decisions with broader energy transition and integrated environmental objectives. In this sense, resource efficiency is positioned as a core component of long-term supply chain planning under uncertainty.

The numerical results further confirm the practical relevance of the proposed methodology. For the small-scale instance, the exact method generated 23 Pareto-optimal solutions in 55.36 s, while the proposed hybrid NSGA-II algorithm produced near-optimal results in 10.26 s, with deviations of 0.30%, 1.53%, 0.03%, and 0.0006% for total cost, carbon emissions, renewable energy use, and water footprint, respectively. In addition, the results demonstrated that increasing renewable energy utilization from 0 to 3280.076 kWh led to a cost increase of 76.33% while reducing the total water footprint from 123,714.527 L to 115,842.346 L and carbon emissions from 192,336.547 kg CO_2 to 185,472.237 kg CO_2. For medium- and large-scale instances, where exact solutions could not be obtained, the proposed hybrid NSGA-II algorithm remained computationally applicable and generated feasible Pareto solutions within 59.05 and 309.62 s, respectively.

The findings of this research offer several key managerial insights for decision-makers aiming to incorporate sustainability objectives into long-term supply chain operations. Beyond methodological contribution, the study highlights the value of quantitative modeling and optimization methods in supporting real-world supply chain decision processes. In increasingly complex and uncertain environments, optimization-based analytical frameworks offer a structured analytical foundation for assessing strategic alternatives that are difficult to evaluate intuitively. In this regard, employing scalable meta-heuristic solution methodologies becomes especially crucial for translating sustainability-oriented planning goals into actionable insights for large-scale systems. By bridging the gap between mathematical complexity and strategic implementation, the proposed framework serves as a strong analytical tool for addressing complex sustainability challenges in modern supply chains.

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Abbreviations

The following abbreviations are used in this manuscript:

AMOVNS	Adapted Multi-Objective Variable Neighborhood Search
AUGMECON	Augmented ε-Constraint
GAMS	General Algebraic Modelling System
GRESB	Global Real Estate Sustainability Benchmark
HV	Hypervolume
IPCC	Intergovernmental Panel on Climate Change
LCA	Life Cycle Assessment
LEED	Leadership in Energy and Environmental Design
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
MOPSO	Multi-Objective Particle Swarm Optimization
NRGA	Non-Dominated Ranking Genetic Algorithm
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
RPD	Relative Percentage Deviation
SA	Simulated Annealing
SDG	Sustainable Development Goals
SSCND	Sustainable Supply Chain Network Design

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