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Sustainable closed-loop supply chain network considering disruption risk under uncertainty

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ABSTRACT

This paper investigates the design of sustainable closed-loop supply chain networks (CLSCNs) under disruption risks and uncertainty. We propose a multi-objective mixed-integer linear programming (MILP) model that optimizes economic, environmental, and social sustainability objectives while minimizing the expected cost and maximizing network resilience against disruptions. The model incorporates various uncertainties, such as demand fluctuations, return rates, and disruption probabilities. We employ a scenario-based stochastic programming approach to address these uncertainties and identify robust solutions. The numerical results demonstrate the effectiveness of the proposed model in designing sustainable and resilient CLSCNs. The model provides valuable insights for decision-makers in optimizing network configuration, resource allocation, and risk mitigation strategies within a closed-loop environment.

1. Introduction

Closed-loop supply chain networks (CLSCNs) have emerged as a prominent strategy for achieving sustainable resource management by recovering and remanufacturing used products at their end-of-life. This approach not only minimizes environmental impact by reducing waste but also offers economic benefits through material recovery and cost savings. However, designing CLSCNs is a complex task due to inherent uncertainties in demand, return rates, and potential disruptions. These

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uncertainties can significantly impact the network's performance and hinder its sustainability goals.

Disruptions, such as natural disasters, political instability, or supplier failures, can further disrupt the smooth flow of materials and products in a CLSCN. These disruptions can lead to production delays, inventory shortages, and increased costs. Therefore, designing a CLSCN that is not only sustainable but also resilient to disruptions is crucial for long-term success.

This paper addresses the challenge of designing a sustainable CLSCN that considers disruption risks and uncertainty. We propose a multi-objective MILP model that simultaneously optimizes economic, environmental, and social sustainability objectives while minimizing the expected cost and maximizing network resilience against disruptions. The model incorporates various uncertainties through scenario-based stochastic programming [1] (see Figure a).

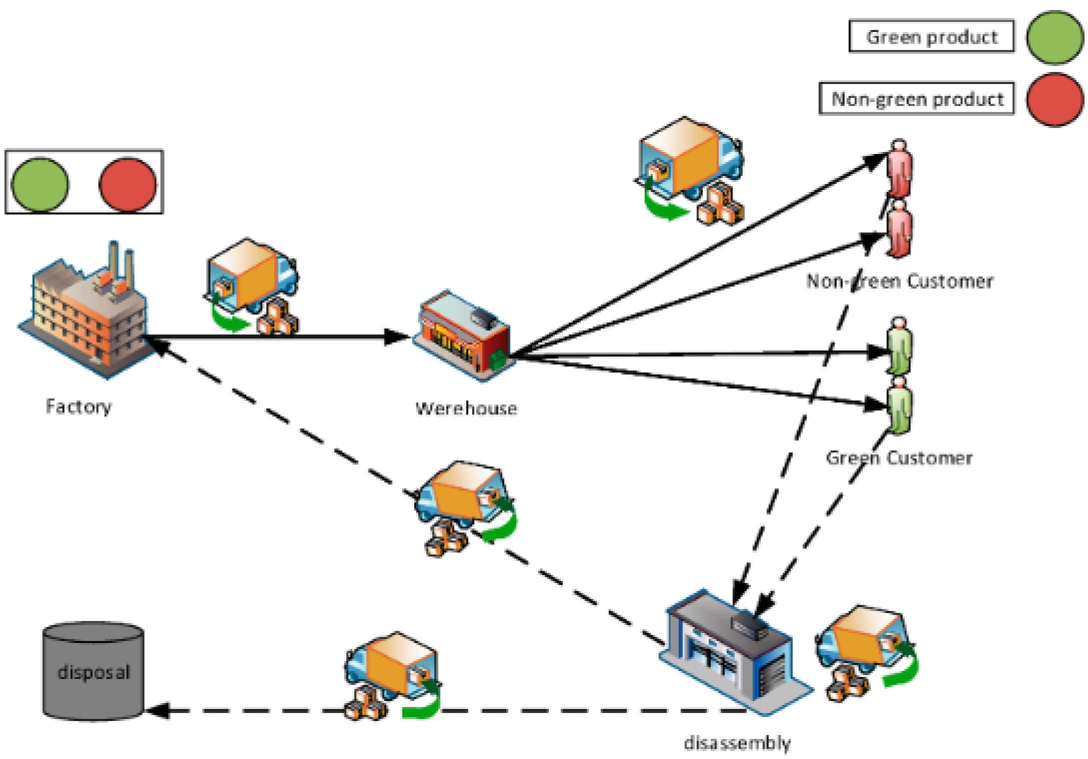
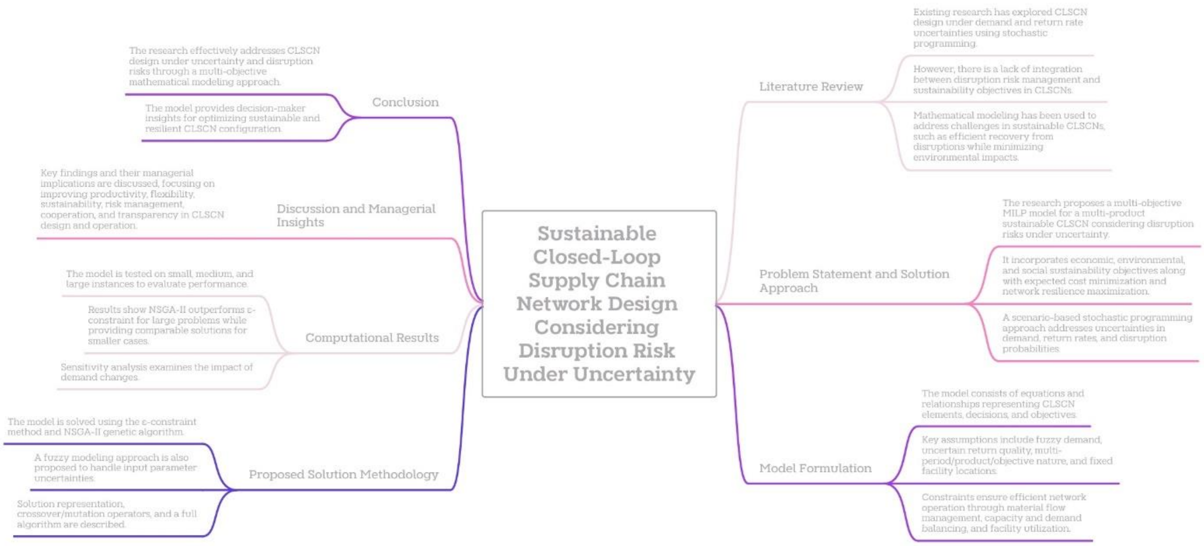


Figure a: Sustainable closed-loop supply chain network.



Supply Chain Management, an all-encompassing and judicious approach to the orchestration of goods, services, and information from their inception as raw materials until they reach the hands of the ultimate consumer. With its encompassment of meticulous planning, flawless execution, and vigilant control over every aspect entailed in sourcing, procurement, conversion, and logistics management; Supply Chain Management emerges as a nexus where efficiency meets precision.

Within this realm lie not only mere activities but a finely woven network of coordination and collaboration with channel partners - be they suppliers crafting raw materials with finesse or intermediaries guiding them through their transformative journey; perhaps even third-party service providers orchestrating seamless transitions between production stages leading up to the smiling faces of euphoric customers upon receipt.

In essence, SCM marries supply with demand across vast expanse spanned by companies synchronizing efforts towards satiating customer cravings while optimizing resource utilization including distribution capacity along with inventory intricacies meticulously managed by skilled laborers striving for perfection. The paramount goal resonating through each strand of this intricate web is none other than efficacious fulfillment leaning on reduced surplus costs coupled with prompt deliveries ensuring that products gleam forth in all their glory before discerning consumers eager for a prized possession. The five essential stages in the realm of Supply Chain Management are as follows:

Firstly, there is the phase of Planning, where intricate strategies are devised to synchronize the supply and demand, anticipating future requirements so as to ensure a seamless availability of materials, equipment, and skilled labor. Next comes Sourcing, which entails the meticulous task of identifying suppliers who are capable of providing the necessary raw materials and components required for production.

Following this is Production, where all activities are meticulously managed to transform these raw materials into refined finished goods through a careful process.

Then arises Distribution, wherein the coordination of delivering these goods to customers takes place efficiently utilizing an extensive network comprising distributors and retailers.

Lastly but certainly not least is Returns - dealing with returned or faulty products alongside overseeing reverse logistics operations seamlessly within SCM's domain. Indeed, Supply Chain Management stands at the core of creating substantial net value while establishing a competitive infrastructure. Additionally, it successfully harnesses global logistics opportunities along with expertly synchronizing supply and demand factors whilst globally measuring performance metrics effectively.

This research is arranged into five sections. Section 2 defines the literature review and recent studies in area of CLSC sustainability and tries to show the gap in research. Section 3 suggests methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

2. Review and survey related works

Recent years have seen a growing research interest in designing sustainable Closed-Loop Supply Chain Networks (CLSCNs). Various studies have delved into different facets of CLSCNs such as network configuration, production planning, and reverse logistics [1, 2]. However, there is a gap in the literature concerning the explicit consideration of disruption risks and uncertainties in the design of sustainable CLSCNs.

Researchers [3, 4] have explored the design of CLSCNs under demand uncertainties, introducing stochastic programming models to optimize network configuration and resource allocation in scenarios with fluctuating demands. Similarly, [5] has investigated CLSCN design amidst uncertain return rates, proposing strategies for capacity planning and inventory management.

While there is substantial research on managing disruption risks in traditional supply chains [6, 7], there remains a lack of integration of disruption risk management with sustainability objectives in CLSCNs.

Systems for the supply chain (SC) comprise a unified structure of products, services, and related activities. One of the most important steps in building a successful supply chain is choosing suppliers carefully who will produce the items or provide the services. As a result, selecting the best supplier becomes essential to improving and streamlining the supply chain's flow [1]. In the modern world, supply chains have evolved into organized systems that support both forward and backward flow of commodities, creating what is known as a closed-loop supply chain (CLSC). The cooperative network of components that make up CLSCs functions in concert with one another [2]. By their actions, they significantly contribute to the preservation of fossil fuels, non-renewable resources, water, and land.

Driven by rising environmental concerns, manufacturers and retailers are increasingly working together to design more eco-friendly products and improve the efficiency of closed-loop supply chains (CLSCNs) [4]. Research is actively exploring ways to create more effective collaborative models that encompass various aspects of sustainability (e.g., resource use, waste reduction) [5]. Additionally, developed nations are placing a growing emphasis on reverse supply chains, recognizing their potential to significantly improve environmental sustainability [6].

Reverse supply chains, including reverse logistics, are gaining a lot of attention because to the effects that product manufacture has on the environment [7, 8, 9]. A challenging task that requires decision-making at both the strategic and operational levels is managing yield within a supply chain [10]. Planned return management, facility kinds, and locations are only a few of the variables that go into strategic decisions [10, 11]. On the other hand, operational planning is concerned with matters like how often waste items are collected, the logistics of transportation, and optimizing routes to optimum efficiency [12].

Although yield management decision-making is different from operational decision-making, the two processes are closely related and frequently need independent evaluations because of their near proximity in the supply chain [10]. Facilities kinds and placements are examples of strategic decisions that are usually imposed by upstream government entities and carried out by downstream organizations [10, 11]. To guarantee efficacy at both levels, this calls for analyzing recycling management across a range of product kinds [13-15].

The emergence of new logistics structures that incorporate closed-loop supply chain principles demonstrates significant progress in enhancing resource utilization efficiency. These structures optimize the flow of materials throughout the entire product lifecycle, from acquiring raw materials to collecting and reusing end-of-life products [16, 17].

In today's world, returned products are no longer seen as waste, but rather as valuable assets within the supply chain [18]. A key objective of reverse supply chains is to minimize environmental impact through resource recovery and reduced waste [19]. Environmental concerns now outweigh the costs associated with collecting returned products. This shift is driven by the recognition of the detrimental effects of excessive carbon emissions from traditional waste disposal methods [19].

It's important to distinguish between reverse logistics and closed-loop supply chains (CLSCNs). While reverse logistics focuses specifically on the flow and management of returned products [20], CLSCNs encompass both forward and reverse supply chain operations, creating a holistic system for resource recovery and reuse [21]. Therefore, reverse logistics is a subset of the broader CLSCN framework.

Similar to any project, ensuring a supply chain's success hinges on continuous and proactive risk management practices. Effectively managing risks across all stages of the supply chain lifecycle is crucial. Project risks, which are uncertain events that can disrupt project goals like schedule, cost, and quality, exist from the very beginning. Limited information about activity-specific risks during the planning phase can lead to delays and cost increases, impacting budgets and quality. As a result, accurate risk assessment and identification are essential. Risk avoidance, risk transfer, risk reduction, and risk acceptance are the four primary methods that are usually used throughout the risk response stage. Based on variables including resource availability, risk severity, and other project-specific concerns, project managers select these tactics. Risk reduction seeks to lessen the chance of prospective dangers, whereas risk avoidance is completely removing them [22].

However, putting risk avoidance into practice might occasionally make project management more difficult [23].

Beyond project-related risks, various factors introduce uncertainty into supply chains, including political issues, demand fluctuations, technological advancements, and financial considerations [24]. Research has increasingly focused on building resilience in sustainable supply chains to navigate these disruptions [25]. Effective disruption management involves a four-step process: identifying potential disruptions, assessing their impact, making informed decisions, and continuously monitoring the situation [26].

One useful method for handling these uncertainties in supply chain management is fuzzy logic [27]. Fuzzy logic, in contrast to conventional binary logic (true/false), permits the inclusion of ambiguity and partial truths, allowing for more sophisticated modeling of complex systems and decision-making procedures [27]. The construction of fuzzy post-quantum Bernstein polynomials is one area in which this approach has shown value, in addition to supply chains [28–32].

Researchers have employed various mathematical models to address challenges in sustainable closed-loop supply chains (CLSCNs), particularly those related to disruptions. For example, Sanei and Pishwai et al. [33] developed a model to manage crises within a sustainable pharmaceutical supply chain network. Their model aimed to ensure efficient recovery from disruptions while minimizing negative environmental impacts. Similarly, Khalifazadeh et al. [34] proposed a mathematical model focused on minimizing costs and maximizing system reliability within a four-level CLSCN. This model helps decision-makers design a network that is both cost-effective and resilient to disruptions. Furthermore, Zhalechian et al. [35] investigated the environmental impact of disruptions within a sustainable CLSCN. Their location-routing-inventory model considers the environmental consequences of disruptions alongside traditional factors like cost and efficiency. These studies highlight the potential of mathematical modeling to design and manage sustainable CLSCNs that are robust in the face of disruptions.

Mathematical models for sustainable CLSCNs extend beyond just disruption management. Researchers have incorporated various objectives into their models to achieve a more holistic approach. For example, Rahmani and Mahoodian [36] created a model in their supply chain network architecture that takes into account both CO2 emissions and system dependability. This strategy aids in network optimization for both operational effectiveness and environmental sustainability. A multi-objective fuzzy model was presented by Khalili Nasr et al. [37] that addresses a broader variety of objectives. Their methodology integrates environmental issues, maximizes job prospects, and minimizes expenses. This illustrates how fuzzy logic may manage the inherent uncertainties related to these complex goals inside a CLSCN.

Dong et al. [38] focused on a different set of objectives in their model. They considered random demand and reproduction systems to identify profitable producers, allocate distributors effectively, and assess material flow across various supply chain tiers. This highlights the flexibility of mathematical modeling to address diverse challenges and goals in CLSCN design.

Mathematical models have become a powerful tool for tackling various challenges in sustainable closed-loop supply chains (CLSCNs). These models go beyond basic network design and incorporate complexities like uncertainty, environmental impact, and social considerations.

Dibet et al. [13] addressed uncertainty and product recovery in their multi-period, multi-commodity model. This model considers factors like product quality fluctuations and varying recovery rates to optimize decision-making within a CLSCN. Wu [39] presented a paradigm for dynamic competitive games with government involvement. This model aims to minimize environmental costs within a CLSCN, considering the potential impact of government regulations on supply chain operations. Moradi et al. [40] focused on mitigating costs associated with disruptions. Their multi-level supply chain network model employs robust optimization techniques to account for uncertain parameters and minimize fixed costs and transportation costs arising from disruptions. Kalantari et al. [41] developed a fuzzy robust stochastic optimization approach specifically for sustainable CLSCNs. This model tackles the challenge of balancing environmental impact reduction with maximizing financial (net present value) and social benefits within a CLSCN, while also accounting for inherent uncertainties. These diverse studies showcase the wide range of mathematical models being developed to address the complexities of sustainable CLSCN design and management.

The growing field of mathematical modeling for sustainable CLSCNs boasts a diverse range of applications. These models can be tailored to address specific industry needs and sustainability goals. A mixed-integer programming (MIP) model was created for the avocado sector by Salehi

Amiri et al. [42]. Their model takes into account not just conventional considerations but also the creation of jobs and related expenses, which reflects the CLSCN's social sustainability component.

Kalantari et al. [43] focused on a multi-objective approach in their model for a stable closed-loop supply chain. Their model seeks to maximize net present value (NPV) while minimizing carbon emissions, demonstrating the ability to balance economic and environmental goals within a CLSCN. Moving beyond traditional industries, Garai & Sarkar [44] explored the application of CLSCN principles in the realm of customer-centric reverse logistics for sectors like herbal medicine and biofuels. Their model highlights the potential of CLSCNs for promoting resource recovery in diverse product categories. Devika et al. [47] tackled a multi-objective CLSC problem using a mixed-integer programming model. They further developed novel hybrid metaheuristic methods to solve this model efficiently, showcasing advancements in optimization techniques for complex CLSCN design.

In order to tackle uncertainty in the tire business, Fatollahi-Fard et al. [48] suggested a multi-channel, multi-product, and multi-period model for CLSC network architecture. Their concept builds a more resilient and flexible network by taking into account the inherent risks of the supply chain. Lastly, a thorough CLSC network model that concurrently optimizes social, economic, and environmental factors using a multi-objective approach was provided by Ali et al. [49]. Their concept shows how CLSCNs can support more general sustainability objectives. The adaptability and strength of mathematical models in maximizing sustainable CLSCNs across a range of sectors and sustainability goals are demonstrated by these instances.

3. Problem statement and Solution approach

This section presents the methodology for designing a sustainable CLSCN with disruption risk considerations under uncertainty.

The model consists of mathematical equations and relationships that represent the different elements and decisions involved in designing a sustainable closed-loop supply chain network (CLSCN) under disruption risks and uncertainty.

3.1. Problem Definition

This research proposes a multi-level, multi-product, and multi-period sustainable CLSC network model. It considers disruption risks from returned products, production issues, and distribution challenges. The model encompasses various elements like markets, collection points, production facilities, and recycling sites. It also factors in different production levels for cleaner manufacturing and resource reduction. Additionally, the model incorporates diverse technologies for producing reusable products.

The research explores various disruptions faced by distributors, including driver stress and economic sanctions on producers. It acknowledges how outdated technology, unsuitable materials, and a lack of market focus can hinder supply chain performance. Therefore, the study emphasizes the importance of technology selection, production/distribution center location, and network flow optimization.

The model takes into account the social effect of these measures, risks associated with returned products, and the overall expenses of the supply chain (facility, transportation, procurement, and manufacturing). The approach makes use of fuzzy set theory to handle data uncertainties in real-world scenarios. The model incorporates repair teams and accompanying expenses for hazards linked to repairs. The performance of supply chains in conditions of economic boom and recession is also examined.

The research uses a multi-objective mathematical model that takes uncertainty-accounting disruption risks into consideration while designing the multi-product CLSC network. This paradigm enables the simultaneous optimization of cost cutting, the reduction of environmental effect (from transportation and facilities), and the enhancement of social welfare. The formulation and solution of a mixed-integer multi-objective mathematical programming model employs both deterministic techniques (epsilon-constrained method with GAMS software) and meta-heuristic techniques (NSGA-II with MATLAB).

Key Model Assumptions

- Fuzzy demand to reflect real-world uncertainties
- Uncertainty in returned product quality
- Multi-period, multi-product, and multi-objective nature
- Fixed facility locations chosen from pre-defined options
- Fixed cost of goods and product transportation within each scenario

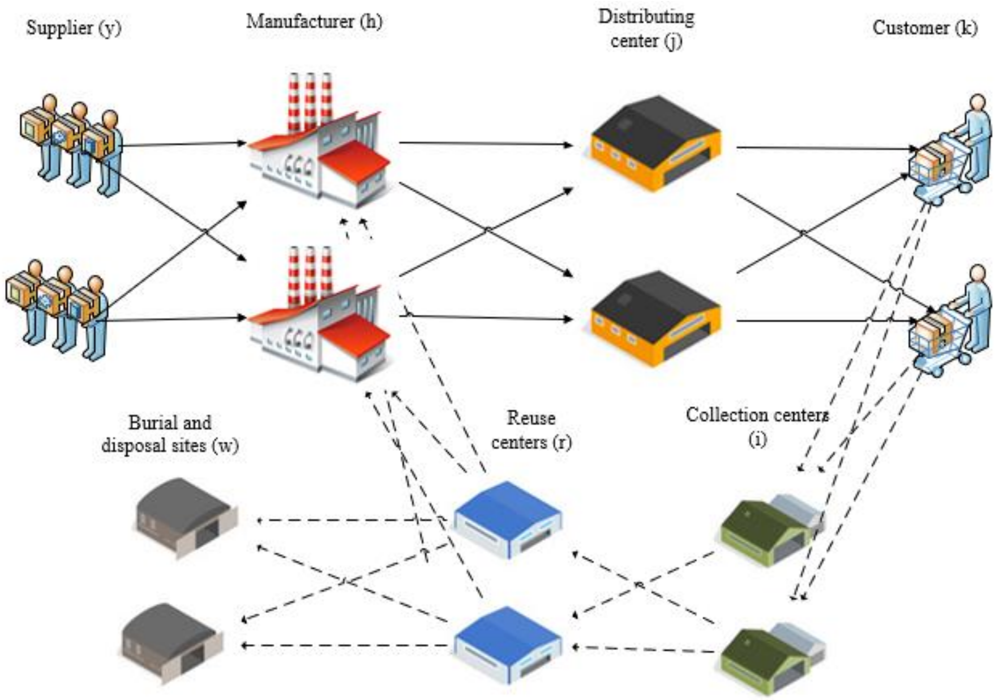


Figure 1. Graphical structure of the proposed model

Figure 1 (not included) depicts the CLSC cycle, showcasing the flow of products from production to distribution, customer returns, refurbishment, reuse, and recycling.

Overall, this research presents a comprehensive approach to designing a resilient and sustainable CLSC network that can adapt to various disruptions and uncertainties.

3.2. Notation

This section provides an explanation for each symbol used to represent the problem's sets, parameters, and variables.

Indices

Sets	Description
y	The set of suppliers $y \in Y = \{1,2, \dots\}$,
h	The set of manufacturers $h \in H = \{1, ,2, \dots\}$,
j	The set of distributors $j \in J = \{1,2, \dots\}$,
k	The set of customers $k \in K = \{1,2, \dots\}$,
i	The set of collection centers $i \in I = \{1,2, \dots\}$,
r	The set of re-use centers $r \in R = \{1,2, \dots\}$,
w	The set of burial and disposal sites $w \in W = \{1,2, \dots\}$,

p	The set of products $p \in P = \{1,2,\ldots\}$,
q	The set of quality type $s \in S = \{1,2,\ldots\}$,
s	The set of scenarios $s \in S = \{1,2,\ldots\}$.

Parameters:

$\boldsymbol{li_y}$	Center y's volume capability
$\boldsymbol{li'_{hv}}$	Center h's ability to revamp products using technology v
$\boldsymbol{li_w}$	Capacity of establishment w
$\boldsymbol{li_{hv}}$	Center h's capacity to utilize technology v
$\boldsymbol{li_i}$	Maximum potential of center i
$\boldsymbol{li_r}$	Capability of center r
$\boldsymbol{li_j}$	Capacity of establishment j
$\boldsymbol{\widetilde{cb}_w}$	Center w's carbon footprint
$\boldsymbol{\widetilde{cb}_i}$	CO2 emissions from center i's operations
$\boldsymbol{\widetilde{cb}_r}$	The amount of CO2 emitted by center r
$\boldsymbol{\widetilde{cb}_j}$	Carbon emissions associated with center j
$\boldsymbol{cpk}$	Emissions resulting from delivering one unit of product per distance unit
$\boldsymbol{\tilde{h}_w}$	Establishment costs of center w
$\boldsymbol{\tilde{h}_p}$	Center p's fixed establishment cost
$\boldsymbol{\tilde{h}_i}$	The initial expense of setting up center i
$\boldsymbol{\tilde{h}_j}$	Fixed start-up cost for center j
$\boldsymbol{vl_{ps}}$	Quantity of product p in scenario s following recycling
$\boldsymbol{\widetilde{d}_{ks}^{pt}}$	Customer demand for product p in period t from segment k in scenario s
$\boldsymbol{fo_{ps}}$	Unit production cost of product p under scenario s
$\boldsymbol{f'o_{ps}}$	The expense of collecting one unit of product p in scenario s
$\boldsymbol{pg^{s}{}_{pq}}$	The price of returned product p with quality q in scenario s
$\boldsymbol{d_{ihvqs}^{p}}$	Transportation distance/cost of delivering product p with quality q from center i to center h using technology v in scenario s
$\boldsymbol{d_{yhs}^{p}}$	Shipping costs/distance for product p from center y to center h in scenario s

d_{hjs}^{p}	Transporting product p from center h to center j, including distance and cost, in scenario s
d_{kis}^{p}	Transportation costs/distance for delivering product p from customer k to center i in scenario s
d_{irqs}^{p}	Shipping expenses/distance for delivering product p from center i to center r with quality q in scenario s
d_{iwqs}^{p}	Distance/travel cost for transporting product p from center i to center w with quality q in scenario s
d_{rhqs}^{p}	Shipping costs/distance for delivering product p from center r to center h with quality q in scenario s
d_{jks}^{p}	Distance/cost of product transportation from center to customer in scenario s
pr_s	Probability of occurrence for scenario s
$r_{k,q,s}^{pt}$	Return rate of product p with quality q from customer site k during period t in scenario s
rr'^{pt}	Return rate of product p from collection center to burial site during period t
rr^{pt}	Return rate of product p from collection center to the manufacturer during period t
rr''^{pt}	Return rate of product p from collection center to recycling center during period t
pol_{jt}	Total pollution emitted during establishment of center j in period t
pol_{it}	Total pollution emitted during establishment of center i in period t
pol_{rt}	Total pollution emitted during establishment of center r in period t
pol_{wt}	Total pollution emitted during establishment of center w in period t
α_{hts}	1 if there is no disruption in production center h during period t in scenario s, otherwise 0
β_{yts}	1 if there is no disruption in supply center y during period t in scenario s, otherwise 0
cm_{hts}	Repair cost of manufacturing center h during period t in scenario s
cm_{yts}	Repair cost of supply center y during period t in scenario s

Decision variables:

Binary variables:

x_j	If center j is formed, it will be assigned a value of 1; otherwise, it will be assigned a value of 0.

x_i	In the event that center i is established, its assigned value will be 1; if not, its value will be 0.
x_r	Center r will have a value of 1 if it is established; otherwise, it will have a value of 0.
x_w	Should center w be established, its value will be 1; otherwise, it will be 0.
y_{ht}	If repair group is sent to center h during period t, it is equal 1,
y_{yt}	If repair group is sent to center y during period t, it is equal 1.

Positive variables:

z_{ihvqs}^{pt}	Number of product p sent from center i to center h by technology v with quality q during period t in scenario s
z_{hvjs}^{pt}	Number of product p sent from center h to center j by technology v during period t in scenario s
z_{jks}^{pt}	Number of product p sent from center j to customer k during period t in scenario s
z_{rhqs}^{pt}	Number of product p sent from customer j to center k with quality q during period t in scenario s
z_{iwqs}^{pt}	Number of product p sent from center j to center w with quality q during period t in scenario s
z_{yhs}^{pt}	Number of product p sent from center y to center h during period t in scenario s
z_{irqs}^{pt}	Number of product p sent from center i to center r with quality q during period t in scenario s

3.3. Model Formulation

In this section, all equation used to describe mathematical modeling, are explained.

$$Min\ f_1 = (\sum_{j\in J} h_j x_j + \sum_{i\in I} h_i x_i + \sum_{r\in R} h_r x_r + \sum_{w\in W} h_w x_w) + pr_s(\sum_t \sum_s (\sum_{p\in P} \sum_{y\in Y} \sum_{h\in H} \beta_{hts}. d_{yhs}^{p} z_{yhs}^{pt} + \sum_{p\in P} \sum_{y\in Y} \sum_{j\in J} mdx_{jks}^{st} + \sum_{p\in P} \sum_{j\in J} \sum_{k\in K} d_{jk,s}^{p} z_{jks}^{pt} + \sum_{h\in H} \sum_{s\in S} \sum_{t\in T} y_{ht}. cm_{hts} + \sum_{y\in Y} \sum_{s\in S} \sum_{t\in T} y_{yt}. cm_{yts} \quad (1)$$

$$Min\ f_2 = \sum_{r\in R} x_r.\ cb_r + \sum_{i\in I} x_i.\ cb_i + \sum_{w\in W} x_W.\ cb_w + \sum_{j\in J} x_j.\ cb_j + \sum_{s\in S} w_{sen}. \sum_{t\in T} CEM\ [\sum_t \sum_s (\sum_{p\in P} \sum_{y\in Y} \sum_{h\in H} d_{yhs}^{p} z_{yhs}^{pt} + \sum_{p\in P} \sum_{y\in Y} \sum_{j\in J} mdx_{jks}^{st} + \sum_{p\in P} \sum_{j\in J} \sum_{k\in K} d_{jk,s}^{p} z_{jks}^{pt} + \sum_{s\in S}\ (\sum_{p\in P} \sum_{k\in K} \sum_{h\in H} d_{kis}^{p} z_{kis}^{pt} + \quad (2)$$

$\sum_{p\in C}\sum_{q\in Q}\sum_{i\in I}\sum_{r\in R} d^{p}_{irqs} z^{pt}_{irqs} + \sum_{p\in P}\sum_{q\in Q}\sum_{i\in I}\sum_{w\in W} d^{p}_{iwqs} z^{pt}_{iwqs} +$
$\sum_{v\in V}\sum_{p\in P}\sum_{q\in Q}\sum_{i\in I}\sum_{h\in H} d^{c}_{ihqs} z^{ct}_{ihvqs} + \sum_{p\in P}\sum_{q\in Q}\sum_{r\in R}\sum_{h\in H} d^{p}_{rhqs}\, z^{pt}_{rhqs})]$

$$Min\ f_3 = \sum_{t\in T}\sum_{j\in J} pol_{jt}.x_j + \sum_{i\in I}\sum_{t\in T} pol_{it}\ .x_i + \sum_{r\in R}\sum_{t\in T} pol_{rt}\ .x_r + \sum_{w\in W}\sum_{t\in T} pol_{wt}.x_w \qquad (3)$$

Subject to:

$$\sum_{w\in W} x_w \geq 1 \qquad (4)$$

$$\sum_{i\in I} x_i \geq 1 \qquad (5)$$

$$\sum_{j\in J} x_j \geq 1 \qquad (6)$$

$$\sum_{r\in R} x_r \geq 1 \qquad (7)$$

$$\sum_{q_2}\sum_{y\in Y} z^{pt}_{irqs} = rr^{pt}\sum_{q}(\sum_{k\in K} z^{pt}_{kiqs}) \qquad \forall i\in I, p\in P, t\in T, s\in S \qquad (8)$$

$$\sum_{i\in I} z^{pt}_{kiqs} = r^{p}_{kqs}.\sum_{p\in P}\sum_{k\in K} z^{pt}_{jks} \qquad \forall k\in K, j\in J, t\in T, q\in Q, s\in S \qquad (9)$$

$$\sum_{q1}\sum_{h\in H} \alpha_{hts}.z^{pt}_{ihvqs} = rr^{pt}\sum_{q}(\sum_{k\in K} z^{pt}_{kiqs}) \qquad \forall i\in I, v\in V, p\in P, t\in T, s\in S \qquad (10)$$

$$\sum_{h\in H}(\alpha_{hts}.z^{pt}_{hvjs} + w^{pt}_{hjs}) = \sum_{l\in L} z^{pt}_{jks} \qquad \forall j\in J, v\in V, p\in P, t\in T, s\in S \qquad (11)$$

$$\sum_{q2}\sum_{w\in W} z^{pt}_{iwqs} = rr^{pt}\sum_{q}(\sum_{k\in K} z^{pt}_{kiqs}) \qquad \forall p\in P, t\in T, i\in \mathrm{I}, s\in S \qquad (12)$$

$$\sum_{q_2}\sum_{i\in I} z^{pt}_{irqs} = \sum_{q}\sum_{h\in H} z^{pt}_{rhqs} \qquad \forall r\in R, p\in P, t\in T, s\in S \qquad (13)$$

$$\sum_{q_1}\ \sum_{h\in H}\alpha_{hts}.z^{pt}_{ihvqs} + \sum_{q_2}\ \sum_{r\in R} z^{pt}_{irqs} + \sum_{q_3}\ \sum_{w\in W} z^{pt}_{iwqs} = \sum_{q}\ \sum_{k\in K} z^{pt}_{kiqs} \qquad \forall i\in I, \forall h\in H, v\in V, t\in T, q\in Q, \forall j\in J, k\in K, w\in W, r\in R, t\in T, p\in P, s\in S \qquad (14)$$

$$\sum_{y\in Y} z^{pt}_{yhs} + \sum_{q_1}\ \sum_{i\in I}\alpha_{hts}.z^{pt}_{ihvqs} + \sum_{q\in Q}\sum_{r\in R} z^{pt}_{rhqs} = \sum_{j\in J}\alpha_{hts}.z^{pt}_{hvjs} \qquad \forall h\in H, v\in V, p\in P, t\in T, s\in S \qquad (15)$$

$$rr^{pt} + rr^{pt} + rr^{pt} = 1 \qquad \forall p \in P, t \in T \qquad (16)$$

$$\sum_{j \in J} z_{jks}^{pt} \geq d_{ks}^{pt} \qquad \forall k \in K, p \in P, t \in T, s \in S \qquad (17)$$

$$\sum_{p \in P} \sum_{h \in H} z_{yhs}^{pt} \leq li_{y} \qquad \forall y \in Y, t \in T, s \in S \qquad (18)$$

$$\sum_{p \in P} \sum_{j \in J} z_{hvjs}^{ct} \leq li_{hv} \qquad \forall h \in H, v \in V, t \in T, s \in S \qquad (19)$$

$$\sum_{p \in P} \sum_{k \in K} z_{jks}^{pt} \leq li_j x_j \qquad \forall j \in J, t \in T, s \in S \qquad (20)$$

$$\sum_{q_3} \sum_{p \in P} \sum_{i \in I} z_{iwqs}^{pt} \leq li_w x_w \qquad \forall w \in W, t \in T, s \in S \qquad (21)$$

$$\sum_{p \in P} (\sum_{q_1} \sum_{i \in I} \alpha_{hts} . z_{ihvqs}^{pt} + \sum_{q} \sum_{r \in R} z_{rmqs}^{pt}) \leq li_{hv} \qquad \forall h \in H, v \in V, t \in T, s \in S \qquad (22)$$

$$\sum_{qs_2} \sum_{p \in P} \sum_{i \in I} z_{irqs}^{pt} \leq li_r x_r \qquad \forall r \in R, t \in T, s \in S \qquad (23)$$

$$\sum_{q_1} \sum_{p \in P} \sum_{i \in I} \alpha_{hts} . z_{ihvqs}^{ct} + \sum_{q_3} \sum_{p \in P} \sum_{w \in W} z_{iwqs}^{pt} + \sum_{q_2} \sum_{p \in P} \sum_{r \in R} z_{irqs}^{pt} \leq li_r \, x_r \qquad \forall i \in I, v \in V, t \in T, s \in S \qquad (24)$$

$$1 - \alpha_{hts} \leq y_{ht} \qquad \forall h \in H, t \in T, s \in S \qquad (25)$$

$$1 - \beta_{yts} \leq y_{yt} \qquad \forall y \in Y, t \in T, s \in S \qquad (26)$$

$$z_{ihvqs}^{pt}, z_{hvjs}^{pt}, z_{jks}^{pt}, z_{rhqs}^{pt}, z_{kiqs}^{pt}, z_{iwqs}^{pt}, z_{yhs}^{pt}, z_{irqs}^{pt} \geq 0 \qquad \forall i \in I, \forall h \in H, v \in V, t \in T, q \in Q, \forall j \in J, k \in K, w \in W, r \in R, t \in T, p \in P, s \in S \qquad (27)$$

$$x_j, x_i, x_r, x_w, y_{ht}, y_{yt} \in \{1,0\} \qquad \forall j \in J, i \in I, r \in R, w \in W, \forall h \in H, y \in Y, t \in T \qquad (28)$$

The model employs three objective functions to achieve a sustainable and socially beneficial CLSC network:

Minimize Overall Cost (Objective 1): This function aims to reduce total supply chain expenses, including construction, material flow, transportation, product returns, waste disposal, collection, and production costs.

Reduce Carbon Emissions (Objective 2): This function minimizes CO2 emissions generated by constructing new facilities and transporting products throughout the network.

Enhance Risk Mitigation (Objective 3): This function focuses on minimizing risks associated with disruptions within the supply chain.

By simultaneously optimizing these three objectives, the model strives to achieve the greatest societal benefit.

Ensuring Smooth Supply Chain Operations

Several constraints are incorporated to guarantee the efficient operation of the CLSC network:

Facility Availability (Constraints 4-7): These constraints ensure the presence of essential facilities, including waste disposal sites (4), return product collection centers (5), distribution centers (6), and at least one recycling center (7).

Material Flow Management (Constraints 8-15): These constraints maintain a balance throughout the material flow. Constraint (8) ensures an equilibrium between collection and recycling centers, while constraint (9) guarantees complete collection of returned products from customers (100% collection rate). Constraints (11-13) manage product flow by specifying the volume of goods delivered to customers (11), balancing product collection and disposal (12), and ensuring equilibrium at the recycling node (13). Additionally, constraints (14) and (15) define the quantities of goods routed from customers to collection centers and from manufacturers to distributors.

Capacity and Demand Constraints (Constraints 16-20): These constraints ensure capacity limitations are not exceeded. Constraint (16) ensures the sum of returned product coefficients equals 1. Constraint (17) guarantees that all customer demands are met. Constraints (18-20) limit supplier, constructor, and distributor capacities, respectively.

Facility Utilization (Constraints 21-23): These constraints promote the utilization of available facilities. Constraint (21) mandates the use of existing waste disposal sites if they are available. Constraint (22) ensures the utilization of production centers for product refurbishment. Constraint (23) guarantees that recycling centers are operational.

Infrastructure Maintenance (Constraints 24-26): Constraint (24) defines the number of collection centers required. Constraints (25) and (26) address potential breakdowns by dictating the repair or rebuilding of facilities when necessary.

Decision Variables (Constraints 27-28): These constraints define the types of decision variables used within the model.

These constraints ensure the model remains realistic and practical by reflecting real-world limitations and operational needs within the sustainable CLSC network.

3.4. Proposed fuzzy model

This study fuzzified the model using Tan and Cao [53] technique. Regarding the current level of demand uncertainty, center establishment costs, and CO2 emissions from established centers, a triangular fuzzy technique is used. These ambiguous parameters are defined as follows:

$\widetilde{cb}_w$	Center w's carbon footprint
$\widetilde{cb}_i$	CO2 emissions from center i's operations
$\widetilde{cb}_r$	The amount of CO2 emitted by center r
$\widetilde{cb}_j$	Carbon emissions associated with center j
$\tilde{h}_w$	Establishment costs of center w
$\tilde{h}_p$	Center p's fixed establishment cost
$\tilde{h}_i$	The initial expense of setting up center i
$\tilde{h}_j$	Fixed start-up cost for center j
$\widetilde{d_{ks}^{pt}}$	Customer demand for product p in period t from segment k in scenario s

Our goal is to apply classical methods to solve a linear mathematical model. By taking these actions, we can accomplish this:

In this case, the values of A, B, and C are fixed. The suggested method is used to transform a fuzzy constraint into a distinct membership function. A linear normal fuzzy model is presented by Tan and Cao [53] by defining the goal function as follows:

$$Max\ C^t x \qquad i = I = \{1,2,\dots,m\} \tag{29}$$

Subject to:

$$A_i x \le b_i,$$

$$x \ge 0$$

LP (α)

$$MaxC^t\ x \qquad i = I = \{1,2,\dots,m\} \tag{30}$$

Subject to:

$A_i x \leq b_i + (1-\alpha)p_i,$
$\alpha \in [0,1]$
$x \geq 0.$

The parameter α in the optimization problem has values ranging from 0 to 1. The optimal value, vector, and solution of the equation LP_α are denoted as LP_α, B_α and z_α, respectively, while the linear-term coefficient $pi \geq 0$ is non-negative. Depending on the value of α selected, the right coefficient $b + (1-\alpha)p$ fluctuates, and P0 denotes the difference between the optimal and secondary vectors. The optimal values of LP1 and LP0, respectively, are chosen as z1 and z0, respectively, to execute the suggested procedure, provided that $p_0 = z_0 - z_1 > 0$.

3.5. Proposed solution algorithm

3.5.1. ϵ-constraint method

This study will make use of a popular multi-objective optimization technique called the ρ-constraint approach. With this approach, the other objective functions become constraints with an upper bound of ε, and only one objective function is chosen for optimization [45, 46, and 6]. For the epsilon approach to be effective, one of the conflicting goals has to stay in the objective function, and other functions need to be limited by establishing an upper bound. In this way, the multi-objective problem effectively turns into a single-objective problem.

The objective functions of the issue have a limit such that all potential Pareto solutions for the multi-objective problem may be repeated from the upper limit to the lower limit by modifying the problem's right-side vector. This procedure provides the best possible solution and resolves the issue. Potential Naturally, by changing the epsilon, we may get different values for the main goal function. We generate all possible Pareto solutions for the multi-objective problem that is supplied. The general form of the ϵ-constraint problem is as follows.

$$\begin{aligned} &\max f_i(x) \\ &s.t \\ &\quad f_j(x) \leq \epsilon_i \quad \forall i \neq j \\ &\quad x \in X \end{aligned} \tag{31}$$

3.5.2. NSGA-II

A potential populace Based on the genetic algorithm, P is originally considered a productive population, in accordance with the natural characteristic of reproduction. Consequently, this sorting method is used to rate the community, and each individual is assigned a Pareto rank. At this stage, many optimization problems become Pareto optimization problems. In order to do this, the mutation and crossover operators that will result in the ultimate number of children are specified using the Q and N sets. After then, each child is paired with a single parent, creating a mixed population. After the combined population has been sorted, the N best individuals are then considered as the population for the next generation.

3.5.3. Solution representation

Manufacturers, suppliers, and the length of repairs are shown in Figure 2 as rows and columns, respectively. The cell numbers also ensure that the work service will be dispatched to the location or not. The Roulette cycle structure is used to choose the best parents for each kid from the created population before performing the crossover operation. This means that solutions with a higher density distance satisfy the selection requirement.

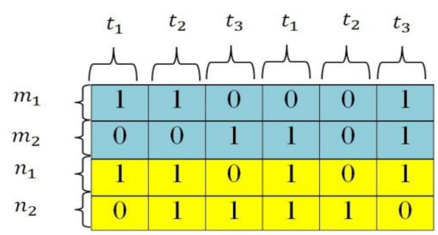


Figure 2: Chromosome representation.

3.5.4. Crossover and mutation operators

For location variables, the crossover operation is carried out point by point. Based on the method, convergent solutions to the issue are produced by this site selection structure. In this work, crossover operation is carried out by establishing two locations for chromosomal selection [50–52]. A chromosome is chosen at random for the mutation procedure. Because multiple scenarios are presented and the range of solutions is increased by the random selection of chromosomes. A random selection of chromosomes is employed in this study; however, the mutations are reversed (Figure 3).

The Taguchi technique is presented as the basis for setting the study's parameters in Tables 1 and 5. The NSGA-II algorithm that follows is then put into practice in accordance with the Taguchi L9 design. Figure 4 displays the S/N diagram following the implementation of the Taguchi technique and data entry in MINITAB software.

Parent

81	54	46	62	71	48
6	61	28	95	401	100
47	44	57	401	461	75
100	321	32	63	123	91

Child

81	54	46	62	71	47
100	401	95	28	61	6
47	44	57	401	461	75
100	321	32	63	123	91

Figure 3: Mutation operator

Table 1 - Parameters and their value levels for the NSGA-II algorithm

Parameters	Values of each level		
	Level 1	Level 2	Level 3
Rate of Crossover (RC)	0.5	0.6	0.7
Rate of Mutation (Rm)	0.4	0.5	0.6
Number of potentials in the Population (N-pop)	50	100	150
Maximum iteration (Max-iteration)	50	150	200

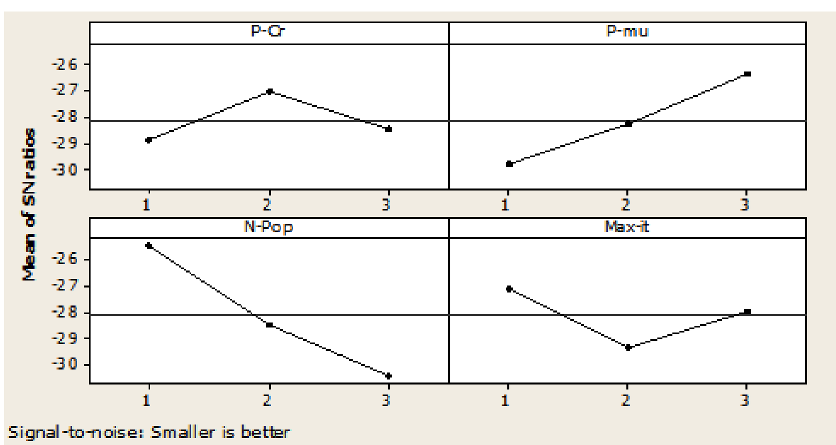


Figure 4. Output of Taguchi method in NSGA-II algorithm

Table 2: Tuning the parameters.

Parameters	Description	Value
nPop	Population number	150
MaxIt	Iteration number	80
Rc	Cross over rate	0.6
Rm	Mutation rate	0.5

3.5.5. Full algorithm

There exist many techniques for analyzing the genetic algorithm's efficiency. The average distance from the average ideal distance (MID) measure is one of these metrics, for instance. Equation 32 is used to generate this index. The objective function in the method has two values: $f_{1,total}^{max}$and $f_{1,total}^{min}$. In equation 32, n represents the number of Pareto points.

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f_{1i} - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}}\right)^2 + \left(\frac{f_{2i} - f_2^{best}}{f_{2,toal}^{max} - f_{2,total}^{min}}\right)^2}}{n} \quad (32)$$

4. Computational results

4.1. Simulated instances

This component of the research displays the output of the mathematical model so that the model's efficacy may be evaluated. Table 3 looks at numerical samples in different sizes. Ten issues for this reason, three numerical examples have been considered: numerical examples 1-4 on a small scale, numerical examples 5-7 on a medium scale, and numerical examples 8–10 on a vast scale. Where f_1^{best}, f_2^{best} are the ideal point's coordinates.

Table 3- Various scales examples.

Scale	Examples	Disposal centers	Collection centers	Manufacturers	Recycling centers	Customers	Distribution centers	Supplier
Small Scale	E1	1	2	1	1	1	2	1
	E2	2	1	1	1	1	2	2
	E3	2	2	2	2	2	2	3
	E4	3	2	3	3	2	2	3

Scale	Examples	Disposal centers	Collection centers	Manufacturers	Recycling centers	Customers	Distribution centers	Supplier
Medium Scale	E5	3	2	3	4	2	3	3
	E6	3	3	4	4	3	3	4
	E7	4	3	4	4	3	3	4
	E8	4	4	4	4	3	4	4
Large Scale	E9	5	5	5	4	3	4	5
	E10	6	6	5	5	4	5	6

Table 4 shows the outcomes of solving the model in small, medium, and large dimensions. The solution discoveries are based on the issue dimensions' classification through the use of the epsilon constraint technique and evolutionary meta-heuristic methodology. The findings indicate that the deterministic ϵ-constraint technique solves problems faster than the genetic meta-heuristic method, although the epsilon constraint approach takes longer. The deterministic ϵconstraint method, however, is unable to solve the problem on a large scale, given that the calculation error between the meta-heuristic method and the deterministic method in the first and third objective functions is less than 1% and in the second objective function less than 6%.

Given that the calculation error between the epsilon constraint method and NSGA-II is less than 0.1 in the 95% confidence interval, we can therefore conclude that, over the long term and for very large problems, the meta-heuristic method can solve and estimate the value of the objective function better than the epsilon limit method.

Table 4- Comparison between finding for exact and meta-heuristic method.

No	**Epsilon constraint**				**NSGA-II**				**Error**		
	f_1	f_2	f_3	Time(s)	f_1	f_2	f_3	Time(s)	f_1	f_2	f_3
1	625	213.6	3.11	1.11	631	225.3	3.46	1.01	0.009	0.05	0.001
2	661	358.3	4.58	25.69	674	364.1	4.77	3.6	0.008	0.03	0.004
3	684	365.3	5.17	36.14	697	371.5	5.39	5.14	0.007	0.04	0.009
4	689	371.8	5.98	84.74	702	382.1	6.14	12.17	0.007	0.05	0.008
5	978	583.9	6.10	657.11	1022	621.7	6.25	22.17	0.006	0.04	0.008

No	Epsilon constraint				NSGA-II				Error		
	f_1	f_2	f_3	Time(s)	f_1	f_2	f_3	Time(s)	f_1	f_2	f_3
6	1058	614.9	7.87	974.12	1125	647.5	7.94	33.69	0.005	0.03	0.009
7	1236	728.3	7.93	1473.8	1361	751.6	8.07	37.17	0.005	0.05	0.008
8	1894	892.4	8.47	1971.7	1911	911.6	8.66	42.57	0.004	0.05	0.007
9	2068	1034.1	8.98	2037.11	2230	1162.4	9.11	56.33	0.002	0.04	0.005
10	2540	1298.7	9.51	2975.64	2487	1319.7	9.68	61.28	0.002	0.02	0.002

Table 4 displays the outcomes of using the assessment criteria to determine how effective the NSGA-II approach was. Based on the data gathered, the standard average of MID is 6.56. As such, the results of the proposed solution technique may be trusted to handle complicated problems. Figures 5 and 6 show the times needed to solve small-, medium-, and large-scale problems. It is evident that the solution time of the Epsilon constraint approach increases faster than that of the NSGA-II method. However, the increase in solution time is the steadier level in the NSGA-II technique.

Table 4- Performance evaluation standards.

MID
0
6.13
6.16
6.32
6.51
6.59
6.65
6.76
6.81

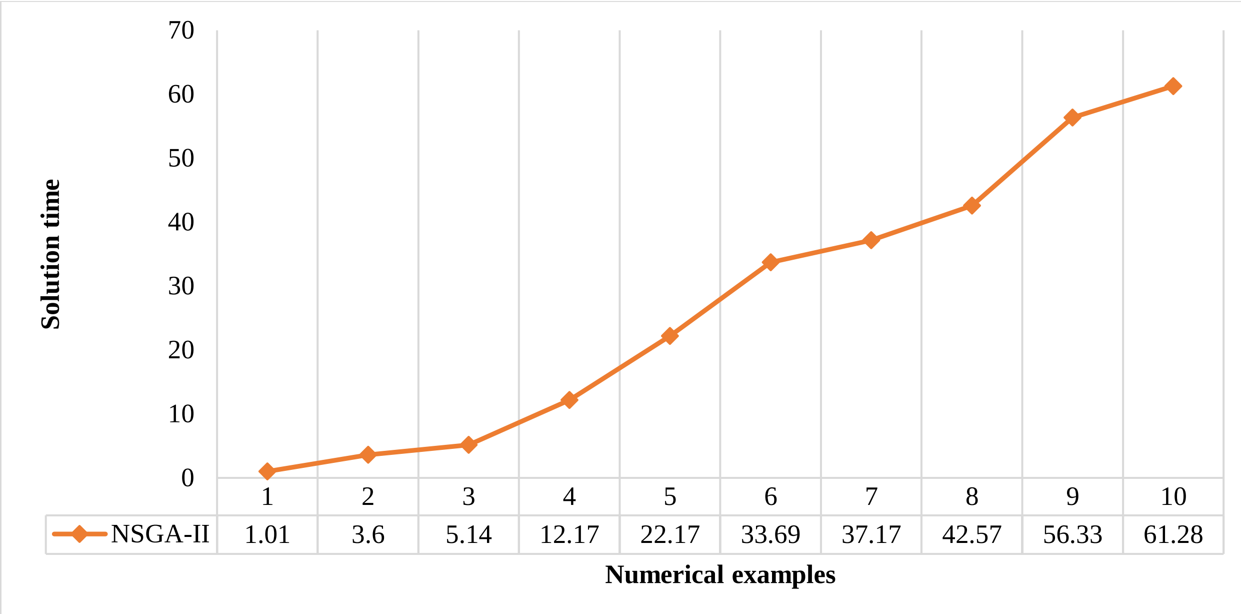


Figure 5. Solution time in NSGA-II method.

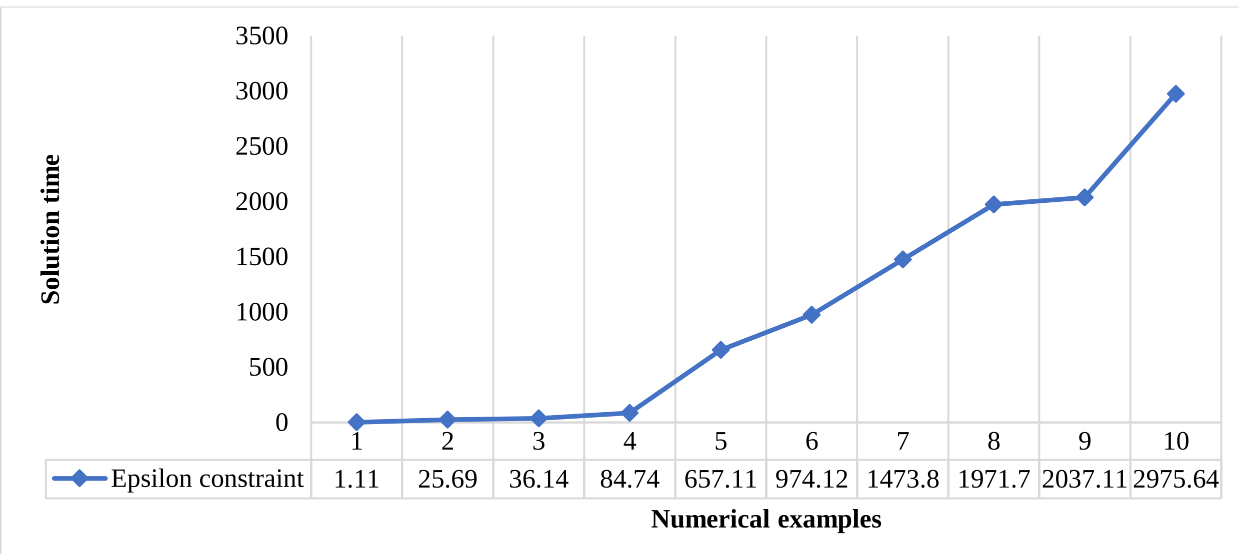


Figure 6. Solution time in Epsilon constraint method.

4.2. Calibration analysis

As a pilot effort, this research involved five suppliers, five different product variations, four distributors, five collection sites, 10 key consumers, and the plastics industry. Following the procurement of the raw materials, plastic nylon is manufactured and supplied to customers. After that, purchasers gather the trash and classify it as scrap material based on its quality. Some of these wastes are recycled so they may be used again, while some are buried. Through the mitigation of the environmental externalities resulting from the set goals, our study seeks to ameliorate the social repercussions. Table 5 displays the numerical outcomes of applying the mathematical model to the real inquiry.

Based on scenarios of boom and recession, Table 5 shows the amount of product supply flow to industrial locations for each time period. The first scenario is said to depict a boom, whereas the second is thought to depict a recession. The findings demonstrate that, in the case of a recession, the shipping flow between the first production and supply centers would be equal to 98 and 124 throughout the course of two periods. This is despite the fact that under the boom scenario, this flow transfer equals 124 and 395.

Table 5- The product flows from supplier center to producer centers.

Type/ cycle Producer and supplier	Type 2- Cycle2	Type2- Cycle1	Type1- Cycle2	Type1- Cycle1
Supplier1 – Producer 1	98	124	124	365
Supplier1 – Producer 3	258	279	419	478
Supplier2- Producer 2	457	364	574	578
Supplier2- Producer 4	689	398	916	574
Supplier3- Producer 1	367	405	589	368
Supplier3 – Producer 4	714	458	1287	475
Supplier4 – Producer 3	513	517	873	366
Supplier4 – Producer 4	657	598	987	314
Supplier5 – Producer 2	698	687	573	755
Supplier5 – Producer 5	547	697	429	719

4.3. Sensitivity analysis

We adjust the basic parameters of the model in this section of the study to assess the effects of these adjustments on the value of the objective function. Figure 7 shows the number of centers that can be built to build recycling centers in response to increasing demand. Recessions make this problem much more common. For example, the number of recycling facilities that can be built increases from one to three if demand increases by 5%.

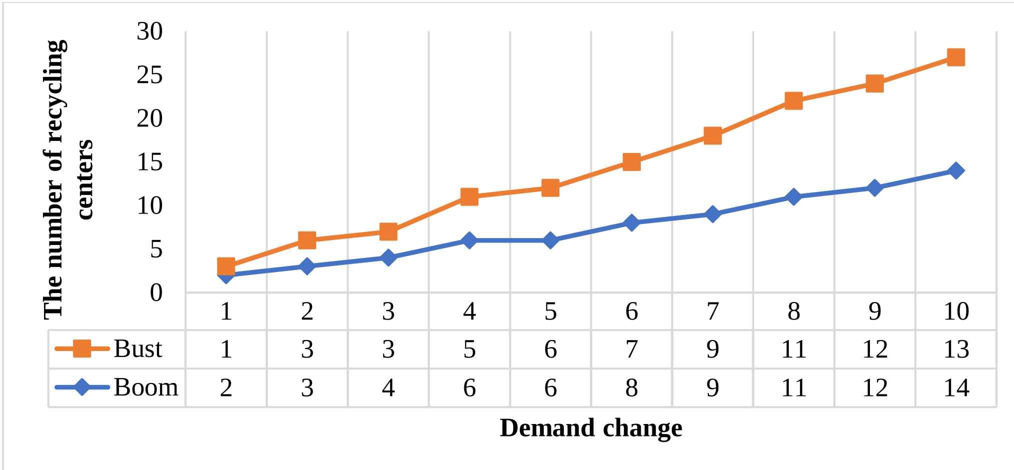


Figure 7. Changing demand and its effect to the costs

Figure 8 illustrates how, in two deterministic and fuzzy model scenarios, the total costs alter in response to variations in demand. As can be shown, in two scenarios, the overall costs grow as demand rises. Expenses in an uncertain scenario are more than those in a predictable one. Furthermore, compared to a deterministic environment, a fuzzy environment has a larger cost rise due to an increase in demand.

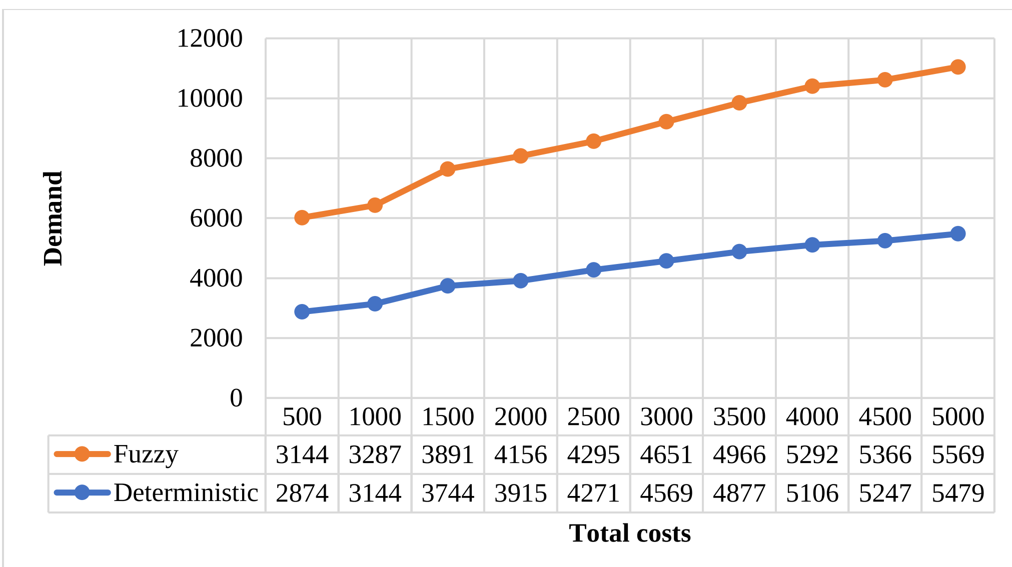


Figure 8. The impact of changing demand on expenses in fuzzy and deterministic models.

In the realm of Supply Chain Management, there have been recent illuminations that have sparked discourse and reflection among scholars and practitioners alike. One such conceptualization is Factor Market Rivalry (FMR), which delves into the notion of fierce competition for essential resources within the supply chain landscape.

This theory underscores the nuances involved in managing material flows, temporal dimensions, and inter-firm dynamics within the intricate web of supply chain interactions.

Complementing this perspective is the Theory of the Supply Chain, a framework that probes into the very structure and boundaries that define these interconnected systems. By offering fundamental principles regarding configuration, this theory lays a critical foundation for advancing our understanding of SCM's complexities. Moreover, the Resource-Based View (RBV) beckons us to consider how an organization's reservoir of resources and capabilities can be leveraged to carve out a distinctive competitive edge. Within SCM circles, RBV sheds light on how strategic value can be derived from optimizing supply chain networks.

These theoretical musings not only broaden our intellectual horizon but also pave new pathways for enhancing operational efficiencies and strategic decision-making within contemporary supply chains.

The stakeholder theory posits that every individual or entity involved in a supply chain, whether it be suppliers, customers, or the society as a whole, holds a vested interest in its operations. This theory advocates for companies to actively cultivate and maintain relationships with all stakeholders in order to foster sustainable practices within their supply chain.

In contrast, Institutional Theory delves into the impact of external institutions – encompassing cultural norms, legal systems, and industry regulations–on the organizational structure and behavior of firms operating within a supply chain. It emphasizes the significance of these institutional frameworks in shaping business strategies and decisions.

Meanwhile, Transaction Cost Theory delves into the intricate analysis of transactional expenses incurred throughout various interactions within a supply chain. By exploring the implications behind choices between purchasing goods externally versus internally producing them alongside selecting appropriate governance structures, this theory aids in comprehending the underlying trade-offs inherent in such decision-making processes.

Lastly, Resource Dependence Theory scrutinizes how organizations rely on acquiring resources from their surroundings and delineates how this reliance influences their conduct. Within supply chain management specifically, it entails navigating through interdependencies amongst partners while assessing power dynamics, to streamline resource allocation effectively across interconnected entities.

- The use of artificial intelligence in supply chain management can enhance performance and competitive advantage.
- AI technologies can optimize inventory management, demand forecasting, routing and delivery, quality control, and overall operational efficiency.
- AI-powered systems can analyze large volumes of data, identify patterns, and generate actionable insights for more accurate decision-making.
- AI can improve supply chain visibility, enabling real-time tracking, monitoring, and risk assessment.[64]

  Effective supplier selection is crucial for the success of supply chain management in today's competitive business environment.
- The paper focuses on Multi-Criteria Decision-Making (MCDM) methods for supplier selection within the supply chain context.
- Various MCDM techniques are explored, highlighting their benefits and limitations in supplier selection.

  The study includes numerical results from a case study to demonstrate the practicality and effectiveness of the MCDM approach, offering insights for supply chain managers [65].

5. Discussion and managerial insights

The suggested model has been solved using two methods: epsilon, constraint, and genetics, based on the study's numerical results. Model solving takes less time with the epsilon approach than with the meta-heuristic strategy. The calculation error between the meta-heuristic algorithm and the limit epsilon method in small and medium dimensions for the first and third objective functions, which is less than 1% and less than 6%, respectively, provides additional proof that the meta-heuristic algorithm in large dimensions is a valid limit for problem solving rather than the epsilon method. Moreover, the meta-heuristic approach's traditional mean of MID is 6.56.

The results show that under the recession scenario, the shipping flow from supply center number 1 to production center number 1 is equivalent to 98 and 124 throughout the course of two periods. This is in spite of the fact that this flow transfer equals 124 and 395 in the boom scenario. It has been noted that for both deterministic and fuzzy models, a rise in demand results in an increase in overall costs. Expenses in an uncertain scenario are more than those in a predictable one. Furthermore, compared to a deterministic environment, a fuzzy environment has a larger cost rise due to an increase in demand.

As previously said, creating a multi-objective mathematical model of a multi-product sustainable CLSC network while taking the risk of interruption under unknown situations is one of the challenging and complex issues in the field of supply chain management (SCM).

Key management takeaways in this situation include increasing productivity, fostering flexibility, promoting sustainability, balancing performance and cost, managing risks, facilitating cooperation, strategizing, minimizing energy use, utilizing technology, and ensuring transparency. Productivity involves efficient resource use, flexibility allows systems to adapt to the environment, sustainability promotes process, financial, environmental, and social sustainability, optimism balances performance and cost, risk management involves recognizing and quantifying risks, cooperation facilitates coordination, and strategic planning enhances an organization's competitiveness. Energy efficiency minimizes energy use, technology enhances sustainability and performance, and transparency preserves informational and procedural transparency to win over clients and company associates.

6. Conclusion

This paper presents a multi-objective MILP model for designing sustainable CLSCNs under disruption risks and uncertainty. The model incorporates economic, environmental, and social sustainability objectives along with expected cost minimization and network resilience maximization. We employ scenario-based stochastic programming to address uncertainties in demand, return rates, and disruption probabilities. The numerical results demonstrate the model's effectiveness in providing decision-makers with valuable insights for optimizing a sustainable and resilient CLSCN.

Sustainable closed-loop supply chains (CLSCs) offer a promising approach to resource conservation and environmental protection. However, these networks face challenges due to potential disruptions and inherent uncertainties. This study addressed these challenges by developing a multi-objective mathematical model for a multi-product sustainable CLSC network that considers disruption risks under uncertain conditions [54-62].

The findings demonstrate the effectiveness of the proposed model. We compared two methods for solving the model: the epsilon constraint method and a genetic algorithm. The genetic algorithm proved to be faster and more reliable for large-scale problems, while offering comparable solutions for smaller problems. The model also highlights the significant impact of demand on costs. Both deterministic and fuzzy models (accounting for uncertainty) showed increased costs with higher demand, with the fuzzy model experiencing sharper cost increases [54-58].

This research offers valuable managerial insights for designing and operating sustainable CLSCs under uncertainty. Building a model that incorporates disruption risks is crucial for building resilience. Managers should prioritize improving resource productivity, system flexibility, and all aspects of sustainability (financial, environmental, social, and process). It's also critical to optimize both internal and external operations while maintaining a balance between performance and cost. Ultimately, the effectiveness of sustainable CLSCs may be further increased by emphasizing risk management, teamwork, planning, energy efficiency, technology adoption, and transparency [58–62].

In future research, the model can be extended to incorporate additional complexities, such as different types of disruptions or more sophisticated uncertainty representations. Additionally, real-world case studies can be employed to validate the model's effectiveness in practical applications. By continuously refining these models and applying them in real-world scenarios, we can move closer to achieving sustainable and resilient closed-loop supply chains.

- Under the expansive canopy of Supply Chain Management lies an intricate web that orchestrates the symphony of goods, services, and information from their nascent raw material forms to their ultimate destination in the hands of consumers. This realm is comprised of various phases that delineate the journey: meticulous planning, strategic sourcing, adept production processes, seamless distribution channels, and the often overlooked but crucial element - returns management.
  Amidst this labyrinthine landscape emerge novel theories that seek to unravel the enigmatic complexities inherent in supply chains. Factors like Market Rivalry come into play as competition for vital resources ensues within these interconnected networks. The Theory of the Supply Chain sheds light on its very structure and delineates its boundaries with precision. Meanwhile, proponents of the Resource-Based View theory espouse that competitive advantage springs forth from judicious use of resources and capabilities.
- In this grand tapestry known as Supply Chain Management, Stakeholder Theory serves as a guiding principle - advocating for harmonious relationships with all parties involved to

ensure sustainability at every step. Institutional Theory posits how external institutions exert influence over firms nestled within this supply chain ecosystem.

- Transaction Cost Theory elucidates on monetary expenses incurred during transactions while delving into governance structures implemented in SCM practices. Furthermore, Resource Dependence Theory unveils insights into managing dependencies amongst partners and navigating power dynamics present within these intricate alliances. In essence, these new theoretical frameworks offer a panoramic view into realms previously unexplored within the ethereal domain of Supply Chain Management.

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