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Research article

Optimization of a bi-objective sustainable supply chain model under uncertainty based on the Internet of Things

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Abstract: Environmental uncertainties present significant challenges to sustainable supply chain management (SSCM), and often result in elevated costs, unsustainable production practices, and operational disruptions. In this study, we present a novel sustainable supply chain model with multiple objectives, utilizing the Golden Eagle Algorithm (GEA) for optimization. The model simultaneously addressed economic, environmental, and operational objectives, which included production, transportation, inventory management, shortages, recycling, and pollution mitigation. To manage the inherent complexity and uncertainty of decision variables, a descriptive-analytical research methodology was employed. Given the large-scale, NP-hard nature of the problem, exact solution methods, or commercial optimization software, such as GAMS and Simplex, proved infeasible. The GEA was implemented with parameters calibrated via the Taguchi method (Max Iterations = 23, Population Size = 40, Attack Propensity = 1.7–2, Cruise Propensity = 0.5–1). Ten randomly generated problem instances were used to rigorously evaluate algorithmic performance. Algorithm performance was assessed using multiple metrics, including MID (convergence), DM, NPS, and SNS (diversity and spread). Our results demonstrated that the GEA effectively explored the solution space, avoids local optima, and produces high-quality solutions. In smaller-scale problems (Example 8), the algorithm exhibited superior computational efficiency, whereas in larger-scale instances (Example 10), it achieved enhanced solution diversity (high DM) alongside effective convergence. These findings indicated that the model is feasible, robust, and practically applicable, and provides supply chain managers with a trustworthy tool to support their decision-making. Furthermore, the model's efficiency was demonstrated through numerical calculations.

Keywords: golden eagle algorithm; sustainable supply chain; customer satisfaction; robust; Iot
Mathematics Subject Classification: 00A06, 90C70, 65K10

1. Introduction

In today's volatile, economically uncertain global environment, firms tend to be more conservative in their expansion and investment decisions. As a result, rather than pursuing aggressive growth, many companies have shifted their attention to building environmentally responsible, long-term, sustainable supply chains. A green supply chain emphasizes integrating eco-friendly practices throughout the product lifecycle, including resource extraction, production, distribution, consumption, and end-of-life recovery. This approach emphasizes responsible resource use, environmental protection, the reduction of harmful production activities, and, ultimately, the optimization of economic and environmental benefits [1]. Given the increasing environmental degradation and pollution caused by industrial waste, the quality of people's lives is a significant concern.

Traditionally, the primary focus of supply chain leaders has been on their organizations' financial goals, with limited emphasis on environmental and social considerations. This lack of attention to critical non-economic factors has resulted in a significant oversight concerning the broader impacts an organization may have on its surroundings. However, given contemporary developments in the business landscape over the last decade, it has become evident that pursuing purely economic motives is not a prudent way to ensure an organization's sustainability and long-term profitability [2].

Sustainable supply chain management provides numerous benefits to organizations, including reducing risks and environmental pollution [3] and improving customer relationships [4,5]. Nonetheless, designing a sustainable supply chain presents an important obstacle, as the conventional focus of supply chain design centers on economic considerations, primarily cost reduction. Nevertheless, incorporating environmental and social dimensions into the equation may increase costs, pointing to the importance of optimizing SSC. A resilient, sustainable supply chain ensures consistent operations during uncertain conditions, reducing the risks linked to disruptions and inefficiencies [6]. In sustainable supply chain management, businesses rely on a range of techniques, technologies, and managerial practices to make their supply chains more environmentally and socially sustainable [7].

Uncertainty across the supply chain landscape poses significant risks and can negatively impact overall performance. The inherent complexity of supply chains often results in the inability to determine and specify critical parameters accurately. Multiple factors contribute to these uncertainties, such as parameter variability, ambiguous decisions, and the lack of essential data [8]. Furthermore, increasing demand volatility and the dynamic nature of economic environments complicate the development of environmentally friendly and sustainable supply chains and pose significant research challenges. Reduced investment resulting from economic uncertainty makes it harder for companies to adopt new technologies or materials. Traditional sustainable supply chains face multiple obstacles, including vulnerability, complexity, cost, and uncertainty. Implementing IoT helps improve environmental sustainability while reducing operational costs.

The goal of sustainable supply chain management is to preserve resilience in the face of unpredictability while optimizing social, environmental, and economic performance. Although researchers have primarily focused on economic and environmental indicators, a comprehensive sustainability assessment also requires attention to social dimensions, including employee welfare, community responsibility, and ethical practices. Incorporating these social factors into operational indicators enables a more holistic evaluation of supply chain performance.

Adopting IoT introduces additional sources of uncertainty, such as data transmission delays, equipment failures, and information distortions, which can propagate across procurement, production, and recycling stages. Accounting for these uncertainties is essential to developing robust, resilient supply chain strategies that can effectively respond to real-world operational challenges.

Economic downturns may reduce consumer demand for environmentally friendly products, as affordability becomes a higher priority. Disruptions such as machinery failures, fires, currency fluctuations, wars, and pandemics can further constrain production, distribution, and recycling capabilities. Additionally, customer returns may increase when product quality falls short of expectations. These challenges highlight the importance of sustainable, resilient, and adaptable supply chains that maintain operational continuity under uncertainty.

Mathematical models can help address these complex problems, but large-scale instances often require innovative solution approaches. The proposed model incorporates multiple real-world considerations, including customer satisfaction, capacity reductions due to disruptions, product returns, IoT-related uncertainties, and demand fluctuations driven by inflation. To efficiently solve large-scale NP-hard problems, we introduce the Golden Eagle Algorithm (GEA).

Global supply chains face increasing challenges due to environmental uncertainty, economic volatility, and operational disruptions. Traditional supply chain management has primarily focused on cost reduction, often neglecting environmental and social considerations. In contrast, sustainable supply chain management (SSCM) emphasizes responsible resource utilization, environmental protection, and system resilience, while balancing economic, environmental, and social objectives.

Although sustainable supply chain management (SSCM) has received growing attention, designing supply chains that remain sustainable under uncertainty remains a major challenge. Key sources of uncertainty include demand fluctuations, capacity disruptions, product returns, and the dynamic adoption of IoT technologies. Effectively addressing these factors is essential for achieving resilient, cost-effective, and environmentally sustainable operations.

Optimization models for SSC often fail to incorporate all relevant sources of uncertainty or are limited to small-scale problems that can be solved using methods such as GAMS or Simplex. However, large-scale NP-hard problems require advanced metaheuristic approaches. In this study, we propose a GEA-based optimization framework for large-scale SSC problems that integrates IoT-enabled data, customer satisfaction parameters, and multi-level disruptions to provide a realistic and robust representation of modern supply chains. The major contributions of this study are as follows:

1. Design a multi-objective sustainable supply chain model that simultaneously reduces costs and environmental impacts while accounting for uncertainty.
2. Integration of IoT data, capacity disruptions, product returns, and inflation-driven demand variability into the model.
3. Application of the Golden Eagle Algorithm (GEA) to efficiently solve large-scale NP-hard SSC problems.

4. Execution of comprehensive numerical experiments to evaluate algorithm performance and derive managerial insights.

This study offers practical advice for managers looking to improve supply chain resilience, cost effectiveness, and environmental sustainability in complex and uncertain operational contexts.

2. Literature Review

Improving supply chains with a focus on sustainability means finding ways to generate profits while protecting the environment and benefiting society. The increasing challenges in SSCM, including demand fluctuations, production and logistics disruptions, customer-driven product returns, and environmental sustainability pressures, demand comprehensive approaches that account for the interplay of risks, uncertainties, and emerging technologies. For instance, Yang et al. (2025) introduced an integrated framework combining Total Interpretive Structural Modeling (TISM), MICMAC analysis, and Complex Network Theory to identify and assess hierarchical relationships among critical risk factors in the vaccine supply chain. Their findings emphasize that understanding the structural dependencies among risk components enhances system robustness and resilience; insights directly applicable to SSCM amid uncertainty. [9]. Such frameworks offer a robust methodological basis for analyzing compound risks and developing strategies that concurrently enhance efficiency and sustainability.

2.1. Cost Optimization and Environmental Performance

Researchers have narrowly concentrated on cost minimization and environmental mitigation [5,10,11]. For example, John et al. [10] introduced an MILP model that accounted for transportation-related carbon emissions but ignored emissions from production and maintenance. Likewise, Homayouni et al. (2021) focused on economic objectives while neglecting critical uncertainties, such as demand volatility and supply disruptions. These studies offer useful groundwork, but their limited integration of operational, environmental, and uncertainty factors significantly restricts their relevance to complex, real-world sustainable supply chains.

2.2. Demand Uncertainty and Inflation Effects

Demand variability, driven by market conditions and macroeconomic factors such as inflation, makes it difficult to operate sustainable supply chains. Researchers rarely investigate the combined effects of demand uncertainty, IoT-enabled monitoring, and capacity disruptions. Overlooking these interactions can lead to strategies that lack resilience under realistic operational conditions, highlighting a critical research gap in accurately modeling supply chain dynamics. The parameters that have been employed in previous research by various scholars are as follows: Modak and Kelle [12] (consumer demand), Jabbarzadeh et al. [13] (market demand), Shaw et al. [14] (demand), Golpîra et al. [15] (demand for market-related information), Zahiri et al. [16] (demand) and Heidari-Fathian et al. [17] (demand for blood products).

2.3. Disruptions and Multi-Echelon Capacity Reductions

Supply chain disruptions, including supplier failures, production halts, and logistics delays, can profoundly impact overall performance. Researchers often address disruptions in isolation without accounting for capacity reductions across echelons or incorporating IoT-enabled strategies for real-time mitigation. This limitation diminishes the practical applicability of current models, particularly in large-scale supply chains, where disruptions propagate across nodes and operational stages. Studies indicate that disruption capacity is rarely addressed in sustainable supply chains. For example, Afshar et al. [18] developed a mathematical model for a multi-product, multi-level closed-loop supply chain (SSC) that incorporates disruption risk under conditions of uncertainty. Additionally, Nagasawa [19] investigated the design of a robust closed-loop supply chain with backup suppliers to mitigate disruption risks.

2.4. Product Returns and Customer Satisfaction

Researchers have given limited attention to returns driven by customer perceptions of product quality. Although Barman et al. [20] and Fernando et al. [21] studied return strategies, a detailed assessment of the relationships among returns, customer experience, and sustainable supply chain outcomes remains lacking. Addressing this issue is crucial to creating supply chains that can dynamically adjust to product quality issues.

2.5. IoT Integration in SSCM

IoT technologies enhance traceability, real-time monitoring, and responsiveness in supply chains. Despite their demonstrated potential, the integration of IoT into large-scale SSCM optimization models remains limited. Most researchers implement IoT solutions in isolated operational contexts, rather than within comprehensive frameworks that simultaneously address multi-dimensional uncertainties and large-scale optimization challenges. To fill this gap, Goli et al. [22] developed an integrated optimization model for the adaptive design of IoT-based supply chain networks. In addition, Al-Khatib [23] examined the impact of industrial IoT on long-term performance outcomes.

2.6. Approaches to Uncertainty in SSCM

Uncertainty in SSCM has been addressed using fuzzy, stochastic, and robust optimization methods. Although these techniques offer valuable insights, they are inadequate for solving large-scale NP-hard SSCM problems, which demand adaptive, flexible metaheuristic algorithms capable of handling high-dimensional complexity. The absence of such approaches represents a significant methodological deficiency in the literature. Several authors have employed uncertainty-based approaches in their studies. For instance, Shahbazbeigian et al. [24], Ahmed et al. [25] and Talaei [26] utilized a fuzzy approach; Mohseni et al. [27], Bairamzadeh et al. [28], Sherafati et al. [29], Homayouni et al. [5], Dehghani et al. [30] and Khosrojerdi et al. [31] applied a robust approach; Jabbarzadeh et al. [13], Fattahi and Govindan [32] adopted a random approach.

2.7. Research Gap Summary

Although prior research provides valuable insights, significant gaps remain:

- Integration of multiple sources of uncertainty (demand, inflation, disruptions, and quality-driven returns).
- Consideration of multi-echelon capacity reductions.
- Incorporation of IoT-enabled mitigation strategies.
- Application of advanced metaheuristic algorithms for large-scale SSCM optimization.

In this research, we tackle the shortcomings in the literature by designing a robust SSCM optimization approach that explicitly encompasses:

- The compound effects of inflation on demand.
- Quality-driven product returns and their impact on customer satisfaction.
- IoT-enabled resilience strategies for managing multi-echelon disruptions.

By incorporating these dimensions, the proposed model delivers methodological advancements and practical insights, establishing a solid foundation for decision-makers aiming to develop sustainable, resilient, and efficient supply chains amidst uncertainty.

3. Problem Definition

To our knowledge, no researcher has comprehensively addressed the integrated issues encompassed by the proposed model. Therefore, we delineate the primary focus of this pioneering investigation as follows:

- **Impact of Inflation on Demand:** We investigate how inflation affects customer demand within a closed-loop sustainable supply chain framework.
- **Quality, Customer Satisfaction, and Product Returns:** We emphasize the critical role of maintaining high-quality standards to enhance customer loyalty and minimize product returns.
- **Disruption Capacity:** Capacity reduction is incorporated as a key factor to simulate the effects of disruptions under uncertain conditions.
- **IoT Integration:** Using IoT capabilities enables ongoing data collection and informed decision-making, thereby substantially improving supply chain efficiency and environmental sustainability.
- **Golden Eagle Algorithm Robustness:** The robustness of the Golden Eagle Algorithm is essential for effectively solving complex, uncertain, large-scale SSCM problems.

Figure 1 displays the related conceptual model.

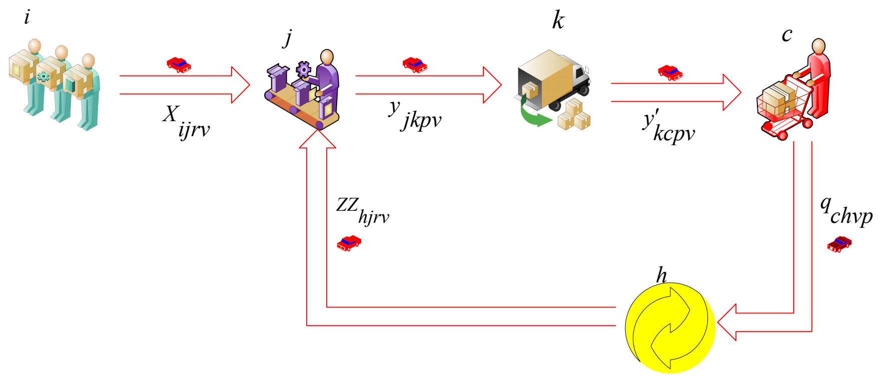

Figure 1. Conceptual Model.

3.1. Mathematical model

3.1.1. Assumptions

1. **Operational Disruptions:** All layers of the sustainable supply chain (SSC) are susceptible to operational disruptions. When disruptions occur, IoT-enabled monitoring systems dynamically update the effective capacity of each layer in real time.
2. **Supply Chain Structure:** The SSC consists of four forward layers, suppliers, factories, distribution centers, and customers, and one reverse recycling layer, reflecting circular manufacturing structures commonly observed in the electronics and home appliance industries.
3. **Product Returns and Quality Control:** Customers return products that fail to meet quality standards. IoT-based quality monitoring classifies returned items and determines appropriate recycling or reprocessing actions.
4. **Modeling Uncertainty:** Operational parameter uncertainties are represented using a stochastic Mulvey scenario framework combined with robust optimization techniques.
5. **Dynamic Parameter Updates:** Demand, capacity-reduction rates, and supply availability are uncertain and dynamically updated based on IoT sensor data. These uncertainties are modeled using interval-based robust parameters.
6. **Cost Uncertainty:** Transportation and shipping costs vary due to fluctuations in energy prices, market conditions, and route reliability.
7. **IoT-Induced Uncertainty:** IoT systems introduce additional uncertainties, such as sensor errors, data latency, and communication failures, which affect quality inspection and decision-making within the SSC.
8. **Environmental Pollution Measurement:** Pollution is quantified across stages, including:
a. Emissions from transportation vehicles.
b. Emissions from factory production activities.
c. Pollution generated during material handling in the recycling process.
9. **Objective Function Complexity:** The objective function incorporates nonlinear cost components, capturing the complex interactions among economic, environmental, and operational variables.

10. **Dynamic IoT Parameters:** All IoT-enabled parameters, including capacity availability and supply reliability, are updated dynamically, rather than treated as fixed values, ensuring consistency with the uncertainty modeling framework.

According to Table 1, the decision indices are as follows:

Table 1. Decision indices.

Index	Group
$s, s' \in S$	Set of scenarios
$i \in I$	Group of suppliers
$j \in J$	Factory collection
$k \in K$	Distributor collection
$c \in C$	Customer collection
$v \in V$	Vehicle collection
$h \in H$	The collection of recycling centers
$t \in T$	Period series
$p \in P$	Product collection
$r \in R$	Collection of raw materials

3.1.2. Parameters

Cx_{ijrvt} : The shipping cost of transporting material (r) from supplier (i) to factory (j) within period (t) using vehicle (v).

IoT_t: Indicates the lack of access to the Internet of Things (IoT) during period (t).

Yi_{ts}: A binary variable representing access to the Internet of Things during period (t), where 1 indicates access and 0 indicates no access.

Czz_{hjrvt} : Shipping cost of materials r from the recycling center h to the factory j within period t using vehicle v.

Cq_{chpvt} : Shipping cost of returned products p from customer c to the recycling center h within period t using vehicle v

Cy'_{kcpvt} : Shipping cost of products p from the distribution center k to customer c within period t using vehicle v.

Cy_{jkpvt} : Shipping cost of products p from factory center j to distributors k within period t using vehicle v.

λ_{rp} : Conversion rate of raw material r to products p.

CI_{jpt} : Inventory cost of the products p at factory j within period t.

CIK_{kpt} : Inventory cost of products p at distributors k within period t.

CIH_{hrt} : Inventory cost of raw material r at recycling center j within period t.

D_{cpts} : Non-deterministic demand for products p from customer c in period t under scenario s.

$capJ_{jpt}$: Factory capacity j for products p within period t.

$capK_{kpt}$: Capacity of the distributors k for products p within period t.

$capH_{hpt}$: Capacity of recycling center h for products p within period t.

φ_{rp} : Percentage of raw materials r that is recyclable from products p.

α_{cp} : Percentage of product (p) demand from customer c directed to recycling.
γ_{vp} : Pollution generated by vehicle (v) per unit of the product (p).
γ'_{vr} : Pollution generated by vehicle (v) per unit of raw material (r).
βJ_{jpts} : Capacity reduction rate due to disruption for factory j and product p within period t under scenario s.
βK_{kpts} : Capacity reduction rate due to disruption for distributor k and products p within period t under scenario s.
βH_{hpts} : Capacity reduction rate due to disruption for recycling center h and products p within period t under scenario s.
η_t : Inflation rate during period t.
P_{pt} : Selling price of products p within period t.
CS_{jpt} : Shortage cost of products p at factory j during period t.
CSK_{kpt} : Shortage cost of products p at distributors k during period t.
CSH_{hrt} : Shortage cost of raw material r at recycling center h during period t.
Bd_t : Total budget for period (t).
q'_{kpt} : Quality of products p for distributor k during period t.
Q_{cpt} : Minimum required quality of products p for customer c within period t.
pp_s : Probability of each scenario.
ω : Unjustified weight of the model.
YJ_j : If factory j is selected 1, otherwise 0.
YK_k : If distributor k is selected 1, otherwise 0.
YH_h : If recycling center h is selected 1, otherwise 0.
yy_{kcpt} : If product p is shipped from distribution center k to customer c in period t, 1, otherwise, 0.
Z_{kcpt} : If the quantity of product (p) delivered from distribution center (k) to customer (c) in period (t) does not meet the minimum quality requirement, the variable takes the value 1; otherwise, it equals 0.

3.1.3. Variables

I_{jpts} : Inventory of product *p* at factory *j* during period *t* under scenario *s*.
IoT_{ts} : Lack of access to the Internet of Things during period *t* under scenario *s*.
S_{jpts} : Shortage of product (p) at factory (j) during period (t) under scenario (s).
IK_{kpts} : Inventory of product *p* at distributor *k* during period *t* under scenario (s).
IH_{hrts} : Inventory of raw material *r* at recycling center *h* during period (t) under scenario (s).
SK_{kpts} : Shortage of product *p* at distributor's *k* during period *t* under scenario *s*.
SH_{hrts} : Shortage of raw materials *r* at recycling center *h* during period *t* under scenario *s*.
x_{ijrvts} : Shipment volume of raw material *r* from supplier *i* to factory *j* during period *t* using vehicle *v* under scenario *s*.
zz_{hjrvts} : Shipment volume of raw material *r* from recycling center *h* to factory *j* during period t using vehicle v under scenario s.

q_{chvpts} : Returned amount of product p from customer c to recycling center h during period t using vehicle v under scenario s.
y'_{kcpvts} : Shipment amount of product p from distribution center k to customer c during period t using vehicle v under scenario s.
y_{jkpvts} : Shipment amount of product p from factory j to distributor k during period t using v under scenario s.
D'_{cpts} : Demand for product p by customer c during period t under scenario (s), considering the inflation rate.
ξ_s : The value of the objective function for each scenario, irrespective of its probability.
θ_s' : Difference between the objective function value and its mean for each scenario.
$\eta^1_{irts}, \eta^2_{jpts}, \eta^3_{kpts}, \eta^4_{hpts}, \eta^5_{cpts}$: Value of constraint violation from an uncertain parameter, reflecting the unjustified nature of the model.

3.1.4. Decision variables

$$Ij_{pts}, Sj_{pts}, IK_{kpts}, IH_{hrts}, SK_{kpts}, SH_{hrts}, x_{ijrvts}, zz_{hjrvts}, q_{chvpts}, y'_{kcpvts}, y_{jkpvts}, D'_{cpts} \geq 0$$
$$yy_{kcpts}, Z_{kcpts}, Yi_{is}, YK_k, YJ_j, YH_h \in \{0,1\}$$
$$\theta_s', \eta^1_{irts}, \eta^2_{jpts}, \eta^3_{kpts}, \eta^4_{hpts}, \eta^5_{cpts} \geq 0$$

Since some parameters in the objective function are uncertain in the mathematical programming problem, obtaining an optimal solution is not straightforward. Robust optimization is a developed method for addressing parameter uncertainty in optimization problems. This approach aims to find near-optimal solutions that remain feasible with ahigh probability under varying conditions. In this study, we adopt Mulvey's approach as a reliable method given the model's scenario-based nature. Below, we present the scenario-based mathematical formulation of the two objective functions using Mulvey's model. It is essential to note that the novel contribution of this study resides in the application of Mulvey's model within a bi-objective (two-objective) optimization framework.

3.1.5. Objective function

We develop a multi-objective mathematical model that simultaneously minimizes total economic costs and environmental pollution across the closed-loop supply chain. The environmental objective has been expanded to include emissions from transportation, manufacturing, and recycling processes, which provides a more comprehensive evaluation of environmental impacts.

Objective 1 – Economic Cost Minimization

Min Z (1) = Total production cost + transportation cost + inventory holding cost + product shortage cost + recycling costs

Where the variables are:

- Production costs
- Transportation costs between factories, distributors, customers, and recycling centers
- Inventory holding costs at factories, distributors, and recycling centers
- Product shortage costs
- Recycling and handling costs

This objective corresponds to Part 1 (Optimality), which aims to minimize inventory levels and all economic expenses in each period.

$$F1_{ts} = \sum_{j\in J}\sum_{p\in P}(I_{jpts}.CI_{jpt} + S_{jpts}.CS_{jpt}) + \sum_{k\in K}\sum_{p\in P}(IK_{kpts}.CIK_{kpt} + SK_{kpts}.CSK_{kpt})$$
$$+\sum_{h\in H}\sum_{r\in R}(IH_{hrts}.CIH_{hrt} + SH_{hrts}.CSH_{hrt}) + \sum_{j\in J}\sum_{i\in I}\sum_{v\in V}\sum_{r\in R} x_{ijrvts}.Cx_{ijrvt}$$
$$+\sum_{j\in J}\sum_{h\in H}\sum_{v\in V}\sum_{r\in R} zz_{hjrvts}.Czz_{hjrvt} + \sum_{c\in C}\sum_{h\in H}\sum_{v\in V}\sum_{p\in P} q_{chvpts}.Cq_{chvpt}$$
$$+\sum_{j\in J}\sum_{k\in K}\sum_{v\in V}\sum_{p\in P} y_{jkpvts}.Cy_{jkpvt} + \sum_{c\in C}\sum_{k\in K}\sum_{v\in V}\sum_{p\in P} y'_{kcpvts}.Cy'_{kcpvt}$$

$$F2_s = \sum_{j\in J}\sum_{h\in H}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T}\gamma'_{vr}.zz_{hjrvts} + \sum_{c\in C}\sum_{h\in H}\sum_{v\in V}\sum_{p\in P}\sum_{t\in T}\gamma_{vp}.q_{chvpts} + \sum_{j\in J}\sum_{i\in I}\sum_{v\in V}\sum_{r\in R}\sum_{t\in T}\gamma'_{vr}.x_{ijrvts}$$
$$+\sum_{j\in J}\sum_{k\in K}\sum_{v\in V}\sum_{p\in P}\sum_{t\in T} y_{jkpvts}.\gamma_{vp} + \sum_{c\in C}\sum_{k\in K}\sum_{v\in V}\sum_{p\in P}\sum_{t\in T} y'_{kcpvts}.\gamma_{vp}$$

Objective 2 – Environmental Pollution Minimization

To address the reviewer's concern regarding insufficient completeness, the environmental objective has been expanded to quantify emissions from three main sources: transportation, production, and recycling/handling activities.

Min Z(2) = Emissions from transportation + Emissions from factory processes + Emissions from recycling/handling

Where the variables are:

- Emissions from shipping products and returned items in each scenario
- Emissions from factory processes (e.g., exhaust gases during manufacturing)
- Emissions from recycling operations and material-handling activities

This objective corresponds to Part 2 (Feasibility) and provides a complete and multi-process environmental assessment.

The first objective function, economic cost minimization, aims to minimize the total system cost under each scenario. $Min(A1_s) = \sum_{t\in T}(F1_{ts}) \quad \forall s \in S$

The second objective function, environmental pollution minimization, aims to minimize the total amount of environmental pollution under each scenario. $Min(A2_s) = F2_s$

When combining the first and second objective functions using a weighted approach, the formulation becomes: $\xi_s = \left(w_1.A1_s + w_2.A2_s\right) \quad \forall s \in S$

3.1.6. Constraints

$$\sum_{v\in V}\sum_{j\in J} x_{ijrvts} - \eta^1_{irts} \le (1 - IoT_{ts}).YI_{is} \qquad \forall i \in I, t \in T, r \in R, s \in S \tag{1}$$

$$\sum_{v\in V}\sum_{k\in K} y_{jkpvts} - \eta^2_{jpts} \le (1 - \beta J_{jpts}).capJ_{jpt}.YJ_j \qquad \forall j \in J, t \in T, p \in P, s \in S \tag{2}$$

$$\sum_{v\in V}\sum_{c\in C} y'_{kcpvts} - \eta^{3}_{kpts} \le (1-\beta K_{kpts}).capK_{kpt}.YK_{k} \qquad \forall k\in K, t\in T, p\in P, s\in S \tag{3}$$

$$\sum_{v\in V}\sum_{c\in C} q_{chpvts} - \eta^{4}_{hpts} \le (1-\beta H_{hpts}).capH_{hpt}.YH_{h} \qquad \forall h\in H, t\in T, p\in P, s\in S \tag{4}$$

$$D'_{cpts} + \eta^{5}_{cpts} = D_{cpts} - (1+\eta_{t}).P_{pt} \qquad \forall c\in C, p\in P, t\in T, s\in S \tag{5}$$

$$\xi_{s'} - \sum_{s\in S} pp_{s}\xi_{s} + \theta_{s'} \ge 0 \qquad \forall s'\in S \tag{6}$$

$$I_{jpts} - S_{jpts} = I_{jpt-1s} - S_{jpt-1s} + \sum_{r\in R}\sum_{v\in V}\sum_{i\in I} x_{ijrvts}.\lambda_{rp} - \sum_{k\in K}\sum_{v\in V} y_{jkpvts} + \sum_{r\in R}\sum_{v\in V}\sum_{h\in H} zz_{hjrvt-1s}.\lambda_{rp}$$
$$\forall j\in J, p\in P, t\in T, s\in S \tag{7}$$

$$IK_{kpts} - SK_{kpts} = IK_{kpt-1s} - SK_{kpt-1s} + \sum_{j\in J}\sum_{v\in V} y_{jkpvts} - \sum_{c\in C}\sum_{v\in V} y'_{kcpvts} \qquad \forall k\in K, p\in P, t\in T, s\in S \tag{8}$$

$$\sum_{k\in K}\sum_{v\in V} y'_{kcpvts} = D'_{cpts} \qquad \forall c\in C, p\in P, t\in T, s\in S \tag{9}$$

$$IH_{hrts} - SH_{hrts} = IH_{hrt-1s} - SH_{hrt-1s}$$
$$-\sum_{v\in V}\sum_{j\in J} zz_{hjrvts} + \sum_{c\in C}\sum_{v\in V}\sum_{p\in P} \varphi_{rp}.q_{chvpts} \tag{10}$$
$$\forall h\in H, t\in T, r\in R, s\in S$$

$$F1_{ts} \le Bd_{t} \tag{11}$$

$$yy_{kcpts} \le \sum_{v\in V} y'_{kcpvts} \qquad \forall c\in C, k\in K, p\in P, t\in T, s\in S \tag{12}$$

$$yy_{kcpts}.MM \ge \sum_{v\in V} y'_{kcpvts} \qquad \forall c\in C, k\in K, p\in P, t\in T, s\in S \tag{13}$$

$$(Q_{cpt} - q'_{kpt}).yy_{kcpts}. \ge (z_{kcpts} - 1).MM \qquad \forall c\in C, k\in K, p\in P, t\in T, s\in S \tag{14}$$

$$(Q_{cpt} - q'_{kpt}).yy_{kcpts} \le z_{kcpts}.MM \qquad \forall c\in C, k\in K, p\in P, t\in T, s\in S \tag{15}$$

$$\sum_{h\in h}\sum_{v\in V} q_{chpvts} \ge \alpha_{cp}.\sum_{v\in V} y'_{kcpvts} - (1 - Z_{kcpts}).MM \qquad \forall c\in C, k\in K, p\in P, t\in T, s\in S \tag{16}$$

$$\sum_{h\in h}\sum_{v\in V} q_{chpvts} \le \alpha_{cp}.\sum_{v\in V} y'_{kcpvts} + (1 - Z_{kcpts}).MM \qquad \forall c \in C, k \in K, p \in P, t \in T, s \in S \tag{17}$$

$$\xi_s = \left(w_1.A1_s + w_2.A2_s\right) \qquad \forall s \in S \tag{18}$$

$$Ij_{pts}, Sj_{pts}, IK_{kpts}, IH_{hrts}, SK_{kpts}, SH_{hrts}, x_{ijrvts}, zz_{hjrvts}, q_{chvpts}, y'_{kcpvts}, y_{jkpvts}, D'_{cpts} \ge 0$$
$$yy_{kcpts}, Z_{kcpts}, Yi_{is}, YK_k, YJ_j, YH_h \in \{0,1\}$$
$$\theta_s', \eta^1_{irts}, \eta^2_{jpts}, \eta^3_{kpts}, \eta^4_{hpts}, \eta^5_{cpts} \ge 0$$

Constraint (1): Specifies the accessibility and availability of IoT data under each scenario, determining the level of information precision for operational decisions.
Constraint (2): Calculates the effective production capacity under each scenario, considering disruption levels and real-time updates from IoT systems.
Constraint (3): Specifies the distributor's available capacity under each scenario, accounting for scenario-based disturbances and operational constraints.
Constraint (4): Determines the maximum allowable shipments to recycling centers under each scenario, considering disruptions and reverse logistics conditions.
Constraint (5): Defines customer demand based on each scenario, incorporating inflation rates and price elasticity to capture market variability.
Constraint (6): The system calculates the total values of the objective functions for each scenario, which are economic cost and environmental emissions.
Constraint (7): Models inventory balance, shortages, receiving quantities, and shipments at the factory for each scenario and period.
Constraint (8): Models inventory balance, shortages, receiving quantities, and shipments at the distributor for each scenario and period.
Constraint (9): Indicates the volume of products dispatched to consumers under each scenario, considering available inventory and capacity constraints.
Constraint (10): Specifies inventory levels, shortages, receiving quantities, and shipments of raw materials at the recycling center under each scenario.
Constraint (11): Enforces the budget constraint for each scenario, ensuring that total operational, transportation, inventory, and recycling costs do not exceed financial limits.
Constraints (12) and (13): Define the binary decision variables for facility activation and routing feasibility under each scenario.
Constraints (14) and (15): Determine whether products with quality levels below the minimum acceptable threshold can be routed to the recycling center.
Constraints (16) and (17): Based on the proportion of defective products, calculate the number of customer returns to the recycling center under each scenario.
Constraint (18): Aggregates economic cost minimization and environmental emission minimization into a single weighted objective function, yielding the final scalar value.

Capacities, demand, emissions, and transportation conditions vary across scenarios and are dynamically updated in real time using IoT data, ensuring that the model accurately reflects system conditions under uncertainty.

4. Experiment and Result Analysis

4.1. Golden Eagle Algorithm Implementation

In this study, the GEA is employed to optimize a multi-objective sustainable supply chain model, incorporating economic, environmental, and operational objectives. The algorithm efficiently explores the feasible solution space, mitigates the risk of entrapment in local optima, and generates high-quality solutions.

1. Chromosome Representation:

Each chromosome is divided into four sections:

Section 1: Factory-related variables (Table 2)

Table 2. Representation of Chromosomes: Section 1.

			K.V.H	
T.P.C	0.13	0.75	....	0.18
	..	..	..	...
	0.78	0.19	...	20

Section 2: Distributor-related variables (Table 3)

Table 3. Representation of Chromosomes: Section 2.

			J.V	
T.P.K	0.113	0.45	....	0.17
	..	..	..	...
	0.78	0.87	...	45

Section 3: Recycling center-related variables (Table 4)

Table 4. Representation of Chromosomes: Section 3.

			J.V	
T.R.H	0.47	0.54	....	0.38
	..	..	..	...
	0.88	0.69	...	36

Section 4: IoT-enabled decision variables (Table 5)

Table 5. Representation of Chromosomes: Section 4.

			R.I.V	
T.P.J	0.63	0.75	....	0.18
	..	..	..	...
	0.23	0.96	...	27

Random values are generated according to normal distributions, with sorting rules applied to ensure the logical and consistent assignment of resources.

2. Variable Assignment and Constraint Handling:

- Constraints 2–5 and 7–17 are applied sequentially to assign feasible values to the decision variables, including production, shipment, inventory, shortages, and customer returns.
- A penalty function is used to adjust infeasible solutions, ensuring convergence toward the Pareto-optimal front.

3. Parameter Tuning:

Key parameters, Maximum Iterations, Population Size, Attack Propensity, and Cruise Propensity, are tuned using the Taguchi method. The initial parameter values are summarized in Table 6.

Table 6. Determining the parameters of the Golden Eagle algorithm for each level.

Parameters	Level1	Level2	Level3
Maxit	10	23	30
Npop	40	65	80
AttackPropensityL1	0.6	1.5	1.7
AttackPropensityU1	1	1.5	2
CruisePropensityL1	0.5	1.4	1.5
CruisePropensityU1	1	1.5	2

4.2. Experimental Examples

Ten random examples are generated to illustrate the feasibility and operation of the algorithm, as summarized in Table 7:

Table 7. Random examples.

examples	$\lvert i\rvert$	$\lvert j\rvert$	$\lvert k\rvert$	$\lvert c\rvert$	$\lvert v\rvert$	$\lvert H\rvert$	$\lvert T\rvert$	$\lvert P\rvert$	$\lvert R\rvert$	$\lvert s\rvert$
1	2	2	1	2	2	2	2	2	2	2
2	3	3	2	3	2	2	3	3	3	3
3	4	3	3	3	3	3	3	4	4	3
4	5	6	6	5	6	5	5	5	6	5
5	6	5	5	5	5	6	5	6	6	5
6	5	5	5	6	6	5	5	5	6	5
7	6	6	6	6	5	5	6	6	5	6
8	5	5	5	5	5	5	6	5	5	6
9	8	10	9	12	15	10	16	12	8	16
10	14	12	14	14	16	12	17	12	11	17

4.3. Performance Metrics

As shown in Table 8, to evaluate the Pareto-optimal solutions, convergence and diversity are assessed using the following metrics:

- MID: Measures convergence toward the true Pareto front.
- DM, NPS, SNS: Measure diversity and distribution across the objective space.

Table 8. Summary of Metrics for Convergence and Diversity Evaluation.

Metric	Evaluation Purpose	Reason for Selection
NPS	Quantifies the richness of the Pareto set	Measures algorithm's ability to explore a wide range of solutions
SNS	Evaluates uniform distribution	Assesses quality of spread and coverage across the Pareto front
MID	Evaluates convergence to ideal point	Measures proximity to true optimal front
DM	Evaluates diversity among solutions	Prevents premature convergence and improves coverage

4.4. Parameter Settings

As shown in Table 9, the final parameter settings are:

Table 9. Golden Eagle Algorithm Parameter Final Adjustment.

Parameters	Amounts
Maxit	23
Npop	40
AttackPropensityL1	1.7
AttackPropensityU1	2
CruisePropensityL1	0.5
CruisePropensityU1	1

4.5. Algorithm Execution Analysis

As shown in Table 10, the algorithm exhibits the shortest execution time in Example 8, indicating superior computational efficiency for smaller-scale problems. Example 10, which achieves the highest DM value, demonstrates the algorithm's effectiveness in handling larger instances. The NPS metric performs best in Example 4 but shows reduced effectiveness in larger datasets. Example 5 achieves the highest SNS value, indicating better solution spread. The algorithm attains the minimum MID distance in Example 4, reflecting improved convergence toward the true Pareto front in smaller instances. These results highlight the algorithm's varying performance across problem scales and confirm its overall feasibility and applicability.

Table 10. Execution Time and Performance Metrics for Random Examples.

Example	DM[1]	NPS[2]	SNS[3]	MID[4]	TIME
1	3.65×10^7	3	0.1872	0.1856	500.6127
2	4.78×10^7	4	0.1995	0.2863	510.6344
3	5.73×10^6	4	0.5138	0.5514	552.3962
4	6.0553×10^6	8	0.5550	0.1222	153.2143
5	3.2527×10^7	6	0.8268	0.8990	187.9759
6	1.2538×10^7	6	0.5600	0.8535	123.3959
7	4.3455×10^7	6	0.7467	0.7546	165.5638
8	8.2470×10^5	5	0.743	0.5955	42.3152
9	1.5767×10^7	3	0.7003	0.5451	5423.6705
10	1.3873×10^8	5	0.6210	0.4457	1100.6573

5. Conclusions

In this research, we employed a descriptive-analytical methodology and introduced an innovative multi-objective sustainable supply chain model, which was addressed using the GEA. Owing to the problem's complexity and NP-hard nature, conventional solvers such as GAMS were unable to efficiently handle large-scale instances, necessitating a metaheuristic approach.

The GEA effectively explored the solution space, avoids entrapment in local optima, and generates high-quality Pareto-optimal solutions. Solution quality was quantitatively assessed using performance metrics, including MID (convergence to the true Pareto front), DM (solution diversity), NPS (richness of the Pareto set), and SNS (uniform distribution across objectives). Tables 8–10 present detailed numerical results, including execution times and problem instance sizes, demonstrating that GEA achieves rapid convergence and high solution diversity, particularly for small- to medium-scale problems, while maintaining solution feasibility across all scenarios.

Execution times ranged from 42 s to 5,400 s, depending on problem scale. Smaller-scale instances required the shortest times, whereas larger instances demanded greater computational effort but still yielded high-quality solutions. These results underscore the algorithm’s scalability and efficiency in addressing high-dimensional, NP-hard problems.

While the GEA demonstrated strong performance, sensitivity analyses on key parameters, such as inflation rates, disruption probabilities, and IoT access likelihood, were not conducted in this study. These omissions are acknowledged as limitations and will be addressed in future work. Furthermore, direct comparative benchmarking against other metaheuristic algorithms (e.g., PSO, GA, NSGA-II) was not performed and will be undertaken in subsequent studies to further validate the algorithm’s relative performance and robustness.

The optimized hybrid model facilitates sustainable supply chain operations by reducing costs, minimizing environmental pollutants, and promoting green practices. The results offer actionable

[1] Diverty Metric

[2] Number of Pareto Solution

[3] Spread of Non-dominatanse Sorting

[4] Means ideal Distance

insights for managers operating in uncertain environments, enabling them to develop effective strategies to mitigate risks from disruptions, demand fluctuations, and product returns.

The study also emphasizes the value of adopting green materials and environmentally responsible practices. Implementing sustainable policies not only diminishes environmental impact, but also improves operational efficiency and profitability. Overall, the findings confirm the feasibility, applicability, and robustness of the GEA for large-scale sustainable supply chain optimization, providing a solid foundation for theoretical development and practical implementation in SSCM under uncertainty.

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Use of Generative-AI tools declaration

The author declares that no artificial intelligence (AI) tools were employed in the creation of this article.

Conflict of interest

The author has declared that they have no relevant financial or non-financial interests to disclose. In this investigation, ethical criteria were followed, including obtaining informed consent and maintaining privacy and confidentiality.

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