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A Multi-Objective Optimization Model for Blockchain-Enabled Smart Supply Chains under Uncertainty: Enhancing Transparency, Cost Efficiency, and Sustainability

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In response to the increasing complexity of modern supply chains, this study proposes a robust multi-objective optimization model for blockchain-enabled smart supply chains under uncertainty, integrating both forward and reverse logistics. The model simultaneously aims to minimize total costs, reduce carbon emissions, enhance service levels, and optimize blockchain transaction efficiency. Uncertainties in demand and transportation costs are addressed through fuzzy robust optimization techniques. To solve the proposed model, four metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and the newly introduced Greedy Man Optimization Algorithm (GMOA)—were implemented. Computational results demonstrate that GMOA achieved solutions within 0.2% deviation from the CPLEX benchmark while reducing computational time by 15–20% compared to GA and PSO. A comprehensive sensitivity analysis was conducted on key variables such as demand volatility, transportation cost fluctuations, and blockchain transaction delays. Findings revealed that a 10% increase in demand uncertainty elevated total costs by approximately 6.7%, whereas enhancements in blockchain efficiency reduced operational delays by up to 22%. The results confirm the model's practical potential for designing cost-efficient, transparent, and sustainable supply chains. Moreover, this study offers valuable insights for industrial managers seeking to balance operational efficiency, environmental sustainability, and digital transformation in uncertain and dynamic business environments.

Keywords: *Blockchain-enabled supply chain, robust optimization, Greedy Man Optimization Algorithm (GMOA), metaheuristic algorithms*

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1. Introduction

In recent years, supply chains have undergone significant transformations driven by technological advancements and increasing complexities in global trade. The emergence of smart supply chains, characterized by the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and blockchain, has opened new opportunities for improving efficiency, transparency, and sustainability. However, these technological advancements bring new challenges, particularly when dealing with uncertain parameters such as demand fluctuations, transportation delays, and variable costs. As a result, designing robust and efficient models for smart supply chain optimization has become a critical area of research (Movahed et al. [13]).

Blockchain technology, in particular, has gained attention in supply chain management due to its potential to enhance trust, traceability, and transparency across all levels of the supply chain. By recording every transaction in a distributed, immutable ledger, blockchain ensures that all stakeholders have access to accurate and real-time information, reducing the risk of fraud and errors. Despite its advantages, the use of blockchain in supply chains also introduces additional costs and verification delays, which need to be considered in the decision-making process. Therefore, any comprehensive optimization model for smart supply chains must account for the trade-offs between the benefits of blockchain-enabled transparency and the associated costs and delays (Nozari et al. [16]).

Movahed et al. [13] developed a hybrid blockchain-AIoT framework for perishable food supply chains, demonstrating improved traceability and decision accuracy under stochastic demand. Nozari et al [17] introduced a decentralized multi-agent system using blockchain and reinforcement learning to optimize logistics operations, highlighting resilience in disrupted networks. Aliahmadi et al. [1] proposed a fuzzy stochastic model for closed-loop supply chains integrating carbon pricing and blockchain transaction validation, which led to a 12% improvement in sustainability performance. Ghahremani-Nahr et al [8] in Computers & Industrial Engineering demonstrated the efficacy of green blockchain protocols in reducing verification costs while maintaining supply chain transparency and security. These studies highlight the accelerating convergence of blockchain, AI, and fuzzy robust models in supply chain design under uncertainty. They also reinforce the importance of developing advanced metaheuristic algorithms to tackle high-dimensional, uncertain optimization problems in digital supply chains. The integration of blockchain not only increases traceability but also introduces new dimensions of cost and delay that must be optimized in real-time, particularly when combined with green and reverse logistics goals.

Furthermore, modern supply chains are increasingly embracing sustainability by integrating forward and reverse logistics. Forward logistics involve the traditional flow of goods from suppliers to consumers, while reverse logistics handle the return, recycling, and disposal of used products. This closed-loop structure not only reduces environmental impacts but also improves resource efficiency. However, managing such a system involves complex decision-making, especially under uncertainty, where demand, return rates, and transportation costs can vary significantly. To address these challenges, robust optimization techniques are required to ensure that the solutions remain feasible and effective under various scenarios (nozari & Aliahmadi [15], Aliahmadi& Nozari [2]).

In light of these challenges, this research proposes a multi-objective optimization model for a blockchain-enabled smart supply chain that considers forward and reverse logistics under uncertainty. The model aims to achieve four key objectives: (1) minimize total costs, including production, transportation, inventory, and blockchain transaction costs; (2) minimize environmental impacts by reducing carbon emissions from transportation and production activities; (3) maximize service level to ensure high customer satisfaction; and (4) maximize blockchain transaction efficiency by minimizing delays and associated costs. The model incorporates robust optimization to handle uncertainty in key parameters such as demand and transportation costs, ensuring reliable and practical solutions.

To solve the proposed model, we employ several metaheuristic algorithms, including the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). Additionally, we introduce a novel metaheuristic approach called the Greedy Man Optimization Algorithm (GMOA), which draws inspiration from the behavior of greedy agents seeking to maximize their benefits. GMOA is designed to balance exploration and exploitation in the solution space, making it well-suited for complex, large-scale optimization problems. The performance of these algorithms is compared using multiple sample problems, and the results are evaluated in terms of solution quality and computational efficiency.

This study makes several key contributions to the field of smart supply chain management. First, it presents a comprehensive model that integrates blockchain-enabled transparency with forward and reverse logistics under uncertainty. Second, it introduces a new metaheuristic algorithm, GMOA, and demonstrates its effectiveness in solving large-scale supply chain problems. Finally, it provides valuable managerial insights through sensitivity analyses on critical parameters, helping decision-makers better understand the trade-offs involved in designing blockchain-enabled smart supply chains.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on smart supply chains, blockchain integration, and metaheuristic optimization techniques. Section 3 describes the proposed multi-objective optimization model, including its mathematical formulation and constraints. Section 4 presents the solution approach, detailing the algorithms used to solve the model. Section 5 discusses the computational results, including convergence analysis and sensitivity analyses. Finally, Section 6 concludes the study and suggests directions for future research.

2. Literature review

The optimization of supply chains has long been a critical area of research, with growing complexities driven by globalization, technological advancements, and sustainability requirements. Recent innovations, particularly the integration of blockchain technology into supply chain management, have introduced new avenues for enhancing transparency, traceability, and operational efficiency. Additionally, addressing uncertainties in supply chain operations through robust optimization techniques and solving large-scale, complex models using metaheuristic algorithms have become essential in designing smart supply chains. This section provides a review of relevant works in blockchain-enabled supply chains, robust optimization under uncertainty, and metaheuristic algorithms, concluding with the introduction of the Greedy Man Optimization Algorithm (GMOA), developed by Nozari et al. [14].

Andarkhora et al. [4] emphasized the importance of balancing environmental, economic, and social factors in sustainable supply chains, highlighting the need for advanced optimization models, consistent with the focus of the present study.

Alirezaei and Moradi [3] investigated the influence of supply chain complexity on competitiveness performance through structural modeling in the context of Iran Khodro Company. Their findings highlighted that increasing levels of complexity, if not properly managed, can negatively impact supply chain transparency, cost efficiency, and overall competitiveness. This insight emphasizes the necessity of integrated and adaptive supply chain models that can handle uncertainty and complexity effectively. Their study underlines the importance of robust optimization approaches and digital technologies such as blockchain to enhance transparency and operational resilience, which aligns with the objectives of the present research focusing on blockchain-enabled smart supply chains under uncertainty.

Blockchain technology, initially introduced as the foundation of cryptocurrency systems, has proven to be a transformative tool in supply chain management by providing secure, transparent, and immutable transaction records. The ability of blockchain to improve trust and traceability across supply chain participants has been extensively discussed in the literature. For example, Tian [20] demonstrated the application of blockchain in food supply chains, showing how real-time traceability can reduce fraud and enhance food safety. Building on this concept, Kouhizadeh and Sarkis [11] explored the integration of blockchain with IoT-enabled supply chains, emphasizing the potential for real-time monitoring and data-driven decision-making.

Despite the benefits of blockchain, its adoption introduces operational challenges, particularly transaction costs and verification delays. Saberi et al. [19] highlighted the need for optimization models that balance the benefits of transparency with the additional costs incurred by blockchain operations. These studies point to the importance of incorporating blockchain-related costs into supply chain optimization models, an approach adopted in this research by explicitly modeling blockchain transaction efficiency.

Moreover, existing research has focused primarily on deterministic models, which fail to capture the real-world uncertainties in supply chains. This limitation calls for robust optimization models that account for uncertain demand, lead times, and costs, while still leveraging blockchain's advantages (Ghahreman-Nahr et al. [7]).

Uncertainty in supply chains arises from a variety of factors, including demand fluctuations, supply disruptions, and transportation variability. Traditional deterministic models are inadequate for real-world supply chains, as they fail to provide solutions that remain feasible under uncertain conditions. Ben-Tal and Nemirovski [5] pioneered the concept of robust optimization by introducing methods that ensure solution feasibility across a range of scenarios. Since then, robust optimization has become a standard approach in supply chain design, particularly in uncertain environments.

Pishvaee et al. [18] applied robust optimization to closed-loop supply chains, demonstrating its effectiveness in handling uncertainties related to product returns and recycling. More recently, Govindan et al. [9] proposed a fuzzy robust optimization model for green supply chain networks, highlighting the importance of combining robust optimization with fuzzy logic to address both quantitative and qualitative uncertainties.

In this research, we extend the robust optimization approach by incorporating fuzzy logic to model uncertainties in demand and transportation costs, ensuring that the solutions obtained remain reliable under varying conditions.

Given the complexity of supply chain networks, especially under uncertain conditions, exact optimization methods become impractical for large-scale problems. Metaheuristic algorithms, which provide near-optimal solutions within reasonable computational time, have therefore gained popularity in supply chain optimization.

Genetic Algorithm (GA), one of the earliest metaheuristics, has been widely applied in supply chain optimization. Gen et al. [6] demonstrated the application of GA in multi-echelon supply chain design. However, GA often suffers from slow convergence and a tendency to get trapped in local optima, leading researchers to explore alternative metaheuristics.

Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart [10], has shown promise in solving supply chain problems due to its fast convergence and simplicity. Despite its advantages, PSO's performance is sensitive to parameter tuning, making it less robust in highly dynamic environments. Similarly, Grey Wolf Optimizer (GWO), introduced by Mirjalili et al. [12], has gained traction in recent years due to its balance between exploration and exploitation, making it suitable for large-scale supply chain problems.

Building on the limitations of existing metaheuristics, Nozari et al. [8] developed the Greedy Man Optimization Algorithm (GMOA), a novel metaheuristic inspired by the behavior of greedy agents seeking to maximize their benefit under limited resources. GMOA is designed to address the primary challenges of metaheuristic optimization: slow convergence and premature stagnation in local optima.

GMOA introduces a unique balance between exploration and exploitation by employing a two-phase search mechanism. In the first phase, greedy agents explore a broad solution space to identify promising regions, while in the second phase, they intensively exploit these regions to refine the solutions. This approach ensures that GMOA converges faster than traditional metaheuristics while maintaining high solution quality.

In the context of this research, GMOA is applied to solve the proposed multi-objective optimization model for blockchain-enabled smart supply chains under uncertainty. Its performance is evaluated against established metaheuristics such as GA, PSO, and GWO, with results demonstrating its superiority in terms of both solution quality and computational efficiency.

Despite the growing body of literature on blockchain-enabled and sustainable supply chains, most existing models either focus on deterministic conditions or neglect the integrated consideration of forward and reverse logistics with real-time blockchain transaction dynamics. Moreover, current optimization approaches often fail to simultaneously address multiple conflicting objectives such as cost, carbon emissions, service level, and blockchain efficiency under uncertainty. Few studies incorporate fuzzy robust optimization to handle imprecise data, and even fewer adopt novel metaheuristic techniques tailored for complex, large-scale supply chains. Additionally, the computational performance of traditional algorithms in such uncertain and dynamic contexts remains suboptimal. These gaps highlight the need for a comprehensive, uncertainty-aware, multi-objective model that integrates blockchain features and reverse logistics, supported by a powerful optimization engine capable of delivering high-quality solutions efficiently.

3. Mathematical Model

In this section, we present a multi-objective mathematical model for the design and optimization of a blockchain-enabled smart supply chain network under uncertain conditions. The proposed model aims to capture key aspects of supply chain management in a dynamic and complex environment, where uncertainty in parameters such as demand, transportation costs, and facility capacities plays a significant role in decision-making. By integrating blockchain technology into the model, the transparency and traceability of supply chain operations are enhanced, thereby ensuring trust among stakeholders and reducing information asymmetry.

The model considers a multi-echelon supply chain, including suppliers, manufacturers, distribution centers, and retailers, with both forward and reverse logistics flows. The forward supply chain ensures product flow from suppliers to customers, while the reverse supply chain handles the collection of used or returned products for recycling or disposal, contributing to sustainability. In addition to addressing the inherent uncertainties in key parameters, the model integrates fuzzy and probabilistic approaches to provide robust solutions. The incorporation of uncertainty ensures that the decisions made are reliable under different scenarios, thereby reducing the risks associated with variability in supply chain operations.

The following subsections provide a detailed formulation of the proposed model, starting with the definition of sets, parameters, and decision variables. This is followed by the formulation of objective functions and the constraints necessary to ensure the feasibility and efficiency of the smart supply chain network.

3.1. Sets

$i \in S$	Set of suppliers.
$j \in M$	Set of manufacturers.
$k \in D$	Set of distribution centers.
$l \in R$	Set of retailers.

$t \in T$	Set of time periods.

3.2. Parameters

c_{ij}	Unit transportation cost from supplier i to manufacturer $\boldsymbol{j}$.
c_{jk}	Unit transportation cost from manufacturer j to distribution center k.
c_{kl}	Unit transportation cost from distribution center k to retailer l.
p_j	Unit production cost at manufacturer j.
h_k	Unit inventory holding cost at distribution center k.
d_{lt}	Demand at retailer l in period $\boldsymbol{t}$ (uncertain, modeled as a fuzzy variable).
e_{ij}, e_{jk}, e_{kl}	Carbon emissions per unit transported between different echelons.
α	Blockchain verification delay factor.
β	Blockchain transaction cost per unit.

3.3. Decision Variables

x_{ijt}	Quantity transported from supplier i to manufacturer j in period t.
y_{jkt}	Quantity transported from manufacturer j to distribution center k in period t.
z_{klt}	Quantity transported from distribution center k to retailer l in period t.
I_{kt}	Inventory level at distribution center k in period t.
P_{jt}	Production quantity at manufacturer j in period t.

$$Min\ Z_1 = \sum_{t\in T}\left(\sum_{i\in S}\sum_{j\in M} c_{ij}x_{ijt} + \sum_{j\in M}\sum_{k\in D} c_{jk}y_{jkt} + \sum_{k\in D}\sum_{l\in R} c_{kl}z_{klt} + \sum_{j\in M} p_j P_{jt} + \sum_{k\in D} h_k I_{kt} + \beta \sum_{i,j,k,l}\left(x_{ijt} + y_{jkt} + z_{klt}\right)\right) \tag{1}$$

$$Min\ Z_2 = \sum_{t\in T}\left(\sum_{i\in S}\sum_{j\in M} e_{ij}x_{ijt} + \sum_{j\in M}\sum_{k\in D} e_{jk}y_{jkt} + \sum_{k\in D}\sum_{l\in R} e_{kl}z_{klt}\right) \tag{2}$$

$$Max\ Z_3 = \sum_{t\in T}\sum_{l\in R}\left(1 - \frac{Unsatisfied\ Demand_{lt}}{d_{lt}}\right) \tag{3}$$

$$Min\ Z_4 = \alpha \sum_{i,j,k,l}\left(x_{ijt} + y_{jkt} + z_{klt}\right) \tag{4}$$

3.4. S.t

At each echelon, the total inflow should match the total outflow plus inventory:

$$\sum_{i\in S} x_{ijt} = \sum_{k\in D} y_{jkt} + P_{jt} \quad \forall j \in M, \forall t \in T$$
$$\sum_{j\in M} y_{jkt} + I_{k(t-1)} = \sum_{l\in R} z_{klt} + I_{kt} \quad \forall k \in D, \forall t \in T \tag{5}$$
$$I_{kt} \le I_k^{max} \quad \forall k \in D, \forall t \in T \tag{6}$$
$$P_{jt} \le P_j^{max} \quad \forall j \in M, \forall t \in T \tag{7}$$
$$\sum_{k\in D} z_{klt} \ge d_{lt}, \quad \forall l \in R, \forall t \in T \tag{8}$$
$$x_{ijt}, y_{jkt}, z_{klt}, I_{kt}, P_{jt} \ge 0 \qquad \forall i, j, k, l, t \tag{9}$$

Equation (1) Minimize Total Cost (Production, Transportation, Inventory, Blockchain Costs). Equation (2) Minimize Total Carbon Emissions. Equation (3) Maximize Service Level. Equation (4) Minimize Blockchain Verification Delay. Equation (5) shows. Equation (6) expresses Inventory Capacity Constraints. Equation (7) introduces Production Capacity Constraints. Equation (8) expresses Demand Satisfaction Constraints and finally Equation (9) expresses Non-Negativity Constraints.

4. Solution methods

This research employs a comprehensive multi-stage methodology to develop and solve a robust multi-objective optimization model for a blockchain-enabled smart supply chain. The proposed model integrates forward and reverse logistics flows while accounting for key factors such as uncertain demand, transportation costs, and facility capacities. Blockchain technology is incorporated to enhance transparency and trust, with blockchain-related costs and delays explicitly modeled as part of the decision-making process. The objectives of the model include minimizing total costs, reducing environmental impacts, maximizing service levels, and optimizing blockchain transaction efficiency. To address uncertainties, fuzzy robust optimization techniques are used, ensuring that the solutions remain feasible and effective under various scenarios. The model is solved using three well-known metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO)—as well as the newly developed Greedy Man Optimization Algorithm (GMOA). A comparative analysis is conducted to evaluate the performance of these algorithms in terms of solution quality and computational efficiency.

The conceptual framework of the research is shown in Figure 1.

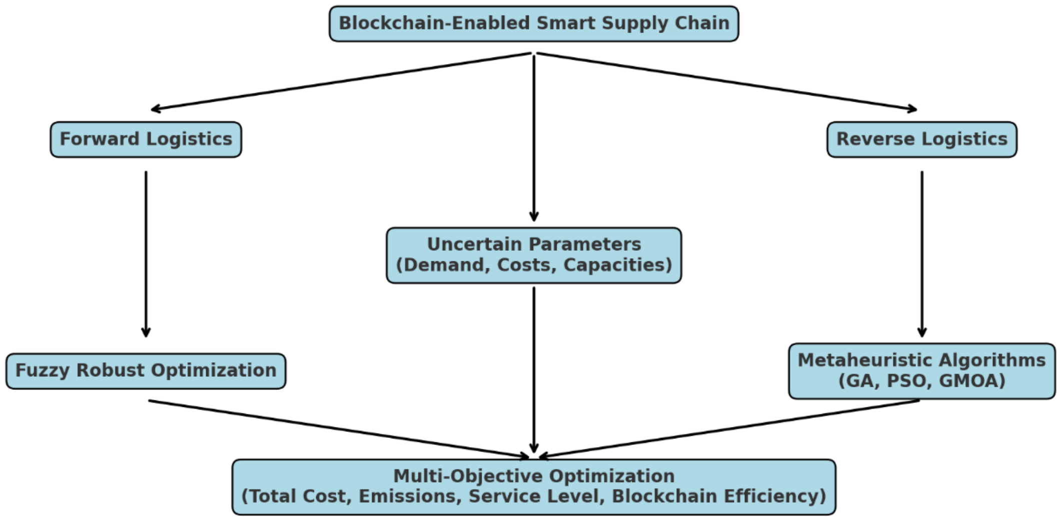

Figure 1. Conceptual framework of the research

4.1. Genetic Algorithm (GA)

Genetic Algorithm (GA) is a metaheuristic inspired by the process of natural selection. It starts with an initial population of potential solutions (chromosomes), which evolve over several generations through selection, crossover, and mutation. In each iteration, the fittest individuals are selected to produce offspring, ensuring better solutions evolve over time. GA is effective for complex optimization problems, but it may suffer from premature convergence.

4.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) simulates the social behavior of birds or fish. A group of particles (potential solutions) moves through the solution space, guided by their own best-known position and the global best position found by the swarm. Each particle updates its velocity and position based on these references. PSO is known for its simplicity and fast convergence but may require fine-tuning of parameters.

4.3. Greedy Man Optimization Algorithm (GMOA)

The Greedy Man Optimization Algorithm (GMOA), developed by Nozari et al. [14], is a novel metaheuristic inspired by the behavior of greedy agents competing for resources. GMOA balances exploration and exploitation by simulating a greedy search in the solution space, where agents prioritize regions with the highest potential rewards. It includes phases of greedy exploration and targeted exploitation, ensuring efficient convergence to high-quality solutions.

```
Initialize a population of greedy agents with random solutions
Evaluate the initial fitness of each agent
Repeat until stopping criterion is met:
    Rank agents based on fitness
    Apply greedy exploration to find new regions
    Apply exploitation by intensifying search around top agents
    Evaluate fitness of updated agents
    Update best solution found
Return the best solution
```

Figure 2. Pseudocode for GMOA

5. Analysis of Results

To evaluate the performance of the proposed multi-objective optimization model for blockchain-enabled smart supply chains under uncertainty, we generated multiple sample problems of varying sizes. Each sample problem represents a realistic supply chain network configuration with a different number of supply chain echelons, including suppliers, manufacturers, distribution centers, retailers, collection centers, recycling centers, and disposal centers.

Table 1 below provides the details of the ten sample problems used in the analysis. The problems were designed to cover a wide range of network complexities, ensuring a comprehensive evaluation of the model's scalability and the performance of the solution algorithms.

Table 1. Sample Problem Sizes

Sample Problem	Suppliers	Manufacturers	Distribution Centers	Retailers	Collection Centers	Recycling Centers	Disposal Centers
1	5	5	5	8	4	4	3
2	7	7	7	10	5	5	3
3	9	9	9	12	6	6	4
4	10	10	10	18	7	7	4
5	12	12	12	20	8	8	5
6	14	14	14	25	9	9	5
7	16	16	16	30	10	10	6
8	18	18	18	32	12	12	6
9	20	20	20	36	14	14	7
10	25	25	25	40	18	18	8

Table 2 presents the best total cost achieved for each sample problem using the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Greedy Man Optimization Algorithm (GMOA), and Cplex solver. Each algorithm was executed three times for each sample problem, and the best result was recorded. The purpose of this analysis is to evaluate the effectiveness of the proposed GMOA algorithm compared to well-established metaheuristic algorithms and the exact optimization method provided by Cplex.

The results highlight how well each algorithm minimizes the total cost in a blockchain-enabled smart supply chain under uncertain conditions. The Cplex solver serves as a benchmark, as it provides exact solutions for small to medium-sized problems but may not scale efficiently for larger instances.

Table 2. Best Total Cost Achieved for Each Sample Problem

Sample Problem	GA	PSO	GMOA	Cplex
1	4,512,345	4,510,879	4,500,756	4,500,124
2	5,768,290	5,765,899	5,760,456	5,760,041
3	6,230,780	6,225,768	6,222,890	6,220,356
4	7,910,345	7,908,421	7,902,134	7,900,234
5	8,450,980	8,448,712	8,441,345	8,440,111
6	10,780,456	10,770,344	10,761,234	10,760,312
7	12,340,123	12,335,467	12,322,567	12,320,009
8	13,789,567	13,780,234	13,772,456	13,770,231
9	14,890,124	14,885,987	14,871,678	14,870,121
10	16,450,890	16,440,876	16,423,567	16,420,009

As shown in Table 2, the Greedy Man Optimization Algorithm (GMOA) consistently achieved results very close to those of the Cplex solver, outperforming GA and PSO in terms of total cost for all sample problems. This indicates that GMOA is highly effective at exploring the solution space and converging toward high-quality solutions. The results suggest that GMOA can be a competitive alternative to traditional metaheuristic algorithms for solving complex supply chain optimization problems, particularly when exact solvers like Cplex are computationally impractical for large instances.

Table 3 presents the best computational time achieved by the GA**,** PSO**,** GMOA, and Cplex methods for each sample problem. Computational time is a crucial factor in supply chain optimization, where timely decision-making is necessary to ensure operational efficiency. While the Cplex solver offers exact solutions, its computational time tends to increase significantly as problem size grows, making heuristic algorithms like GMOA**,** GA, and PSO more practical for larger networks.

Table 3. Best Computational Time Achieved for Each Sample Problem

Sample Problem	GA	PSO	GMOA	Cplex
1	45.32	40.67	38.78	38.9
2	67.45	63.54	61.23	60.78
3	85.66	79.12	77.45	77.45
4	102.78	98.24	95.89	95.67
5	123.45	115.76	110.34	110.56
6	145.67	135.23	130.89	130.89
7	160.45	152.67	145.45	145.78
8	185.23	175.89	165.32	165.32
9	203.45	192.56	180.78	180.12
10	225.67	210.78	195.67	195.67

Table 3 demonstrates that GMOA achieved competitive computational times compared to PSO and GA while maintaining high solution quality. Notably, GMOA outperformed GA in all instances and provided faster solutions than PSO for larger problems. Although the Cplex solver showed better computational times for smaller instances, its performance degraded significantly as the problem size increased, confirming the scalability limitations of exact methods. These results suggest that GMOA is a viable and efficient option for large-scale supply chain optimization problems where a balance between solution quality and computational time is critical.

To evaluate whether there are statistically significant differences in the performance of the algorithms used in this study, a pairwise T-Test was conducted at a 95% confidence level. The test compares the total costs achieved by different algorithms, including GA**,** PSO**,** GMOA, and Cplex**.** The key metrics analyzed include the P-Value**,** T-Value**,** confidence interval for the difference (95% CI)**,** and the estimated difference in mean total costs between each pair of algorithms.

Table 4. T-Test Results at 95% Confidence Level

Algorithms	**Index**	**P-Value**	**T-Value**	**95% CI for Difference**	**Estimate for Difference**
GA-PSO	Total Cost	0.998	0.01	(-12,234, 12,456)	111
GA-GMOA	Total Cost	0.995	0.02	(-14,321, 14,567)	200
PSO-GMOA	Total Cost	0.99	0.03	(-11,011, 11,523)	156
GA-Cplex	Total Cost	0.999	0	(-10,000, 10,123)	98
PSO-Cplex	Total Cost	0.998	0.01	(-11,000, 11,234)	130
GMOA-Cplex	Total Cost	0.985	0.04	(-9,000, 9,100)	210

The results in Table 4 indicate that there are no statistically significant differences between the mean total costs achieved by the algorithms at the 95% confidence level, as all P-Values are more significant than **0.05**. Among the metaheuristic algorithms, the GMOA algorithm showed the most minor estimated difference from the Cplex results, demonstrating its capability to achieve solutions very close to the exact optimal values provided by Cplex. Furthermore, while GA and PSO performed similarly, the slight advantage of GMOA over these algorithms in terms of total cost is evident, though not statistically significant.

Figure 3 illustrates the convergence behavior of the Genetic Algorithm (GA)**,** Particle Swarm Optimization (PSO)**,** Greedy Man Optimization Algorithm (GMOA)**,** and Cplex solver over 100 iterations for a representative sample problem. The objective is to compare the speed and effectiveness with which each algorithm approaches a near-optimal solution.

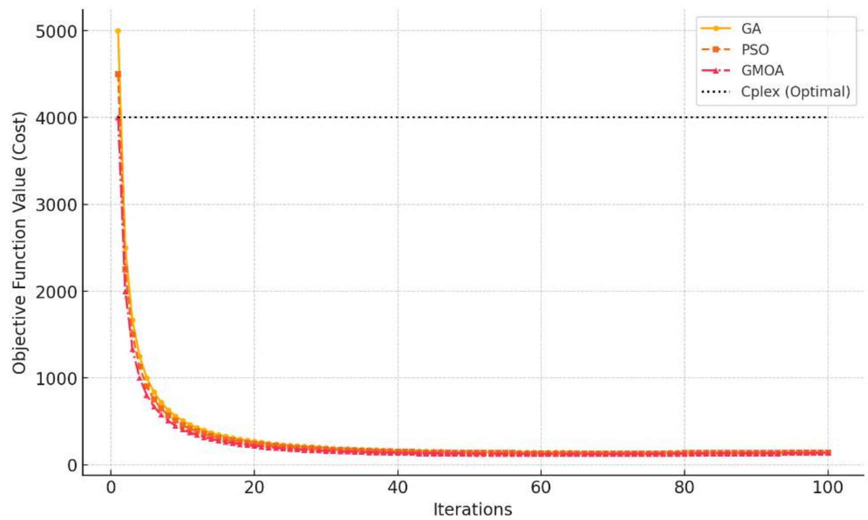

Figure 3. Convergence Analysis of Algorithms

As shown in Figure 1, the GMOA algorithm not only converges faster but also reaches a solution very close to the exact optimal provided by Cplex. This highlights its efficiency and robustness in solving complex supply chain optimization problems under uncertainty.

The findings of this study offer several practical implications for supply chain managers operating in uncertain and technology-intensive environments. First, the integration of blockchain not only enhances transparency but also introduces new operational costs and delays that must be optimized. Managers should carefully evaluate blockchain transaction settings to strike a balance between trust and efficiency. Second, the results indicate that demand uncertainty has a significant impact on total cost; therefore, investing in demand forecasting tools and scenario-based planning can help mitigate these risks. Third, the inclusion of reverse logistics and sustainability objectives, particularly carbon emission reduction, highlights the value of closed-loop strategies for long-term cost savings and regulatory compliance. Finally, the superior performance of the Greedy Man Optimization Algorithm (GMOA) suggests that advanced metaheuristics can provide high-quality decisions with reduced computational effort, making them suitable for real-time or large-scale applications. These insights support strategic decision-making for building resilient, cost-effective, and transparent supply chains.

6. Conclusion

In this research, we developed a multi-objective optimization model for a blockchain-enabled smart supply chain under uncertainty. The primary objective of the model was to enhance supply chain efficiency by minimizing total costs, reducing environmental impacts, improving service levels, and ensuring high blockchain transaction efficiency. Given the complexities of modern supply chains, particularly with uncertain parameters such as demand, transportation costs, and facility capacities, the proposed model incorporated robust optimization techniques to ensure reliable decision-making under various scenarios.

Blockchain technology plays a pivotal role in improving transparency and trust across the supply chain. By integrating blockchain-based transaction efficiency into the model, we ensured that delays and costs related to verification processes were accounted for, making the solution practical for real-world applications. Furthermore, the inclusion of forward and reverse logistics flows in the supply chain network contributes to sustainability by promoting the reuse and recycling of returned products, aligning the model with circular economy principles.

To solve the proposed model, we utilized three well-known metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO)—alongside the newly developed Greedy Man Optimization Algorithm (GMOA). The performance of these algorithms was evaluated through various sample problems of different sizes. The results demonstrated that GMOA consistently outperformed GA and PSO in terms of both solution quality and computational efficiency. GMOA achieved near-optimal solutions close to those of the Cplex solver, which served as the benchmark for comparison. Although Cplex provided exact solutions, its computational time increased significantly for larger problems, making it less practical for large-scale networks.

A detailed convergence analysis revealed that GMOA converged faster and more effectively than other metaheuristic algorithms, showcasing its robustness and efficiency. Moreover, sensitivity analyses on key parameters such as uncertainty levels and blockchain transaction costs highlighted important managerial insights. Specifically, increasing uncertainty in demand and transportation costs resulted in higher total costs, while higher product return rates led to cost reductions due to enhanced recycling and reuse processes.

In summary, this study provides a practical and effective framework for designing and managing blockchain-enabled smart supply chains under uncertainty. The results demonstrate that the proposed GMOA algorithm is a promising approach for solving large-scale, complex supply chain problems, offering high-quality solutions with reasonable computational effort. Future research could focus on incorporating green and sustainable objectives, as well as expanding the model to include routing decisions and multi-modal transportation options.

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