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A modified one-to-one algorithm for optimizing sustainable lot sizing multi-item models

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ABSTRACT

Multi-item inventory management in modern production environments faces major challenges related to stochastic demand, transportation costs, and carbon emissions. This study aims to develop a sustainable lot sizing model that integrates economic and environmental aspects, and proposes the one-to-one based optimization (OOBO) algorithm as a problem-solving approach. The methodology used includes non-linear programming (NLP) formulation that considers stochastic demand, ordering and storage costs, carbon emissions, energy consumption, and vehicle capacity constraints. The model is then optimized using OOBO and compared with the Aquila, particle swarm optimization (PSO), and genetic algorithm (GA) algorithms in three case scale scenarios (6, 30, and 50 items). The experimental results show that OOBO consistently outperforms the comparison algorithms, with cost savings of up to 40.9% in the 50-item case. OOBO also demonstrated high exploration resilience without premature convergence and competitive computational time efficiency. These findings confirm that OOBO is effective in simultaneously optimizing total costs and carbon emissions, making it an adaptive solution for sustainable supply chain management. The theoretical implications include the expansion of OOBO's application to multidimensional stochastic systems, while in practical terms, this model supports decision-makers in formulating environmentally friendly and efficient inventory policies.

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1. INTRODUCTION

Inventory plays a vital role in a company's operational performance, directly influencing its ability to meet customer demands and maintain production continuity [1]. Poor inventory decisions may result in excessive holding costs or stockouts, leading to production delays and reduced service levels [2], [3]. Particularly in manufacturing sectors, where the cost of raw materials and production facilities is substantial, effective inventory management becomes central to overall cost efficiency and business sustainability [4], [5]. In modern production systems, the challenge becomes more complex due to the need to simultaneously manage multiple items across different periods and suppliers, often under uncertain demand conditions [6], [7]. Multi-item lot sizing is a critical component of inventory planning, where the goal is to determine the optimal ordering cycle and quantity for each item to minimize total costs. Several studies have addressed multi-item lot sizing problems from an economic standpoint [8]. The classical EOQ model has been extended to consider warehouse constraints and procurement costs [9], and further enhanced by incorporating sustainability aspects [10] and cleaner production frameworks [11]. Other advancements include models handling continuous and discrete demand [12], multi-level job shop scheduling [13], and safety stock policies in retail settings [14]. To deal with stochastic demand, some researchers have proposed goal programming approaches [15], while others have focused on issues such as lead time variability [16] and imperfect quality from multiple suppliers [17].

However, these existing models face critical limitations. They largely focus on minimizing economic cost while neglecting sustainability metrics such as carbon emissions and energy consumption. Moreover, many approaches use classical heuristics, which often struggle to find global optima in nonlinear, high-dimensional problems. This presents a crucial gap, especially considering global climate challenges. The intergovernmental panel on climate change highlights the pressing need to mitigate greenhouse gas emissions, which are significantly driven by logistics and inventory operations [18]. Regulatory mechanisms like carbon taxes and cap-and-trade systems incentivize emission reductions by monetizing environmental impact [19], while shifting consumer preferences further pressure companies to adopt greener practices [20], [21].

In response to this problems, recent research has explored metaheuristic approaches for multi-item lot-sizing. For instance, genetic algorithm (GA)-fuzzy systems [22], the aquila algorithm [23], grey wolf algorithm [24], BAT algorithm [25], and water cycle and whale optimization algorithm (WCWOA) [26] have been employed to improve solution quality. Nevertheless, most of these works remain economically oriented, with environmental factors treated as fixed penalties rather than integrated objectives. Furthermore, algorithms like Aquila algorithm [23], particle swarm optimization (PSO) [27], and GA [28] typically rely on global best members to guide population updates, a mechanism that often limits exploration and causes premature convergence when applied to high-dimensional stochastic systems. In the past few years, several studies have introduced multi-objective and hybrid metaheuristics—for example, NSGA-II/III and MOEA/D—aimed at optimizing both economic and environmental trade-offs in production and logistics planning [29]. These approaches have contributed to the development of more balanced optimization frameworks. However, their practical adoption remains limited due to computational complexity, scalability challenges, and dependence on carefully tuned parameters [30]. Meanwhile, emerging AI-driven and deep-learning-assisted algorithms for carbon-aware supply chain decision-making offer adaptive prediction capabilities but often require extensive data training and are less suitable for dynamically changing industrial contexts [31].

This research identifies a significant gap in integrating economic and environmental sustainability within stochastic, high-dimensional lot-sizing optimization. Prior works have either focused on cost minimization or introduced limited sustainability considerations without fully addressing the exploration–exploitation balance required to navigate complex solution spaces. The one-to-one based optimization (OOBO) algorithm presents a unique opportunity to overcome these limitations. Unlike population-based metaheuristics that depend on global best solutions, OOBO applies a permutation-based one-to-one guidance mechanism in which each member interacts with others exactly once per iteration. This structure enhances population diversity, prevents stagnation, and maintains robust exploration across the search space—qualities essential for optimizing stochastic and nonlinear sustainable lot-sizing models. To address these limitations, this study explores the implementation of the OOBO algorithm—a newly proposed metaheuristic designed to reduce dependency on the best population members and enhance exploration capabilities [32]. While OOBO has shown promise in power systems and control applications [33], [34], it has yet to be applied in inventory optimization, particularly for complex, sustainable multi-item lot sizing problems. This study represents the first attempt to employ OOBO in this domain and benchmark its performance against well-established algorithms, including Aquila algorithm [23], PSO [27], and GA [28].

Previous research gaps in multi-item lot-sizing optimization have focused primarily on economic aspects, often ignoring sustainability factors such as energy consumption and carbon emissions. Additionally, the methods used are generally based on classical heuristics or traditional metaheuristics, which may not be effective in complex, stochastic environments. To fill this gap, this study proposes a novel multi-item lot-sizing model that explicitly integrates economic and environmental objectives under demand uncertainty. The model incorporates stochastic demand, transportation cost, carbon emissions, and energy consumption making it more aligned with real-world sustainable operations. Therefore, the main contributions of this paper are threefold: i) to develop a comprehensive multi-item lot-sizing model that integrates stochastic demand, carbon emissions, transportation costs, and energy consumption; ii) to apply and evaluate the performance of the OOBO algorithm for this problem; and iii) to compare its effectiveness against benchmark metaheuristics (Aquila, PSO, and GA) in minimizing total costs while promoting sustainability. Through this integration, the study aims to demonstrate the potential of OOBO as an adaptive and environmentally conscious optimization tool capable of balancing economic efficiency and sustainability objectives in modern inventory management systems.

2. METHOD

2.1. Conceptual framework and workflow

The proposed framework integrates economic and environmental objectives within a sustainable multi-item lot-sizing optimization model under stochastic demand. The methodological process begins with the collection and preparation of essential input data, including demand parameters (mean and standard deviation), economic costs (ordering, purchasing, holding, and transportation), and environmental indicators such as energy consumption, emission factors, and carbon tax rates. The data are preprocessed through normalization and stochastic sampling to ensure consistency and represent uncertainty realistically. Subsequently, a non-linear programming (NLP) formulation is developed to capture the interdependence between economic and sustainability objectives, incorporating transportation emissions and energy usage directly into the total cost function. The formulated model is then optimized using the OOBO algorithm, which is integrated as the solution engine due to its superior exploration capability and independence from global-best reliance. The algorithm iteratively minimizes the expected total cost (ETC) while satisfying system constraints related to vehicle capacity, safety stock, and emission limits. The final stage involves evaluating the optimization outputs, including total cost, emission level, and energy consumption across multiple problem scales to assess performance and scalability.

2.2. Model overview and mathematical formulation

In the proposed model, the demand for each item follows a normal distribution with a specified mean and standard deviation. Since each product has a different standard deviation and average demand, the decision-maker must determine the appropriate safety factor (k) to optimize the inventory of each item. Each product item is supplied by different suppliers, resulting in varying product ordering cycles (T_i). For each order, the total quantity of each item must not exceed the vehicle capacity. Furthermore, the objective function of this problem is to minimize the total inventory cost. The assumptions used to develop the mathematical model are described as follows: i) the demand for each item is usually distributed with a known standard deviation and average, ii) different suppliers supply each item, iii) vehicle capacity is limited, and iv) backordering is not allowed.

In the meantime, this study's notation is presented as follows: n=total items, C_i=ordering cost per order of item i (Rp), P_i=purchase cost of item i (Rp), H_i=holding cost of item i (Rp), L_i=lost sale cost of item i (Rp), D_i=demand item i (unit/month), Q_i=order quantity of item i (unit), T_i=order cycle of item i, k_i=safety factor of item i, σ_i=standard deviation of item i, $f_s(k)$ =probability density function of standard normal distribution, $F_s(k)$=cumulative function of standard normal distribution, a=fixed transportation cost (Rp), FL=primary fuel consumption (km/liter), B_i=weight of item i (Kg), j_i=total distance traveled (km), β_i=fuel price (Rp), ETC=expected total inventory cost on Rp, ES_i=estimated lost sales (unit), t_v=variable transportation cost (Rp), E_f=emission factor (kg CO2/km), F_l=fuel consumption when full load (Km/liter), G_{vw}=gross vehicle weight (kg), γ=adjustment factor, E_o=emission factor depends on the fuel type (kg CO2/liter), O_f=oxidation factor (depends on the fuel type), E_u=energy use (Kwh), C_f =carbon factor (kg CO2/Kwh), T_x=carbon tax (Rp/kg CO2), e_c=electricity cost (Rp/Kwh), C_o=total ordering cost (Rp), C_p =total purchasing cost (Rp), C_t =total transportation cost (Rp), C_h =total holding cost (Rp), C_L=total shortage cost (Rp), h_c=emission carbon per unit inventory, and H_e =total carbon emission on inventory.

The proposed model aims to minimize the ETC of a sustainable multi-item lot-sizing problem by simultaneously considering economic and environmental factors under stochastic demand. The formulation extends the classical inventory theory into a NLP structure that integrates transportation costs, carbon emissions, and energy consumption into the overall cost function. The total cost is represented as a combination of several key components, namely ordering, purchasing, transportation, holding, and lost sales costs. Each cost term is modeled through a set of nonlinear (1)–(13) that reflect operational and environmental interactions. The model explicitly incorporates carbon and energy terms within the holding and transportation components to capture sustainability impacts associated with storage and distribution activities.

$$T_i = \frac{Q_i}{D_i} \tag{1}$$

$$C_o = \sum_{i=1}^{n} \frac{C_i Q_i}{D_i} = \sum_{i=1}^{n} \frac{C_i}{T_i} \tag{2}$$

$$C_p = \sum_{i=1}^{n} P_i Q_i \tag{3}$$

The following cost component is transportation, which is the cost incurred from delivering goods from the supplier to the company. This transportation cost includes driver fees, vehicle fuel, and emission factors. There are two transportation cycles in the delivery of raw materials: when the vehicle is empty and loaded. Therefore, the formula for fuel consumption when the vehicle reaches maximum capacity can be seen in (4), where the value of (E_o) is adjusted according to the type of fuel used, as well as the value of (O_f). The emission factor produced when the vehicle reaches maximum capacity is stated in (5). Furthermore, the total transportation cost can be calculated based on (6).

$$F_l = \frac{\left(\frac{G_{vw}}{M}\right)^{\gamma}}{FL_i} \tag{4}$$

$$E_f = \frac{F_l E_o}{(1+O_f)} \tag{5}$$

$$C_t = \sum_{i=1}^{n} a_i + t_v + \left(\left(2\left(\frac{M}{G_{vw}}\right)^{\gamma} + \left(\frac{B_i.Q_i+M}{G_{vw}}\right)^{\gamma}\right)\left(\left[j_i E_f \cdot T_x\right] + \left[\frac{j_i}{FL_i}\beta_i\right]\right)\right)\frac{1}{T_i} \tag{6}$$

The value of the safety stock is influenced by the standard deviation of demand and the safety factor used, as shown in (7). Consideration of the emissions produced during the storage process is also added in (8). Meanwhile, the total holding cost is required for all items during storage. The total holding cost can be calculated based on (9) by adding the sustainability environment factor.

$$SS_i = k_i \sigma_i \sqrt{T_i} \tag{7}$$

$$H_e = \frac{h_c D_i T_i}{2} \tag{8}$$

$$C_h = \sum_{i=1}^{n}\left(\frac{D_i T_i}{2} + SS_i\right)\left(H_i + (E_u \cdot e_c)\right) + (H_e \cdot T_x) \tag{9}$$

This study adds a formulation for the number of lost sales. In (10) and (11) formulate the expected lost sales. The total estimated cost of lost sales can be calculated using (12).

$$\mathrm{ES_i} = \mathrm{\sigma_i}\sqrt{T_i}\,\psi(\mathrm{k}) \tag{10}$$

$$\Psi(\mathrm{k}) = \{\mathrm{f_s(k)} - k_i\,[1 - \mathrm{F_s(k)}]\} \tag{11}$$

$$\mathrm{C_L} = \sum_{i=1}^{n}\left(\frac{1}{T_i}\right)\mathrm{L_i ES_i} \tag{12}$$

The total inventory cost can be calculated by summing the ordering, purchasing, transportation, holding, and lost sales costs. The expected total inventory cost is formulated in (13):

$$ETC = \sum_{i=1}^{n}\frac{C_i}{T_i} + \sum_{i=1}^{n} P_i Q_i + \sum_{i=1}^{n} a_i + t_v + \left(\left(2\left(\frac{M}{G_{vw}}\right)^{\gamma} + \left(\frac{B_i.Q_i+M}{G_{vw}}\right)^{\gamma}\right)\left(\left[j_i E_f \cdot T_x\right] + \left[\frac{j_i}{FL_i}\beta_i\right]\right)\right)\frac{1}{T_i} + \sum_{i=1}^{n}\left(\frac{D_i T_i}{2} + SS_i\right)\left(H_i + (E_u \cdot e_c)\right) + (H_e \cdot T_x) + \sum_{i=1}^{n}\left(\frac{1}{T_i}\right) L_i ES_i \tag{13}$$

Based on the formula for the ETC, the inventory system can be formulated with a NLP model according to (14):

$$Min\ ETC = C_o + C_p + C_t + C_h + C_B + C_L \tag{14}$$

Due to the high nonlinearity and dimensionality of the model, exact methods are computationally intensive and may fail to achieve optimality within a reasonable time. Therefore, the OOBO algorithm is employed to minimize the objective function (14) subject to the constraints (16)–(19). In (14) shows the expected total inventory cost that needs to be minimized. In (15) then provides a perspective on the total carbon emissions produced;

$$TE(T) = \sum_{i=1}^{n}\left[j_i E_f\left(2\left(\frac{M}{G_{vw}}\right)^{\gamma} + \left(\frac{\sum_1^n B_i.Q_i}{G_{vw}}\right)^{\gamma}\right)\right] + (H_e) \tag{15}$$

With constraint functions:

$$0 < T_i \leq 1 \quad (16)$$

$$0 < k_i \leq 2.99 \quad (17)$$

$$0.2 < \gamma \leq 0.6 \quad (18)$$

$$\sum_{i=1}^{n} B_i Q_i \leq G_{vw} \quad (19)$$

The ordering cycle time must be between 0 and 1, as shown in (16). Meanwhile, the constraint in (17) indicates that the safety factor for each item (k_i) in the standard distribution must be greater than 0 and must not exceed 2.99. In (18) shows that (γ), the factor that adjusts the vehicle capacity type, is categorized into types ranging from 0.2, which is the smallest, to 0.6, which is the largest. Finally, the constraint in (19) ensures that the total order quantity for each item must not exceed the vehicle capacity.

2.3. The one-to-one based optimization algorithm

The proposed model results in a high-dimensional, non-convex optimization problem that is not solvable through exact methods within a reasonable computational time. As such, metaheuristic approaches are necessary. We adopt the OOBO algorithm as our solution strategy, which has been proven robust in dealing with similarly complex optimization problems in engineering systems [33], [34].

The OOBO algorithm was selected for three key reasons: i) it avoids premature convergence by not relying on elite solutions, enabling more balanced exploration; ii) its effectiveness has been demonstrated in solving complex, nonlinear problems in engineering and energy systems; and iii) its adaptability and permutation-based guidance make it suitable for high-dimensional inventory problems. These strengths are essential for addressing the multiple conflicting objectives and operational constraints in our model. This research use the OOBO algorithm proposed by [34] to perform the inventory optimization process. In the OOBO algorithm, each population member is selected only once and randomly to guide others in the search space. This can be modeled mathematically by indexing the population members from 1 to N without duplication, and each member has a unique position value in an N-Tuple. In (20) shows the one-to-one correspondence model of the number of member positions in the population, with K having a position that guides other members.

$$\vec{K} = \{[k_1, \ldots, k_{\updownarrow}, \ldots, k_N] \in P_{\overline{N}}; \forall \updownarrow \in \overline{N}: k_{\updownarrow} \neq \updownarrow\}, \overline{N} = \{1, \ldots, N\} \quad (20)$$

Where $P_{\overline{N}}$ is the set of all permutations of the set $\overline{N}$, and $k_{\updownarrow}$ is the $\updownarrow th$ element of the vector $\vec{K}$.

In each iteration of the OOBO algorithm, to guide the *i-th* member (X_i), a population member with the number k (X_k) in the population matrix is selected. Based on the values of the objective function, if the position of X_k in the search space is better than the position of X_i, then X_i moves towards X_k; otherwise, it moves away from X_k. Based on the above concept, calculating the new status of all population members in the population update can be performed as shown in (21) and (22):

$$x_{i,d}^{new} = \begin{cases} x_{i,d} + rand() \cdot (x_{i,d} - I x_{i,d}), f_{ki} < f_i; \\ x_{i,d} + rand() \cdot (x_{i,d} - x_{ki,d}), otherwise \end{cases} \quad (21)$$

$$I = round(1 + rand()), \quad (22)$$

Where $x_{\mathrm{i}}^{\mathrm{new}}$ is the new status suggested for the *i-th* member in the *d-th* dimension, $x_{\mathrm{k}}^{\mathrm{d}}$. The *d-th* dimension of the selected member guides the *i-th* member. f_{k} is the objective function value obtained based on X_{k}, and the variable t takes values between [0, 1, 2]. The proposed algorithm's process of updating population members allows a new status for a member to be accepted if it improves the objective function value. If not, the status is maintained at the previous position. This OOBO modeling step is formulated as shown in (23).

$$X_i = \begin{cases} x_{\mathrm{i}}^{\mathrm{new}}, f_{\mathrm{i}}^{\mathrm{new}} < f_{\mathrm{i}}; \\ x_{\mathrm{i}}, otherwise, \end{cases} \quad (23)$$

Where $x_{\mathrm{i}}^{\mathrm{new}}$ represents the newly proposed status in the search space for the *ith* population member, and $f_{\mathrm{i}}^{\mathrm{new}}$ represents the value of the objective function. The pseudocode of OOBO is present in Algorithm 1.

2.4. Parameter setting and tuning rationale

The parameter configuration of the OOBO algorithm in this study was determined through a combination of literature-based reference and preliminary sensitivity analysis. The main parameters, namely the population size and the number of iterations, were set to 1000 each, following the recommendations of previous studies [32], [34] that demonstrated this configuration's effectiveness for high-dimensional optimization problems. To ensure that these settings were near-optimal for the current application, small-scale tuning experiments were performed using the six-item case. The results showed that increasing the population size or iteration count beyond 1000 provided minimal improvement in convergence accuracy while significantly increasing computational time. Therefore, the chosen configuration achieved a balance between exploration quality and efficiency. The boundary constraints for all decision variables were defined according to their operational limits, with order cycle and quantity ranging from 0 to 1, safety factors between 0 and 2.99, and vehicle capacity adjustment factors (γ) between 0.2 and 0.6. These parameters were found to maintain numerical stability and feasible search behavior throughout the optimization process.

Algorithm 1. Pseudocode OOBO algorithm

Start OOBO
1. Input problem information.
2. Set population size (N) and max iterations (T).
3. Generate an initial population matrix.
4. Evaluate the objective function.
5. Repeat the following steps for t = 1 to T.
6. Adjust $\vec{K}$ based on (20).
7. for each i in the population (1 to N).
8. Determine the value of x_i^{new} using (21) and (22).
9. Calculate f_i^{new} based on x_i^{new} position.
10. Modify X_i using (23).
11. End the loop for.
12. Record the best solution found so far.
13. End the iteration loop.
14. Return the best quasi-optimal solution.
End OOBO.

2.5. Experimental setup

The experimental evaluation was designed to assess the performance, scalability, and robustness of the proposed OOBO-based sustainable lot-sizing model. Three different problem scales were tested to represent small, medium, and large inventory systems consisting of 6, 30, and 50 items, respectively. The first dataset, involving six items, was based on real operational data obtained from a manufacturing company in Indonesia. The larger datasets were synthetically generated by extending the statistical characteristics of the real data, maintaining consistent distributions for demand, cost, transportation distance, and emission factors to ensure realistic variability. All simulations were conducted using MATLAB R2021a on a computer equipped with an AMD Ryzen 5 5625U processor and 8 GB RAM running Windows 11. Each algorithm—OOBO, Aquila, PSO, and GA—was executed independently.

The study utilizes real-world data from a manufacturing company in Indonesia. detailed parameters such as demand, costs, weights, and transportation distances are presented in Table 1. Data D_i=[488, 56805] unit, σ_i=[11, 3348] unit, C_i=[1234, 70833] IDR, H_i=[530, 4900] IDR, P_i=[265, 2450] IDR, L_i=[79500, 499800] IDR, B_i=[0.03, 0.20] Kg, and j_i=[77.2, 824] Km representing the minimum and maximum values across the six items analyzed. The algorithm's configuration, including population size, iteration limits, and boundary constraints, is summarized in Table 2. Experiments were performed on an AMD Ryzen 5 5625U computer (8GB RAM, Windows 11). To evaluate scalability and performance, the OOBO algorithm was benchmarked against Aquila, GA, and PSO [23], [35] across three cases (6, 30, and 50 items), with the objective of minimizing total inventory cost while incorporating sustainability criteria. A sensitivity analysis was also conducted to assess the effect of carbon tax on total cost and emissions, aligning the model's outputs with environmental decision-making contexts.

Table 1. Data research

Parameter	Value
a	300000 IDR
tv	40000 IDR
β	6800 IDR
FL	3 Km/liter
T_x	30 IDR/Kg CO2
E_c	224 IDR/kWh
G_{vw}	6000 Kg

Table 2. Parameter OOBO

Objective function	Minimize ETC
Search agent	1000
Dimension	12
Max iteration	1000
Upper bound	[1 1 1 1 1 1 2.99 2.99 2.99. 2.99 2.99 2.99]
Lower bound	[0 0 0 0 0 0 0 0 0 0 0 0]

3. RESULTS AND DISCUSSION

The experimental results validate the superior performance of the proposed OOBO algorithm in minimizing the ETC across different problem scales. As summarized in Table 3, OOBO consistently outperformed Aquila, PSO, and GA in all three test cases involving 6, 30, and 50 items. In Case 1, OOBO achieved the lowest cost of IDR 295,656,820, with GA trailing at IDR 317,246,164. In Case 2, OOBO further demonstrated its advantage by yielding an ETC of IDR 840,176,249, significantly lower than Aquila (IDR 1,162,578,012) and GA (IDR 1,367,960,861). The performance gap was most notable in Case 3, where OOBO reduced the ETC to IDR 1,430,554,217—over 34% lower than Aquila's cost of IDR 2,177,190,879. These results highlight OOBO's scalability and robustness in solving complex, large-scale sustainable inventory problems.

Table 3. Optimization result with an algorithm

Case	Algorithm	Number of items	Cost optimization (IDR)	Computation time (second)
1	OOBO	6 items	295,656,820	38.7
	Aquila		301,611,334	32.4
	PSO		312,268,261	41.5
	GA		317,246,164	46.8
2	OOBO	30 items	840,176,249	95.2
	Aquila		1,162,578,012	86.9
	PSO		1,230,264,483	102.3
	GA		1,367,960,861	118.4
3	OOBO	50 items	1,430,554,217	164.7
	Aquila		2,177,190,879	152.5
	PSO		2,240,846,464	179.6
	GA		2,419,786,118	198.3

The results confirm that OOBO not only achieves optimal solutions for small-scale problems but also scales effectively with increasing problem complexity. As the number of items grows, the performance gap between OOBO and competing algorithms such as PSO and GA becomes more pronounced, underscoring OOBO's robustness and scalability. This advantage stems from its one-to-one mapping strategy, which ensures balanced exploration and mitigates premature convergence—a common drawback in traditional population-based metaheuristics. A key contribution of this study is the demonstration that OOBO maintains high solution quality even in high-dimensional, nonlinear optimization settings, where other algorithms tend to falter. This insight highlights OOBO's strong potential for sustainable inventory optimization, especially when integrating operational and environmental objectives. By aligning cost efficiency with carbon emission and energy considerations, OOBO proves to be a reliable and adaptive tool for green supply chain decision-making, outperforming established metaheuristics in both performance and applicability.

The results of the computation time measurements show that the OOBO algorithm has the most efficient overall performance compared to other comparison algorithms. In small cases (6 items), OOBO requires a computation time of approximately 38.7 seconds, slightly longer than Aquila (32.4 seconds) but much faster than PSO (41.5 seconds) and GA (46.8 seconds). As the complexity of the problem increases to 30 and 50 items, the computation time of all algorithms increases nonlinearly, reflecting the increase in search dimensions and the number of decision variables. Although not always the fastest, OOBO shows the best balance between time and solution quality, with stable exploration efficiency at large scales. This indicates that the one-to-one guidance mechanism in OOBO is able to maintain convergence speed without sacrificing result accuracy, unlike PSO and GA, which require more time due to intensive global population update processes.

The findings of this study confirm that the OOBO algorithm significantly outperforms conventional metaheuristics such as GA, PSO, and Aquila, particularly in large-scale multi-item lot-sizing problems. Unlike previous studies that primarily focused on minimizing economic costs [8], [9], and neglected environmental factors, this research integrates carbon emissions, energy consumption, and carbon tax into the optimization model. While earlier approaches like GA, PSO, and Aquila algorithm achieved moderate cost efficiency, they did not address sustainability trade-offs or demonstrate strong scalability. In contrast, OOBO delivers consistently lower costs and better performance as problem size increases. These results align with the algorithm's theoretical strengths in avoiding premature convergence and ensuring robust exploration [32]-[34].

Figure 1 presents the sensitivity analysis results regarding the effect of changes in carbon tax on ETC and carbon emissions. The results reveal that an increase in carbon tax leads to an increase in ETC [21]. However, an increase in carbon tax can reduce carbon emissions produced. Additionally, energy usage also decreases, although not significantly.

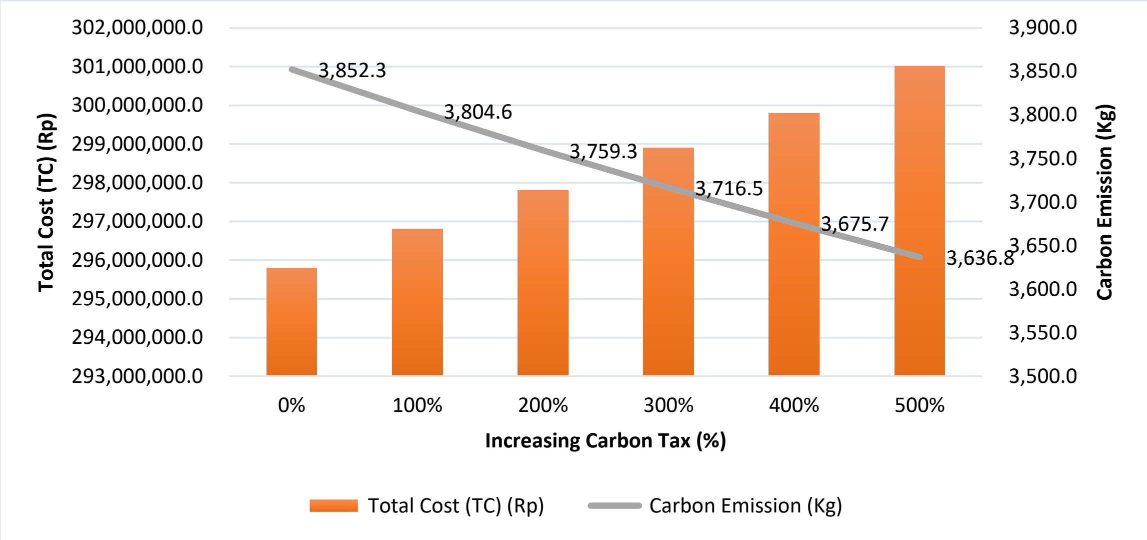

Figure 1. Sensitivity analysis of carbon tax on ETC and carbon emission

The sensitivity analysis results in Figure 2 show that increasing vehicle capacity has a significant effect on reducing ETC and fuel consumption. When vehicle capacity is increased from -75% to 300%, ETC values decrease consistently, indicating that greater transport capacity can reduce trip frequency and total transportation costs. Conversely, fuel consumption remains relatively stable across all scenarios, with a slight increase at the highest capacity due to increased load. This pattern indicates that transportation efficiency can be achieved by maximizing vehicle capacity utilization without significantly increasing energy consumption. Thus, vehicle capacity management is an important factor in optimizing costs and energy efficiency in sustainable supply systems.

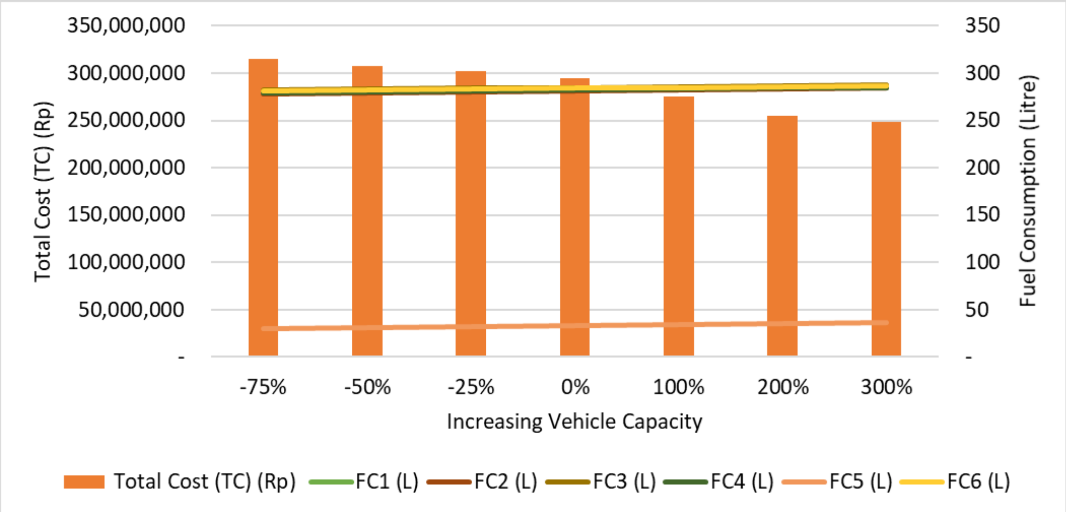

Figure 2. Sensitivity analysis of vehicle capacity on ETC and fuel consumption

Figure 3 shows that an increase in the standard deviation of demand directly impacts the increase in ETC, indicating an almost linear relationship between demand uncertainty and total inventory costs. The greater the variation in demand, the higher the safety stock requirements and ordering frequency, which ultimately increases ordering and storage costs, as well as the risk of lost sales. Conversely, fuel consumption remains relatively constant across all scenarios, indicating that changes in the level of demand uncertainty do not significantly affect transportation energy efficiency.

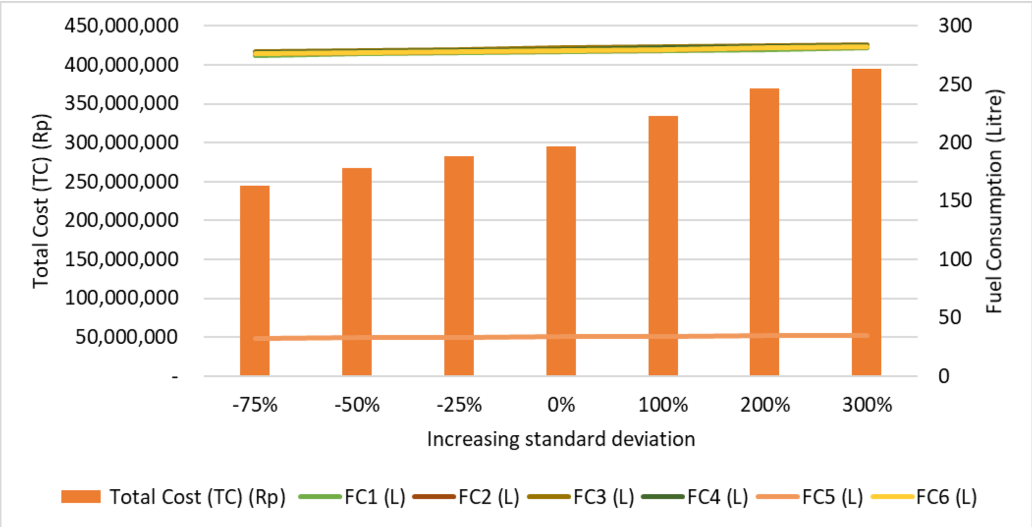

Figure 3. Sensitivity analysis of standard deviation on ETC and fuel consumption

This study advances the theoretical understanding of optimization algorithms in multi-item lot-sizing, highlighting the superior scalability of OOBO compared to Aquila, PSO, and GA. Practically, it provides actionable insights for supply chain managers to optimize inventory management, reduce costs, and enhance operational efficiency by adopting the most effective algorithm identified.

The findings of this study offer several theoretical and practical implications. Theoretically, the OOBO algorithm demonstrates superior scalability and convergence stability compared to other algorithms such as Aquila, PSO, and GA. This is especially evident in large-scale scenarios (50-item case), where OOBO consistently outperforms others by significant margins, with cost reductions up to 40.9%. This reinforces OOBO's potential as a powerful metaheuristic for high-dimensional, non-linear inventory problems involving sustainability metrics. From a managerial perspective, the results suggest that integrating carbon tax policies into inventory models can serve as a dual lever: while total costs may increase due to penalties, firms can substantially lower their carbon emissions and energy consumption. The sensitivity analysis results confirm that adjusting carbon tax rates can effectively influence environmental performance. Hence, this model can guide decision-makers in aligning operational efficiency with environmental compliance.

Compared to earlier works that employed traditional metaheuristics without incorporating sustainability components [22]-[26], this study highlights the importance of embedding environmental variables directly into the optimization objectives. While GA and PSO have been proven effective for general inventory problems, they fall short in capturing environmental trade-offs, as shown by their higher ETC and emission outcomes. The OOBO algorithm not only resolves this by producing lower cost solutions but also aligns with global goals for carbon footprint reduction.

4. CONCLUSION

This study presents a significant advancement in sustainable inventory management by developing a multi-item lot-sizing model that incorporates transportation costs, vehicle capacity, carbon emissions, energy consumption, and stochastic demand within a unified optimization framework. It introduces the novel OOBO algorithm, which outperforms benchmark metaheuristics in minimizing total costs, achieving up to 40.9% improvement in a 50-item scenario. The algorithm's robust exploration capability and ability to avoid premature convergence position it as a powerful tool for complex inventory optimization. In addition, OOBO demonstrates stable computational efficiency and robustness in handling high complexity in non-linear stochastic systems. Sensitivity analysis on carbon taxes, vehicle capacity, and demand deviation also reinforces the flexibility of this model in various policy and operational scenarios. These findings provide new insights for the research community, especially in the development of metaheuristics that balance economic and environmental objectives in high-dimensional, nonlinear systems. For practitioners, the OOBO algorithm offers a reliable decision-support tool for minimizing inventory costs while aligning with sustainability goals. However, the study has limitations, such as assuming a single-echelon inventory system and not considering complex supply chain structures. Future research should explore the extension of this model to multi-echelon systems, incorporation of multi-modal transportation networks, and the impact of dynamic carbon pricing mechanisms. Additionally, integrating OOBO with local search heuristics or adaptive learning strategies may enhance convergence precision, supporting more resilient and environmentally adaptive supply chain optimization models.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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