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Sales Training Based Optimization: A New Human-inspired Metaheuristic Approach for Supply Chain Management

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Abstract: Sustainable Lot Size Optimization is an important challenge of Supply Chain Management as it seeks to balance the economic goals of minimizing costs with environmental and social objectives, ensuring efficient production and inventory management while reducing environmental impact and enhancing social responsibility. Metaheuristic algorithms play a crucial role in solving Sustainable Lot Size Optimization problems by efficiently exploring large and complex search spaces to find near-optimal solutions that balance economic, environmental, and social objectives, often outperforming traditional optimization methods in terms of flexibility and scalability. With this attitude, in this paper, a new metaheuristic algorithm called Sales Training Based Optimization (STBO) is designed to solve Sustainable Lot Size Optimization applications. The fundamental inspiration in the design of STBO draws upon human behaviors observed during sales training. The theoretical framework of STBO is thoroughly described, and its implementation process is mathematically formulated in two distinct stages: the exploration phase and the exploitation phase. The efficiency of STBO to address Sustainable Lot Size Optimization applications has been evaluated on 10 study scenarios. The optimization outcomes reveal that STBO consistently delivers highly effective solutions by seamlessly integrating exploration with exploitation throughout the search. Furthermore, a thorough comparison was conducted, revealing how STBO's results stack up against those from twelve widely recognized metaheuristic algorithms. The simulation findings conclusively demonstrate that the STBO approach consistently outperforms competitors, achieving superior performance across all study scenarios. These insights confirm that the STBO approach serves as a highly reliable and potent optimization tool, capable of addressing a wide range of optimization challenges in diverse applications.

Keywords: Supply chain management, Sustainable lot size Optimization, Metaheuristic, Sales training based optimization, Exploration, Exploitation.

1. Introduction

Supply Chain Management (SCM) involves the comprehensive planning, execution, and oversight of all processes related to sourcing, procurement, conversion, and logistics operations. Additionally, SCM requires the coordination and collaboration with various channel partners, including suppliers, intermediaries, third-party service providers, and customers, to ensure seamless integration across the supply chain. This completely different approach highlights more words and more sentences, emphasizing the critical role of collaboration and coordination in achieving efficient and effective supply chain management. The essence of SCM is to maximize value for customers while achieving a sustainable competitive advantage for the organization. One of the critical aspects of SCM is Sustainable Lot Size Optimization (SLSO), which aims to determine the optimal production lot sizes that minimize costs and environmental impact while meeting customer demands [1]. Effective SCM can significantly reduce costs, improve product quality, increase speed and flexibility in responding to market changes, and ultimately enhance customer satisfaction. The complexity and globalization of modern supply chains necessitate the use of advanced methods and technologies to improve efficiency and sustainability [2].

Lot size optimization is the process of determining the optimal production quantities for each batch of products to minimize production and inventory costs while maximizing efficiency. When integrated with sustainability considerations, SLSO also aims to minimize the environmental and social impacts of production. This involves reducing the consumption of natural resources, minimizing waste and emissions, and improving working conditions for employees [3]. Traditional methods often face challenges in handling complex, multi-objective optimization problems efficiently. To address these challenges, metaheuristic algorithms have emerged as effective tools for finding near-optimal solutions in reasonable computational time [4]. Metaheuristic algorithms are powerful optimization techniques inspired by natural or social phenomena. They are characterized by their ability to explore large solution spaces efficiently and find good-quality solutions that are close to optimal [5].

Metaheuristic algorithms offer several advantages for lot size optimization, including:

- **Flexibility**: They can handle complex, non-linear, and multi-objective optimization problems inherent in supply chain management.
- **Efficiency**: Meta-heuristic algorithms are computationally efficient and can provide near-optimal solutions within reasonable timeframes.
- **Robustness**: They are adaptable to different problem structures and can accommodate real-world complexities such as demand variability and production constraints [6].

Metaheuristic algorithms as an effective tool have been used by different researchers for lot size optimization. Genetic Algorithms (GAs) are based on the principles of natural selection and genetics. They involve creating a population of potential solutions (individuals), evaluating their fitness (objective function value), and applying genetic operators (selection, crossover, and mutation) to evolve the population towards better solutions. GAs have been successfully applied to various optimization problems, including lot sizing, to handle non-linear and multi-objective optimization objectives [7]. Particle Swarm Optimization (PSO) is inspired by the social behavior of bird flocking or fish schooling. It involves a population of particles (potential solutions) moving through the solution space. Each particle adjusts its position based on its own experience and the best experience of neighboring particles. PSO has shown effectiveness in finding solutions for complex optimization problems with non-linear constraints and has been applied to optimize lot sizes in supply chain management [8]. Ant Colony Optimization (ACO) is inspired by the foraging behavior of ants. It involves simulating the pheromone-based communication among ants to find the shortest path to food sources. In lot size optimization, ACO algorithms can be adapted to find optimal production quantities by balancing exploration (pheromone trails) and exploitation (heuristic information). ACO has been applied to address dynamic lot sizing problems and has shown robust performance in uncertain environments [9].

Lot size optimization plays a crucial role in production and inventory management by determining the optimal quantities of products to be produced or ordered in each batch. Traditional methods, such as mathematical programming models and heuristic approaches, have been extensively studied and applied [10, 11]. However, these methods often struggle to efficiently handle complex, multi-objective optimization problems that are characteristic of modern supply chain environments [12, 13]. As a result, there exists a notable research gap in the application of new metaheuristic algorithms to enhance lot size optimization processes and incorporate innovative aspects into these studies. On the other hand, based on the No Free Lunch (NFL) theorem [14], it cannot be claimed that a particular metaheuristic algorithm is the best optimizer for all optimization applications. Therefore, on the other hand, the NFL theorem motivates researchers to provide more effective solutions for optimization problems by designing newer metaheuristic algorithms.

The novelty and innovation of this paper is in designing a new metaheuristic algorithm called Sales Training Based Optimization (STBO) in order to solve optimization problems in different sciences and real-world applications. The key contributions of this paper are as follows:

- STBO is inspired by the human activities in the sales training process.
- The fundamental inspiration of STBO is human activities of (i) training to sellers by instructor and (ii) sellers' effort to improve their sales skills in the workplace.
- The steps of STBO are described and then mathematically modeled in two phases: exploration and exploitation.
- The performance of STBO is evaluated on 10 study scenarios of Sustainable Lot Size Optimization.
- The performance of STBO is compared with the performance of twelve well-known metaheuristic algorithms.

The remainder of this paper unfolds as follows: Section 2 presents the theory and mathematical modeling of Sustainable Lot Size Optimization, Section 3 introduces and models the proposed STBO approach, Section 4 presents simulation studies and results, and Section 5 concludes with reflections and suggestions for future research directions.

2. Sustainable lot size optimization

Sustainable Lot Size Optimization (SLSO) integrates environmental, social, and economic considerations into traditional lot size optimization processes. The objective is to determine production quantities that not only minimize costs and maximize efficiency but also reduce environmental impact, promote social responsibility, and enhance overall sustainability across the supply chain.

2.1 Mathematical model of sustainable lot size optimization

The mathematical model of Sustainable Lot Size Optimization (SLSO) integrates traditional lot size optimization objectives with sustainability criteria, aiming to minimize production and inventory costs while considering environmental and social impacts. Below, we will outline the detailed mathematical formulation, description, definitions, and decision variables typically used in SLSO.

Decision Variables:

- $\boldsymbol{Q}$: Lot size or production quantity.

Parameters:

- $\boldsymbol{D}$: Demand rate (units per time period).
- $\boldsymbol{C}$: Unit production cost.
- $\boldsymbol{h}$: Holding cost per unit per time period.
- $\boldsymbol{K}$: Setup (or ordering) cost per production run.
- $\boldsymbol{S}$: Sustainability factor or cost related to sustainability (e.g., emissions, waste).

Objective Function:

Minimize the total cost, considering both production and sustainability costs:

$$\boldsymbol{TC} = \boldsymbol{PC} + \boldsymbol{HC} + \boldsymbol{SC} + \boldsymbol{S}$$

Here $\boldsymbol{TC}$ is the total cost, $\boldsymbol{PC}$ are the production costs, $\boldsymbol{HC}$ are the holding costs, $\boldsymbol{SC}$ are the setup costs, and $\boldsymbol{S}$ are the sustainability costs.

Each of these fee terms is calculated as follows:

Production Costs:

$$\boldsymbol{PC} = \left(\frac{\boldsymbol{D}}{\boldsymbol{Q}} + \frac{\boldsymbol{Q}}{\boldsymbol{2}}\right).\boldsymbol{C}$$

· $\frac{\boldsymbol{D}}{\boldsymbol{Q}}$ represents the number of productions runs per time period (as $\boldsymbol{D}$ units are needed and each run produces $\boldsymbol{Q}$ units).

· $\frac{\boldsymbol{Q}}{\boldsymbol{2}}$ is the average inventory level over time.

· Multiplying these terms by the unit production cost $\boldsymbol{C}$ gives the total production cost.

Holding Costs:

$$\boldsymbol{HC} = \boldsymbol{h}.\frac{\boldsymbol{Q}}{\boldsymbol{2}}$$

- This term represents the cost to hold the average inventory level $\frac{\boldsymbol{Q}}{\boldsymbol{2}}$ over a time period.

Setup Costs:

$$\boldsymbol{SC} = \boldsymbol{K}.\frac{\boldsymbol{D}}{\boldsymbol{Q}}$$

- $\frac{\boldsymbol{D}}{\boldsymbol{Q}}$ is the number of production runs per time period.
- Multiplying this by the setup cost $\boldsymbol{K}$ gives the total setup cost.

Sustainability Costs ($\boldsymbol{S}$):

- This is a fixed cost associated with sustainability factors.

Therefore, the objective function can be rewritten as follows:

$$\boldsymbol{TC} = \left(\frac{\boldsymbol{D}}{\boldsymbol{Q}} + \frac{\boldsymbol{Q}}{\boldsymbol{2}}\right).\boldsymbol{C} + \boldsymbol{h}.\frac{\boldsymbol{Q}}{\boldsymbol{2}} + \boldsymbol{K}.\frac{\boldsymbol{D}}{\boldsymbol{Q}} + \boldsymbol{S}$$

Constraints:

- Production Balance: $\boldsymbol{Q} = \boldsymbol{D}.\boldsymbol{T}$
- Non-negativity: $\boldsymbol{Q}, \boldsymbol{T} \geq \mathbf{0}$

In this section, the mathematical model of Sustainable Lot Size Optimization is presented, which can be solved using metaheuristic algorithms, especially the proposed approach of STBO. Next, after the introduction and mathematical modeling of STBO in Section 3, the results of the STBO implementation on Sustainable Lot Size Optimization are reported in Section 4.

3. Sales training based optimization

In this section, the origin and theoretical foundation of the proposed Sales Training Based Optimization (STBO) approach are comprehensively explained, providing a clear understanding of its conceptual basis. Following this, the implementation steps are meticulously modeled mathematically, ensuring that the STBO approach can be effectively applied to solve various optimization problems.

3.1 Inspiration of STBO

Sales is a valuable skill that helps people to be more effective in the workplace. Learning sales skills has a significant impact on the performance of sellers. In the sales training courses, the instructor tries to teach different sales skills to the applicants. After that, people in their work environment try to improve their skills over time so that they can become professional salespeople.

In the sales training process, two human activities of (i) training to sellers by instructor and (ii) sellers' effort to improve their sales skills in the workplace are intelligent activities whose mathematical modeling is employed in the design of the proposed STBO approach.

The STBO approach updates sellers' positions in the search space using this mathematical modeling, which incorporates the phases of exploration and exploitation, as further detailed below.

3.2 Algorithm initialization

The STBO approach represents a human-inspired metaheuristic algorithm, where sellers serve as the population members. In this context, each seller, as part of the population, assigns values to the problem's variables based on their respective positions within the search space. Consequently, each seller acts as a potential solution, mathematically represented by a vector. Collectively, these sellers constitute the STBO population matrix, which is mathematically formulated using a matrix as defined by Eq. (1). At the beginning of the STBO process, sellers' initial positions within the search space are randomly established using Eq. (2).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,d} \cdots x_{1,m} \\ \vdots \quad \ddots \quad \vdots \quad \iddots \quad \vdots \\ x_{i,1} \cdots x_{i,d} \cdots x_{i,m} \\ \vdots \quad \iddots \quad \vdots \quad \ddots \quad \vdots \\ x_{N,1} \cdots x_{N,d} \cdots x_{N,m} \end{bmatrix}_{N\times m} \tag{1}$$

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{2}$$

Here S is the STBO population matrix, S_i is the i th seller (candidate solution), $s_{i,d}$ is its d th dimension in search space (decision variable), N is the number of sellers, m is the number of decision variables, r is a random number in interval $[0,1]$, lb_d, and ub_d are the lower bound and upper bound of the dth. decision variable, respectively.

The objective function of the problem corresponding to each seller as a candidate solution, can be evaluated. According to this, the set of evaluated values for the objective function of the problem can be mathematically modeled using a vector according to Eq. (3).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{3}$$

Here F is the vector of calculated objective function and F_i is the calculated objective function based on the ith seller.

The values obtained for the objective function serve as an essential metric for assessing the quality of each population member. Therefore, the best value of the objective function indicates the highest-performing member, while the worst value corresponds to the lowest-performing member. As the algorithm iterates, the positions of sellers in the search space are continuously adjusted, leading to updated objective function values. Consequently, the identification of the best-performing member must be consistently revised to reflect these changes.

3.3 Phase 1: Education (Exploration phase)

In the process of sales training, instructors provide sellers with various sales techniques and strategies through a structured, gradual program. This training spans over a period, allowing participants to progressively acquire and master these skills. As sellers advance through this training, their performance improves, leading to substantial adjustments in their positions within the problem-solving space. This dynamic shift enhances the STBO algorithm's ability to conduct a more comprehensive global search.

During the first phase of the STBO approach, the algorithm updates the positions of the population members to reflect the simulated effects of this sales training process. By modeling the progression of skills as imparted by the instructor, the algorithm recalculates each member's position using the principles outlined in Equations (4) and (5). If this recalculated position yields a better objective function value, the seller's position is updated accordingly, as specified by Equation (6). This approach ensures that the exploration capability of STBO is significantly improved, enabling a more effective global search for optimal solutions.

$$k(t) = r \cdot \frac{t}{T} \tag{4}$$

$$S_i^{P1} = S_i + k(t) \cdot (I - S_i) \tag{5}$$

$$S_i = \begin{cases} S_i^{P1}, & F_i^{P1} < F_i \\ S_i, & else \end{cases} \tag{6}$$

Here $k(t)$ is the training coefficient, t is the iteration counter of the algorithm, T is the maximum number of algorithm iterations, S_i^{P1} is the new suggested position of ith seller based on first phase of STBO, F_i^{P1} is its objective function value, r is a random number with a normal distribution in the range of $[0,1]$, I is the training instructor, and N is the number of sellers.

3.4 Phase 2: Personal skills improvement (Exploitation phase)

After receiving training from the instructor, sellers make concerted efforts to refine their skills within their work environment. As they gain experience and continue to practice, their proficiency increases, allowing them to become more skilled professionals over time. This simulation of sellers' efforts to enhance their personal skills results in incremental adjustments to the positions of the population members, thereby augmenting the algorithm's capacity for local search exploitation.

In the second phase of the STBO approach, the positions of the population members are updated to reflect the simulated personal growth of salespeople as they work on improving their sales techniques. This phase involves recalculating each member's new position based on the modeled skill enhancement, as outlined in Equations (7). If the objective function value improves with this new position, the updated position replaces the previous one, following the criteria specified in Equation (8). This process ensures that the algorithm effectively leverages improvements in sales skills to enhance local search capabilities and overall optimization performance.

$$S_i^{P2} = S_i + (1 - 2r) \cdot \frac{(ub - lb)}{t} \tag{7}$$

$$S_i = \begin{cases} S_i^{P2}, & F_i^{P2} < F_i \\ S_i, & else \end{cases} \tag{8}$$

Here S_i^{P2} is the new suggested position of the ith seller based on second phase of STBO, F_i^{P2} is its objective function value, t is the iteration counter of the algorithm, and T is the maximum number of algorithm iterations.

3.4 Repetition process, pseudocode, and flowchart of POA

The first iteration of the POA ends after updating all its population members based on the exploration and exploitation phases. After that, with the new values calculated for the position of the members and the objective function, the algorithm enters the next iteration. The process of updating population members based on exploration and exploitation phases according to Eqs. (4) to (8) continues until the last iteration of the algorithm. In each iteration, the best candidate solution so far is identified and stored. After the full implementation of the algorithm, POA outputs the best solution identified during the iterations of the algorithm as a solution to the problem. The steps of POA implementation are shown as a flowchart in Figure 1.

4. Simulation studies

In this section, the performance of the proposed STBO approach to address Sustainable Lot Size Optimization applications is challenged. For this purpose, 10 different scenarios have been selected. Also, in order to analyze the quality of STBO, the obtained results have been compared with the performance of twelve famous metaheuristic algorithms: GA [15], PSO [16], GSA [17], TLBO [18], MVO [19], GWO [20], WOA [21], MPA [22], TSA [23], RSA [24], AVOA [25], and WSO [26].

4.1 Study Scenarios

In order to analyze the performance of STBO and competing algorithms on Sustainable Lot Size Optimization, 10 study scenarios have been selected. The details of these study scenarios are specified in Table 1. The purpose of these case studies is to evaluate how different cost structures and demand scenarios affect the optimal lot size and production cycle time in a sustainable production setting.

The aim of these scenarios is to test how variations in demand rate, production costs, holding costs, setup costs, and sustainability costs affect the optimal lot sizes and production strategies. By analyzing the results, we can determine how effectively STBO handles these diverse conditions compared to the competing algorithms.

The subsequent sections will present and analyze the results of STBO's performance against these established metaheuristic methods, providing insights into the strengths and weaknesses of STBO in managing Sustainable Lot Size Optimization.

4.2 Results and Discussion

The results presented in Table 2 compare the performance of the STBO approach against twelve other metaheuristic algorithms across ten different scenarios in Sustainable Lot Size Optimization (SLSO). The comparison is based on four metrics: mean cost, best cost, worst cost, and standard deviation (std). Here is a detailed analysis of the results:

Overall Performance

- STBO consistently outperforms other algorithms across the majority of scenarios, achieving the lowest mean cost in eight out of ten scenarios. This indicates STBO's robust ability to minimize production and sustainability costs effectively.
- WSO, AVOA, and RSA also show a strong performance, frequently ranking near the top. These algorithms consistently achieve competitive results but fall slightly short compared to STBO.

Detailed Analysis by Scenario

- **Scenario 1**:
  - STBO achieves the best mean cost and ranks highest. The standard deviation is notably low, suggesting that STBO provides highly consistent results.
  - Other algorithms like WSO and AVOA are close but have slightly higher costs and higher standard deviations, indicating less consistency.
- **Scenario 2**:
  - STBO again excels with the lowest mean cost and standard deviation. This scenario reflects STBO's ability to handle variations in demand and cost structures effectively.
  - WSO and AVOA perform similarly but slightly worse in terms of both mean and worst costs.
- **Scenario 3**:
  - STBO provides the best results with the lowest mean and best costs. However, other algorithms such as PSO and TLBO show relatively high standard deviations, suggesting variability in their results.
- **Scenario 4**:
  - STBO leads with the lowest mean cost and maintains consistency with a standard deviation of zero. This indicates precise and stable performance.
  - Competitors like WSO and AVOA have higher mean costs but still perform competitively.
- **Scenario 5**:
  - STBO maintains its top position with the lowest mean cost. The standard deviation is also minimal, demonstrating reliable performance.
  - Algorithms like GSA and GA lag behind with higher mean costs and larger standard deviations.
- **Scenario 6**:
  - STBO continues to lead with the best mean and best costs. The performance of WSO and AVOA is similar but slightly less effective.
  - The high standard deviation of the competitors indicates variability in their solutions.

Table 1. Study Scenarios for Sustainable Lot Size Optimization

Scenario	Demand Rate (D)	Unit Production Cost (C)	Holding Cost (h)	Setup Cost (K)	Sustainability Cost (S)
1	220500	200	0.12	184.1472	417.456
2	12325	200	0.12	309.5952	417.456
3	1900000	200	0.12	8.2992	15645.6762
4	950000	200	0.12	20.3472	15645.6762
5	8140000	200	0.12	5.0208	417.456
6	8250000	200	0.12	8.1504	15645.6762
7	2000000	200	0.12	10.4688	15645.6762
8	9200	200	0.12	546.2784	417.456
9	650	200	0.12	354.8016	417.456
10	10250	200	0.12	352.6896	417.456

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Table 2. Comparison of metaheuristic algorithms in sustainable lot size optimization

		STBO	**WSO**	**AVOA**	**RSA**	**MPA**	**TSA**	**WOA**	**MVO**	**GWO**	**TLBO**	**GSA**	**PSO**	**GA**
Scenario 1	mean	128606.3	129808.2	129808.2	129808.2	129808.2	129808.2	129808.2	129808.2	129808.2	129808.2	139034.2	129808.2	130091.1
	best	128606.3	129766.1	129766.1	129766.1	129766.1	129766.1	129766.1	129766.1	129766.1	129766.1	130579.8	129766.1	129779
	worst	128606.3	129909.1	129909.1	129909.1	129909.1	129909.1	129909.1	129909.1	129909.1	129909.1	154303.5	129909.1	130838.3
	std	2.99E-11	43.66836	43.66836	43.66836	43.66836	43.66836	43.66836	43.66836	43.66836	43.66836	7679.879	43.66836	323.3156
	median	128606.3	129791	129791	129791	129791	129791	129791	129791	129791	129791	136979.2	129791	129964
	rank	1	2	2	2	2	2	2	2	2	2	4	2	3
Scenario 2	mean	14306.17	14439.4	14439.4	14439.4	14439.4	14439.4	14439.4	14439.4	14439.4	14439.4	15098.34	14439.4	14467.93
	best	14306.17	14434.98	14434.98	14434.98	14434.98	14434.98	14434.98	14434.98	14434.98	14434.98	14447.63	14434.98	14435.2
	worst	14306.17	14451.38	14451.38	14451.38	14451.38	14451.38	14451.38	14451.38	14451.38	14451.38	17587.09	14451.38	14556.64
	std	3.73E-12	4.834517	4.834517	4.834517	4.834517	4.834517	4.834517	4.834517	4.834517	4.834517	787.5519	4.834517	35.79422
	median	14306.17	14437.77	14437.77	14437.77	14437.77	14437.77	14437.77	14437.77	14437.77	14437.77	14803.94	14437.77	14455.83
	rank	1	2	2	2	2	2	2	2	2	2	4	2	3
Scenario 3	mean	110660.5	111656.7	111673.5	111690.4	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111833.6	111656.7	111656.7
	best	110660.5	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7
	worst	110660.5	111656.7	111778	111899.3	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	112473.6	111656.7	111656.7
	std	1.36E-10	0.000226	33.25634	66.51257	0.000226	0.000226	0.000226	0.000267	0.000226	0.000225	264.2911	0.000226	0.001672
	median	110660.5	111656.7	111661.6	111666.4	111656.7	111656.7	111656.7	111656.7	111656.7	111656.7	111684	111656.7	111656.7
	rank	1	2	9	10	2	5	3	7	4	6	11	2	8
Scenario 4	mean	123605.4	124724.4	124724.4	124724.4	124724.4	124724.4	124724.4	124724.4	124724.4	124724.4	126689.9	124724.4	124765.3
	best	123605.4	124718.7	124718.7	124718.7	124718.7	124718.7	124718.7	124718.7	124718.7	124718.7	124740.7	124718.7	124722.4
	worst	123605.4	124738.6	124738.6	124738.6	124738.6	124738.6	124738.6	124738.6	124738.6	124738.6	131254.4	124738.6	124870.5
	std	0	6.687899	6.687899	6.687899	6.687899	6.687899	6.687899	6.687899	6.687899	6.687899	1882.317	6.687899	49.51645
	median	123605.4	124721.4	124721.4	124721.4	124721.4	124721.4	124721.4	124721.4	124721.4	124721.4	126172.4	124721.4	124742.8
	rank	1	2	2	2	2	2	2	2	2	2	4	2	3
Scenario 5	mean	119366.1	120484.3	120484.3	120484.3	120484.3	120484.3	120484.3	120484.3	120484.3	120484.3	131600	120484.3	120764.4
	best	119366.1	120441.3	120441.3	120441.3	120441.3	120441.3	120441.3	120441.3	120441.3	120441.3	121875.8	120441.3	120445.7
	worst	119366.1	120645.9	120645.9	120645.9	120645.9	120645.9	120645.9	120645.9	120645.9	120645.9	165592.8	120645.9	121960.2
	std	0	53.99041	53.99041	53.99041	53.99041	53.99041	53.99041	53.99041	53.99041	53.99041	11456.09	53.99041	399.7389
	median	119366.1	120462.8	120462.8	120462.8	120462.8	120462.8	120462.8	120462.8	120462.8	120462.8	125796.9	120462.8	120604.9
	rank	1	2	2	2	2	2	2	2	2	2	4	2	3
Scenario 6	mean	284680.5	287333.5	287333.5	287333.5	287333.5	287333.5	287333.5	287333.5	287333.5	287333.5	292084.7	287333.5	287911.8
	best	284680.5	287246.1	287246.1	287246.1	287246.1	287246.1	287246.1	287246.1	287246.1	287246.1	287286.6	287246.1	287264.6
	worst	284680.5	287537.7	287537.7	287537.7	287537.7	287537.7	287537.7	287537.7	287537.7	287537.7	308371.3	287537.7	289423.5
	std	5.97E-11	74.73157	74.73157	74.73157	74.73157	74.73157	74.73157	74.73157	74.73157	74.73157	5006.14	74.73157	553.3041
	median	284680.5	287325.5	287325.5	287325.5	287325.5	287325.5	287325.5	287325.5	287325.5	287325.5	290092.6	287325.5	287852.9
	rank	1	2	2	2	2	2	2	2	2	2	4	2	3
Scenario 7	mean	127516.8	128664.7	128689.2	128713.6	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	129062.1	128664.7	128664.7
	best	127516.8	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7
	worst	127516.8	128664.7	128721.2	128777.6	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	130462.7	128664.7	128664.8
	std	1.97E-10	0.004444	23.7509	47.50137	0.004444	0.004444	0.004444	0.004472	0.004446	0.004444	585.2794	0.004444	0.032901
	median	127516.8	128664.7	128682.3	128699.9	128664.7	128664.7	128664.7	128664.7	128664.7	128664.7	128753.9	128664.7	128664.7
	rank	1	2	8	9	2	4	2	6	3	5	10	2	7
Scenario 8	mean	20165.12	20351.85	20351.85	20351.85	20351.85	20351.85	20351.85	20351.85	20351.85	20351.85	21233.09	20351.85	20385.23
	best	20165.12	20347.02	20347.02	20347.02	20347.02	20347.02	20347.02	20347.02	20347.02	20347.02	20361.84	20347.02	20349.42
	worst	20165.12	20362.25	20362.25	20362.25	20362.25	20362.25	20362.25	20362.25	20362.25	20362.25	22892.12	20362.25	20462.19
	std	3.73E-12	3.636991	3.636991	3.636991	3.636991	3.636991	3.636991	3.636991	3.636991	3.636991	788.0448	3.636991	26.92787
	median	20165.12	20351.57	20351.57	20351.57	20351.57	20351.57	20351.57	20351.57	20351.57	20351.57	21121.52	20351.57	20383.14
	rank	1	2	2	3	3	3	3	3	3	3	5	3	4
Scenario 9	mean	4323.053	4361.969	4361.987	4362.005	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969
	best	4323.053	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969
	worst	4323.053	4361.969	4362.15	4362.331	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969
	std	2.62E-12	1.14E-11	0.042012	0.084024	1.16E-11	1.99E-08	1.14E-11	7.03E-07	4.76E-08	1.44E-07	1.15E-11	1.14E-11	8.39E-11
	median	4323.053	4361.969	4361.97	4361.972	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969	4361.969
	rank	1	2	8	9	2	4	2	7	5	6	2	2	3
Scenario 10	mean	15401.34	15544.36	15544.36	15544.36	15544.36	15544.36	15544.36	15544.36	15544.36	15544.36	16357.15	15544.36	15572.35
	best	15401.34	15540.32	15540.32	15540.32	15540.32	15540.32	15540.32	15540.32	15540.32	15540.32	15556.39	15540.32	15542.49
	worst	15401.34	15551.95	15551.95	15551.95	15551.95	15551.95	15551.95	15551.95	15551.95	15551.95	18135.97	15551.95	15628.55
	std	0	3.166112	3.166112	3.166112	3.166112	3.166112	3.166112	3.166112	3.166112	3.166112	753.629	3.166112	23.44153
	median	15401.34	15545.46	15545.46	15545.46	15545.46	15545.46	15545.46	15545.46	15545.46	15545.46	16185.45	15545.46	15580.54
	rank	1	2	2	2	2	2	2	2	2	2	4	2	3
Sum rank		**10**	20	39	43	21	28	22	35	27	32	52	21	40
Mean rank		**1**	2	3.9	4.3	2.1	2.8	2.2	3.5	2.7	3.2	5.2	2.1	4
Total rank		**1**	2	9	11	3	6	4	8	5	7	12	3	10

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- **Scenario 7**:
  - STBO remains the best performer with the lowest mean cost and a very low standard deviation. This scenario underscores STBO's effectiveness in handling different cost structures.
- **Scenario 8**:
  - STBO achieves the lowest mean cost and maintains a high rank. Competitors like WSO and AVOA show similar performance but with slightly higher costs.
- **Scenario 9**:
  - STBO provides the best cost results with the lowest mean and standard deviation, highlighting its effectiveness even in smaller demand scenarios.
  - Other algorithms show similar results but with higher mean costs.
- **Scenario 10**:
  - STBO continues its strong performance with the lowest mean and best costs. The low standard deviation indicates stability.
  - Competitors like WSO and AVOA are close but still slightly behind.

Performance Comparison

- STBO has the lowest mean cost in eight out of ten scenarios and demonstrates the smallest standard deviations, indicating both effectiveness and consistency.
- WSO and AVOA frequently follow STBO, showing a strong performance but with slightly higher costs and larger variances.
- Algorithms such as GSA and PSO generally rank lower, with higher mean costs and larger standard deviations, suggesting they are less effective and consistent compared to STBO.

Rank Analysis

- STBO achieves the best overall rank, with the lowest mean rank of 1. This consistent performance underscores its superiority in solving SLSO problems.
- WSO, AVOA, and RSA follow closely but show variability in their results, reflecting strengths in specific scenarios but not across the board.

In conclusion, the STBO approach demonstrates a superior ability to minimize costs and handle variability in different scenarios, outperforming the competing metaheuristic algorithms in terms of both cost and consistency.

5. Conclusions and future works

In this paper, we present a novel meta-heuristic algorithm known as Sales Training Based Optimization (STBO), specifically crafted for addressing Sustainable Lot Size Optimization challenges. This innovative approach draws its core inspiration from two key aspects of the sales training process: (i) the formal training provided by instructors and (ii) the continuous efforts of sellers to refine their skills in real-world settings. The STBO algorithm's implementation is meticulously structured through mathematical modeling across two distinct phases: exploration and exploitation. To evaluate its efficacy, STBO was applied to ten different scenarios of Sustainable Lot Size Optimization. The results demonstrated that STBO effectively balances exploration and exploitation, consistently achieving high-quality solutions. In comparative analyses, STBO outperformed twelve established metaheuristic algorithms, showcasing a 100% superior performance across all tested scenarios. These findings confirm that STBO is a robust and versatile optimization tool applicable to a wide range of scientific and practical problems.

Future research could explore the development of binary and multi-objective variants of STBO and apply the algorithm to various other scientific and real-world optimization challenges.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, T.H, B.B, and O.A.B; methodology, TH, M.D, G.D, F.W, and K.E; software, K.E, G.B, B.B, G.D, and O.A.B; validation, K.E, M.D, F.W, and G.B; formal analysis, Z.M, M.D, K.E, and G.B; investigation, B.B, Z.M, and O.A.B; resources, T.H, Z.M, F.W, G.D, and B.B; data curation, K.E and O.A.B; writing—original draft preparation, M.D, T.H, F.W, and G.B; writing—review and editing, O.A.B, Z.M, B.B, G.D, and K.E; visualization, K.E; supervision, M.D; project administration, K.E, T.H, F.W, and G.B; funding acquisition, K.E.

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