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On the Application of Potter Optimization Algorithm for Solving Supply Chain Management Application

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Abstract: Supply Chain Management (SCM) applications represent real-world optimization tasks that require handling using appropriate optimization techniques. Metaheuristic algorithms are powerful optimization tools that are effective for solving complex optimization problems such as SCM. In this article, a new metaheuristic algorithm named Potter Optimization Algorithm (POA) is introduced to deal with optimization problems, especially in SCM applications. POA is mathematically modelled by the inspiration of the human process of pottery in two phases of exploration and exploitation. The exploration phase is designed based on mathematical modeling of making extensive changes to the clay (or other pottery materials) according to the given pattern. The exploitation phase is designed based on mathematical modelling of making precise and limited changes on the made pottery with the aim of creating more similarity to the given pattern. The effectiveness of the proposed POA approach to address real-world applications in SCM has been evaluated on sustainable lot size optimization. The optimization results show that POA has been able to provide effective solutions for sustainable lot size optimization case studies by managing exploration, exploitation, and balancing them during the search process at both global and local levels. In addition, the results obtained from the implementation of POA have been compared with the performance of twelve well-known metaheuristic algorithms. The analysis of the optimization results shows that POA has 100% superior performance compared to competing algorithms by providing better results in all ten case studies.

Keywords: Optimization algorithm, Supply chain management, Human-inspired, Potter, Exploration, Exploitation.

1. Introduction

Supply Chain Management (SCM) is crucial for the seamless functioning of modern businesses, ensuring the smooth flow of products, services, and information from suppliers to end consumers. It encompasses a vast array of activities such as procurement, production, inventory management, logistics, and distribution, all designed to enhance the efficiency and effectiveness of the entire supply chain network [1]. In the current competitive and global market, proficient SCM is vital for companies aiming to secure a competitive advantage, boost customer satisfaction, and drive sustainable growth [2]. At its core, SCM involves the coordination and cooperation of multiple entities including suppliers, manufacturers, distributors, retailers, and customers, ensuring timely product delivery while minimizing costs and maximizing value [3]. This interconnectedness brings to light the intricate nature of SCM, which must navigate challenges like fluctuating demand, supply chain interruptions, inventory management, and shifting consumer preferences [4].

With the advent of digital technology and globalization, SCM has become even more complex, necessitating innovative approaches and tools to optimize processes and mitigate risks [5]. Technologies like big data analytics, artificial intelligence, blockchain, and the Internet of Things (IoT) are increasingly utilized to enhance visibility, transparency, and agility across supply chains. Consequently, SCM has evolved from traditional methods to a more comprehensive and strategic approach, emphasizing not only operational efficiency but also sustainability, resilience, and customer-centricity [6]. This evolution highlights the importance of SCM as a critical component for business success and competitive advantage in today's interconnected global economy [7]. Effective SCM practices enable organizations to optimize resource use, reduce waste, and create value for all participants in the supply chain [8].

In this dynamic SCM environment, the application of metaheuristic algorithms has emerged as a transformative method for addressing complex optimization challenges [9]. Metaheuristic algorithms, inspired by natural processes or human behaviors, are iterative techniques designed to search for optimal solutions within vast solution spaces efficiently. These algorithms have become prominent in SCM for their ability to solve intricate problems related to route planning, inventory optimization, and demand forecasting amid uncertainty and variability. By utilizing these algorithms, businesses can successfully balance competing objectives such as cost reduction, lead time minimization, and service level improvement, thus enhancing overall supply chain performance. The problems and challenges in SCM are often formulated as optimization tasks that require sophisticated techniques for effective solutions [10].

In general, optimization techniques fall into two groups: deterministic and random approaches [11]. Although the deterministic approaches are successful in dealing with convex and linear optimization problems , they lose their efficiency when faced with practical optimization problems that are complex, non-convex, and non-linear [12, 13]. Disadvantages and weaknesses of deterministic approaches led researchers to design stochastic algorithms, especially metaheuristic algorithms, to be able to achieve suitable solutions for practical and real-world optimization problems [14].

Metaheuristic algorithms, which are inspired by natural and evolutionary processes, are able to find appropriate solutions for optimization problems based on random search in the problem solving space without the need for gradient information [15].

Due to their advantages, metaheuristic algorithms have attracted the attention of researchers to deal with optimization tasks. These advantages include: simple and understandable concepts, easy implementation, efficiency in nonlinear, discrete, and unknown search spaces, and efficiency in solving non-convex, NP-hard, nonlinear, and non-derivative optimization problems [16].

Despite these advantages, the important issue is that due to the nature of stochastic search, there is no guarantee of achieving the global optimum using metaheuristic algorithms. This fact and the desire to achieve more effective solutions for optimization problems are the main motivation for the development of countless metaheuristic algorithms [16].

As the main research question, is there a need to introduce newer metaheuristic algorithms despite the algorithms introduced so far and available in the literature? Referring to the No Free Lunch (NFL) theorem [17], this question is answered that in no way can it be claimed that a particular algorithm is the best optimizer for all optimization applications. In fact, the NFL theorem says that there is no set hypothesis for the success or failure of an algorithm. Therefore, there is always the possibility of designing a newer algorithm that performs better. By keeping this field of study active, the NFL theorem motivates researchers to be able to achieve better solutions for optimization problems by designing newer metaheuristic algorithms.

The novelty and novelty aspects of this study are in the design of a new metaheuristic algorithm called Potter Optimization Algorithm (POA) to deal with optimization tasks in different sciences. The main contributions of this study are listed below:

- Inspired by human activities during the pottery process, POA is designed.
- The theory of POA is expressed and mathematically modeled in two phases (i) exploration: based on the modeling of extensive changes made on clay and (ii) exploitation: based on the modeling of small and precise changes on the manufactured clays.

- The efficiency of POA has been evaluated to address the applications of Supply Chain Management (SCM) for sustainable lot size optimization.
- The results obtained from POA are compared with the performance of twelve competing metaheuristic algorithms.

In the following, the organization of the article is as follows, which is presented first in section 2 of the literature review. Then, in section 3, the proposed approach of Potter Optimization Algorithm (POA) is introduced and mathematically modeled. In section 4, the performance evaluation of POA has been discussed in order to deal with sustainable lot size optimization. Finally, conclusions and several research suggestions are provided in Section 5.

2. Literature review

In recent years, metaheuristic algorithms have garnered significant interest across a wide range of disciplines, including computer science, engineering, mathematics, and various other scientific fields. By leveraging concepts such as natural evolution, collective behaviour, random searches, and similar principles, these algorithms strive to optimize complex problems through diverse methodologies. Metaheuristic algorithms can be categorized into four primary groups based on their foundational design concepts: swarm intelligence, evolutionary processes, physical phenomena, and human-inspired methods. Each group draws inspiration from different natural or conceptual processes to address and solve optimization challenges effectively.

Swarm-based metaheuristic algorithms are crafted to tackle optimization problems by mimicking the collective behaviours observed in nature among various living organisms. These algorithms draw inspiration from the group dynamics of creatures like ants, bees, birds, and even anteaters, and they are employed to optimize a range of issues including routing, scheduling, and production planning. For instance, Particle Swarm Optimization (PSO) is a widely recognized metaheuristic inspired by the flocking behaviour of birds searching for food. In PSO, the optimization task is akin to identifying the optimal position within a multidimensional space [18]. Similarly, Ant Colony Optimization (ACO) is inspired by the foraging behaviour of ants and relies on pheromone trails to guide the search for optimal solutions, proving particularly effective for complex optimization problems [19]. Other notable swarm-based algorithms include the Migration-Crossover Algorithm (MCA) [20], Adax Optimization Algorithm (AOA) [21], Walrus Optimization Algorithm (WaOA) [22], and Swarm Space Hopping Algorithm (SSHA) [23].

Evolutionary-based algorithms, on the other hand, draw from biological sciences and principles of evolution, such as natural selection, genetic diversity, and heredity. The Genetic Algorithm (GA) [24] is a prime example, inspired by the genetic processes found in nature. In GA, a population of potential solutions (chromosomes) is iteratively evolved through processes mimicking natural selection, crossover, and mutation to generate new, improved generations.

Physics-based algorithms are grounded in physical principles and laws, utilizing concepts like fluid dynamics, gravity, and diffusion to optimize problems. Simulated Annealing (SA) is a prominent optimization method inspired by the annealing process in metallurgy. This algorithm employs probabilistic techniques to accept or reject changes in the solution space, gradually reducing the probability of accepting inferior solutions as it "cools" over time, thereby converging towards an optimal solution [25]. Other physics-based algorithms include Kepler Optimization Algorithm (KOA) [26], Charged System Search (CSS) [27], Electromagnetic Field Optimization (EFO) [28], and Prism Refraction Search (PRS) [29].

Human-based algorithms leverage insights from human cognitive processes, behaviours, and decision-making patterns. These algorithms often model human activities like learning, memory, and personal development. For instance, Teaching-Learning Based Optimization (TLBO) is inspired by educational processes, where solutions are viewed as learners, and the optimization is driven by interactions between teachers and students [30]. The Mother Optimization Algorithm (MOA) is another example, inspired by maternal principles of education and nurturing by mother Eshrat [14]. Algorithms such as Human Mental Search (HMS) [31], Dollmaker Optimization Algorithm (DOA) [32], and Ali Baba and the Forty Thieves (AFT) [33] draw from various aspects of human interaction and cognition to guide the search for optimal solutions.

These diverse metaheuristic approaches demonstrate the versatility and effectiveness of nature-inspired and concept-driven optimization techniques in solving a broad array of complex problems across different domains.

Based on the best knowledge obtained from the literature review, no meta-heuristic algorithm inspired by human activities during the pottery process has been designed so far. This is while making pottery from clay and beautifying it are intelligent activities that can be the basis for designing a new metaheuristic algorithm. In order to address this research gap, a new metaheuristic algorithm based on the mathematical modeling of the pottery process has been introduced and designed, which is discussed in the next section.

3. Potter optimization algorithm

In this section, the theory of the proposed new Potter Optimization Algorithm (POA) approach has been explained first, then it has been mathematically modeled for implementation on optimization problems.

3.1 Inspiration of POA

The art of pottery and pottery is one of the oldest and most widespread decorative arts that has been popular among societies throughout the world for many years. In this art, objects, artistic and decorative pieces are made from clay. The basic material of pottery art is clay. This composition has a flexible and moldable structure and it can be molded to give it a specific shape during the construction of the parts.

In general, in the pottery process, the steps of making a piece of pottery such as a pot or container are as follows:

1- First, you have to prepare the mixture of the raw material, which is clay and water.

2- Next, a suitable dough should be prepared by kneading the clay mixture completely and removing all the bubbles inside it.

3- After the clay dough is ready, you can start shaping the dough and use special pottery tools and devices to make the desired piece.

4- Now the piece of clay should be allowed to be exposed to the air and dry.

5- After it is completely dry, it is time to firing it in the kiln.

6- After placing the dishes in the kiln and finishing their firing, they should be removed and allowed to cool.

7- The final stage of pottery involves decorating and adding a glaze or coating to the surface of the pottery. These steps are among the stages of beautification and decoration, and depending on the taste, different designs and paintings can be executed on raw clay dishes.

In the pottery process, two stages are generally more significant: (i) shaping the pottery paste based on the existing pattern and (ii) the stage of decorating and beautifying the made pottery. These two prominent human activities in pottery are the main source of inspiration in the design of the proposed POA approach.

3.2 Algorithm initialization

T The proposed POA approach is a population-based meta-heuristic algorithm that, by benefiting from the power of searching its members, is able to scan the problem solving space and converge to suitable solutions for optimization problems. Each POA member specifies values for the decision variables based on its position in the problem solving space. Therefore, each POA member corresponds to a candidate solution for the given problem, which is mathematically modeled using a vector. POA members together create these vectors, which are mathematically modeled using a matrix according to Eq. (1). The initial position of each POA member is initialized completely randomly 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, X is the POA's population matrix, X_i is the ith member (i.e., candidate solution), $x_{i,d}$ is its dth dimension in the search space (i.e., decision variable), N is the number of population members (i.e., population size), m is the number of decision variables, r is a random number within the interval $[0,1]$, while lb_d and ub_d stand for the lower and upper bounds of the dth decision variable, respectively.

Corresponding to each POA member representing a candidate solution to the problem, the objective function can be evaluated. Therefore, the evaluated values for the objective function are modeled using a vector according to Eq. (3).

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

Where, F is the vector of objective function values and F_i is the obtained objective function value based on the ith POA member.

3.3 Mathematical modelling of POA

In this subsection, inspired by human activities in the pottery process, POA is mathematically modeled. In order to update the candidate solutions in each iteration, potter's strategies have been used. Two strategies of the potter are more significant in this process: (i) the extensive changes that she/he makes on the clay in order to make a clay structure according to the pattern and (ii) the small and precise changes that she/he makes on the clay made for the purpose of decoration and beautification.

In POA design, based on the modeling of these two strategies, the position of population members in the problem solving space is updated in two phases of exploration and exploitation. Each of these update phases is described and modeled in detail below.

3.3.1 Phase 1: Making extensive changes to the clay (exploration phase)

The potter tries to make a clay vessel according to a pattern by using the paste obtained from the mixture of clay and water. These changes on the clay are very extensive and its modeling leads to extensive changes in the position of the population members. These sudden changes in the position of the population members lead to the algorithms being able to properly scan different parts of the problem solving space. Therefore, this phase of implementation in POA leads to the ability of the algorithm in discovery in order to manage the global search. In the design of POA, it is assumed that the potter follows a pattern in order to make a pottery vessel. For each member of the POA, a pattern is considered, which is specified using Eq. (4).

$$P_i: p_{i,j} = x_j^{best} + r \cdot (x_{i,j} - x_j^{best}) \tag{4}$$

Here, P_i is the given pattern for ith POA member, $p_{i,j}$ is its jth dimension, X^{best} is best population member, x_j^{best} is its jth dimension, and r is a random number within the interval $[0,1]$.

After choosing the appropriate pattern, the potter tries to shape the pottery material in such a way that it becomes similar to the pattern. Based on the modeling of this potter's behavior, a new random position is calculated for each POA member using Eq. (5). Then, if the new objective function is improved, this new position replaces the previous position of the corresponding member using Eq. (6).

$$x_{i,j}^{P1} = x_{i,j} + r \cdot (p_{i,j} - I \cdot x_{i,j}), \tag{5}$$

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

Where, X_i^{P1} is the new position for the ith member based on exploration phase of POA, $x_{i,j}^{P1}$ is its jth dimension, F_i^{P1} is its objective function value, r is a random number drawn from the interval $[0, 1]$, and I is randomly selected number, taking values of 1 or 2.

3.3.2 Phase 2: Making precise small changes and beautification on the made pottery (exploitation phase)

After making raw pottery, the potter tries to beautify and decorate it by paying attention to small and precise details. This potter's strategy leads to the creation of small changes on pottery, which modeling of this process corresponds to the creation of precise and targeted small changes in the position of POA population members. These small displacements lead the algorithm to converge to more effective and even global optimal solutions near the solutions discovered in the promising regions. Therefore, the modeling of this potter's strategy leads to the ability of POA in exploitation in order to manage local search.

In POA design, Eq. (7) is used to make these small changes in the position of population members. Using this equation, a random position near each POA population member is generated. Then, if the value of the objective function is improved, this new position replaces the previous position of the corresponding member using equation Eq. (8).

$$x_{i,j}^{P2} = x_{i,j} + r \cdot (\frac{x_j^{best} - x_{i,j}}{t+1}) \tag{7}$$

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

Here, X_i^{P2} is the new calculated position for the ith POA member based on exploitation phase of POA, $x_{i,j}^{P2}$ is the its jth dimension, F_i^{P2} is its objective function value, and t is the iteration counter.

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

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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. POA for sustainable lot size optimization

In this section, we explore the application of the Potter Optimization Algorithm (POA) for tackling optimization challenges in supply chain management (SCM). Our focus is on demonstrating the capability of POA in sustainable lot size optimization, where the goal is to balance environmental responsibility with economic efficiency within supply chain operations.

Sustainable lot size optimization aims to determine production batch sizes that not only minimize costs but also address environmental and social impacts. Traditional lot sizing models prioritize reducing costs such as setup, inventory holding, and ordering costs. However, sustainable lot size optimization expands this scope to include critical factors like energy consumption, resource utilization, waste reduction, emissions, and broader social considerations. This holistic approach is essential in today's context, where sustainability is increasingly recognized as a strategic imperative in supply chain management.

The sustainable lot size optimization process incorporates a variety of factors. These include energy usage, raw material consumption, waste generation, emissions, and social impacts, in addition to economic costs. The objective is to identify batch sizes that reduce costs while also minimizing negative environmental impacts and promoting social responsibility across the supply chain.

A comprehensive mathematical model for sustainable lot size optimization integrates both economic and environmental costs. The aim is to find the optimal lot size for each stage of the supply chain to minimize CO2 emissions and overall costs. This model includes constraints such as production capabilities, inventory storage limits, and demand satisfaction requirements. Furthermore, specific sustainability criteria are integrated to limit the CO2 emissions related to manufacturing, transportation, and storage activities.

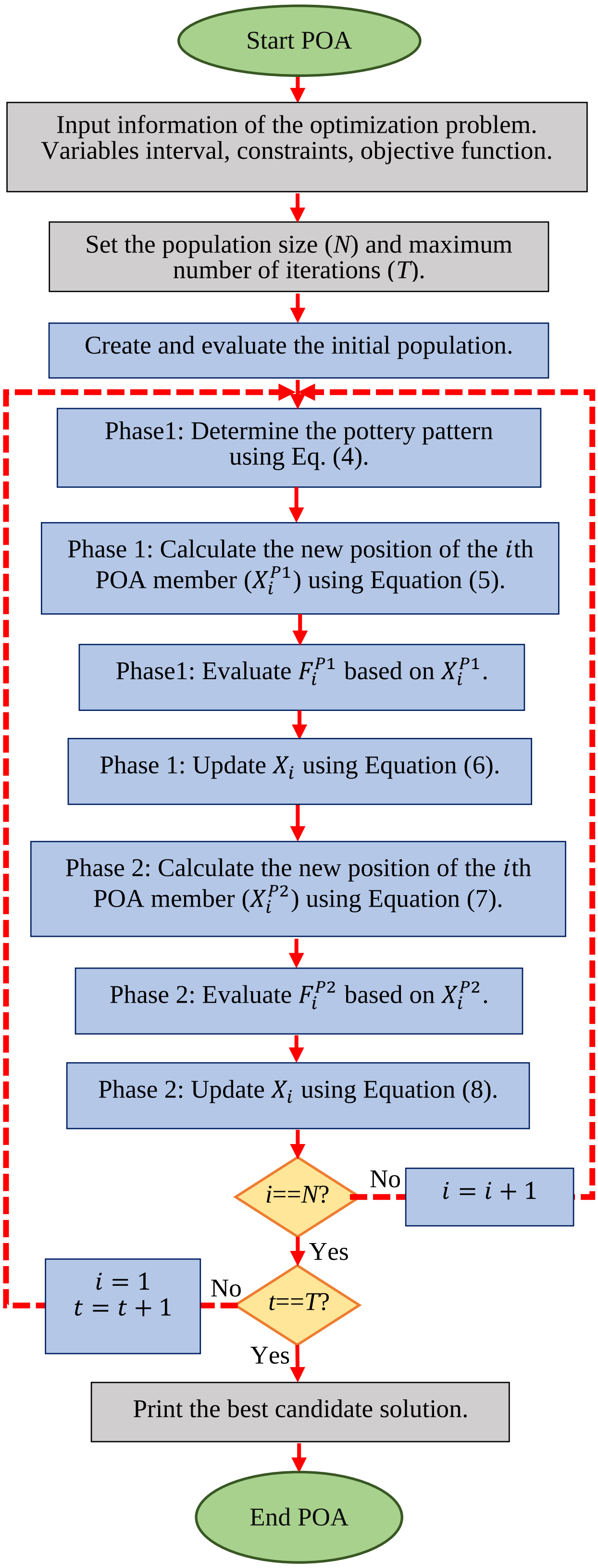

Figure. 1 flowchart of POA

To achieve this, the company seeks to minimize inventory shortages, optimize surplus inventory, and determine the ideal lot sizes. Upon receiving customer demand, any inventory shortages prompt decisions on whether to initiate production or place orders. Excess inventory is managed as backlog, requiring strategies to prevent surplus and reduce waste effectively. The mathematical formulation of sustainable lot size optimization is outlined as follows: [34]:

$$TC = C_c \cdot \frac{D}{Q} + C_p \cdot P \cdot \frac{Q+SS}{2} + p \cdot A \cdot \frac{D}{Q} + C_e \cdot \frac{D}{Q}$$

Objective Function: Minimize TC (Total Cost), which comprises:

Where:

TC: total cost (objective function);
C_c**:** Order cost/unit;
C_p**:** Holding cost/unit;
P**:** Price;
p**:** Shortage cost/unit;
A**:** Expected shortage/cycle;
D**:** Annual demand;
C_e**:** Footprint emission cost;
Q**:** Quantity;
SS**:** Shortage.

Constraints:

1. **Production Constraints**: These include limits on the number of units that can be produced within a specific period, factoring in machinery capacity and workforce availability.
2. **Inventory Capacities**: These cover storage limitations for both raw materials and finished products.
3. **Demand Fulfillment**: Ensuring that production meets customer demand within designated timeframes to avoid shortages and backlogs.
4. **Sustainability Criteria**: These include specific restrictions on CO2 emissions at different supply chain stages, including production, transportation, and storage.

In sustainable lot size optimization, the balance between economic viability and environmental responsibility is crucial. The audit process is deterministic, aiming to ensure that both economic and environmental objectives are met efficiently.

The POA method evaluates and identifies optimal lot sizes that minimize both costs and environmental impact. This dual focus is increasingly important as businesses strive to meet sustainability goals while maintaining economic competitiveness. By leveraging the capabilities of POA, supply chain managers can make informed decisions that balance cost savings with environmental and social responsibility, driving long-term value and resilience in their operations.

This approach represents an evolution in supply chain management practices. Traditional strategies that focused solely on cost reduction are now being enhanced with sustainability considerations, reflecting a broader understanding of value creation. Effective SCM today requires integrating advanced optimization techniques like POA with a commitment to sustainable practices, ensuring that supply chains are not only efficient but also responsible and resilient.

In this comprehensive study, we evaluate the performance of the POA in the context of sustainable lot size optimization within supply chain management. To provide a robust benchmark, the POA is rigorously compared against twelve prominent metaheuristic algorithms. These algorithms include: Genetic Algorithm (GA) [24], Particle Swarm Optimization (PSO) [18], Gravitational Search Algorithm (GSA) [35], Teaching-Learning Based Optimization (TLBO) [30], Multi-Verse Optimizer (MVO) [36], Grey Wolf Optimizer (GWO) [37], Whale Optimization Algorithm (WOA) [38], Marine Predator Algorithm (MPA) [39], Tunicate Search Algorithm (TSA) [40], Reptile Search Algorithm (RSA) [41], African Vultures Optimization Algorithm (AVOA) [42], and White Shark Optimizer (WSO) [43].

The primary objective of this comparative study is to assess the efficacy of POA in optimizing sustainable lot size within supply chains. Sustainable lot size optimization seeks to balance economic efficiency with environmental and social responsibility. This involves minimizing costs such as setup, holding, and ordering, while also reducing negative environmental impacts and enhancing social welfare.

In our experiments, the POA and the twelve competing algorithms were applied to solve sustainable lot size optimization problems. The performance metrics focused on the total cost (TC), which includes both economic and environmental costs. The results, as summarized in Table 1, demonstrate that POA consistently outperformed the other algorithms in optimizing the objective function, delivering superior values for TC. In addition, the convergence curves showing the performance of PROPOSEDNA and competing algorithms are presented in Figure 2.

Table 1. Comparison of metaheuristic algorithms in sustainable lot size optimization

		POA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
Part 1	mean	129912.7	130022.2	130022.2	130022.2	129938.1	129938.1	129938.1	129938.1	129938.1	129938.1	140839.9	129938.1	131214.9
	best	129905.7	129937.1	129937.1	129937.1	129906.9	129906.9	129906.9	129906.9	129906.9	129906.9	130805.4	129906.9	130260.3
	worst	129929.5	130151.6	130151.6	130151.6	130012.9	130012.9	130012.9	130012.9	130012.9	130012.9	158891.7	130012.9	132665.5
	std	7.255931	65.26202	65.26202	65.26202	32.35775	32.35775	32.35775	32.35775	32.35775	32.35775	9083.005	32.35775	731.7206
	median	129909.9	130011.6	130011.6	130011.6	129925.4	129925.4	129925.4	129925.4	129925.4	129925.4	138409.3	129925.4	131095.6
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Part 2	mean	14451.41	14459.9	14459.9	14459.9	14453.97	14453.97	14453.97	14453.97	14453.97	14453.97	15232.6	14453.97	14554.13
	best	14450.68	14451.94	14451.94	14451.94	14450.7	14450.7	14450.7	14450.7	14450.7	14450.7	14464.14	14450.7	14464.85
	worst	14453.4	14491.34	14491.34	14491.34	14462.85	14462.85	14462.85	14462.85	14462.85	14462.85	18168.08	14462.85	14906.61
	std	0.803303	9.010596	9.010596	9.010596	3.582321	3.582321	3.582321	3.582321	3.582321	3.582321	929.8919	3.582321	101.0272
	median	14451.14	14457.71	14457.71	14457.71	14452.76	14452.76	14452.76	14452.76	14452.76	14452.76	14883.72	14452.76	14529.53
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Part 3	mean	111778.3	111780	111799.9	111819.8	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111987.4	111778.3	111797
	best	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3
	worst	111778.3	111786	111924.4	112067.7	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	112743.6	111778.3	111864.4
	std	3.75E-05	2.484254	40.16624	79.42862	0.000167	0.000168	0.000167	0.000226	0.000167	0.000167	312.2935	0.000167	27.85357
	median	111778.3	111778.6	111784.7	111790.9	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111810.6	111778.3	111781.2
	rank	1	8	10	11	2	5	3	7	4	6	12	2	9
Part 4	mean	124855	124876.7	124876.7	124876.7	124858.7	124858.7	124858.7	124858.7	124858.7	124858.7	127181.1	124858.7	125109.8
	best	124854	124854.7	124854.7	124854.7	124854.4	124854.4	124854.4	124854.4	124854.4	124854.4	124880.3	124854.4	124862.3
	worst	124857.4	124922.2	124922.2	124922.2	124869.2	124869.2	124869.2	124869.2	124869.2	124869.2	132573	124869.2	125619.5
	std	1.111261	17.56583	17.56583	17.56583	4.955656	4.955656	4.955656	4.955656	4.955656	4.955656	2224.656	4.955656	196.9488
	median	124854.5	124873.1	124873.1	124873.1	124856.4	124856.4	124856.4	124856.4	124856.4	124856.4	126567.8	124856.4	125069.1
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Part 5	mean	120579.1	120706.1	120706.1	120706.1	120604.2	120604.2	120604.2	120604.2	120604.2	120604.2	133738.8	120604.2	122077.1
	best	120571.9	120604.9	120604.9	120604.9	120572.3	120572.3	120572.3	120572.3	120572.3	120572.3	122224.5	120572.3	120942.9
	worst	120605.9	120999.4	120999.4	120999.4	120723.9	120723.9	120723.9	120723.9	120723.9	120723.9	173922.8	120723.9	125365.3
	std	8.971042	102.5695	102.5695	102.5695	40.00627	40.00627	40.00627	40.00627	40.00627	40.00627	13544.13	40.00627	1150.014
	median	120575.5	120670	120670	120670	120588.3	120588.3	120588.3	120588.3	120588.3	120588.3	126892.1	120588.3	121672.3
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Part 6	mean	287571.1	287662.3	287662.3	287662.3	287623	287623	287623	287623	287623	287623	293237.2	287623	288746.2
	best	287556.6	287567.3	287567.3	287567.3	287558.3	287558.3	287558.3	287558.3	287558.3	287558.3	287588.8	287558.3	287681.2
	worst	287605	287855.4	287855.4	287855.4	287774.3	287774.3	287774.3	287774.3	287774.3	287774.3	312455.6	287774.3	290912
	std	12.41739	70.39266	70.39266	70.39266	55.37523	55.37523	55.37523	55.37523	55.37523	55.37523	5913.924	55.37523	789.2456
	median	287569.8	287648.2	287648.2	287648.2	287617.1	287617.1	287617.1	287617.1	287617.1	287617.1	290888	287617.1	288588.7
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Part 7	mean	128804.9	128808.6	128837.5	128866.4	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	129274.4	128804.9	128846.8
	best	128804.9	128804.9	128805	128805	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9
	worst	128804.9	128821.8	128884.2	128950.9	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	130929.4	128804.9	128994.4
	std	0.000738	5.50195	29.26837	57.08067	0.003293	0.003293	0.003293	0.003327	0.003295	0.003294	691.5816	0.003293	61.68811
	median	128804.9	128805.7	128834.1	128854.9	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	128910.3	128804.9	128814.3
	rank	1	7	8	10	2	4	2	6	3	5	11	2	9
Part 8	mean	20369.67	20380.64	20380.64	20380.64	20372.67	20372.67	20372.67	20372.67	20372.67	20372.67	21413.96	20372.67	20501.46
	best	20368.87	20371.72	20371.72	20371.72	20369.09	20369.09	20369.09	20369.09	20369.09	20369.09	20383.83	20369.09	20401.48
	worst	20371.4	20399.29	20399.29	20399.29	20380.37	20380.37	20380.37	20380.37	20380.37	20380.37	23372.98	20380.37	20710.61
	std	0.604322	8.239371	8.239371	8.239371	2.694968	2.694968	2.694968	2.694968	2.694968	2.694968	930.8639	2.694968	92.38019
	median	20369.63	20378.79	20378.79	20378.79	20372.46	20372.46	20372.46	20372.46	20372.46	20372.46	21282.76	20372.46	20480.69
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Part 9	mean	4366.721	4366.721	4366.742	4366.764	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721
	best	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721
	worst	4366.721	4366.721	4366.935	4367.149	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721
	std	2.9E-12	7.61E-12	0.049642	0.099285	8.47E-12	2.35E-08	8.44E-12	8.31E-07	5.63E-08	1.71E-07	8.35E-12	8.32E-12	8.64E-11
	median	4366.721	4366.721	4366.723	4366.725	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721
	rank	1	2	9	10	2	5	3	8	6	7	2	2	4
Part 10	mean	15557.64	15567.53	15567.53	15567.53	15560.15	15560.15	15560.15	15560.15	15560.15	15560.15	16520.57	15560.15	15675.94
	best	15556.97	15557.52	15557.52	15557.52	15557.16	15557.16	15557.16	15557.16	15557.16	15557.16	15572.27	15557.16	15563.7
	worst	15558.9	15585.05	15585.05	15585.05	15565.78	15565.78	15565.78	15565.78	15565.78	15565.78	18621.95	15565.78	15872.33
	std	0.526081	7.780655	7.780655	7.780655	2.346052	2.346052	2.346052	2.346052	2.346052	2.346052	890.239	2.346052	87.23705
	median	15557.82	15566.18	15566.18	15566.18	15560.97	15560.97	15560.97	15560.97	15560.97	15560.97	16317.73	15560.97	15660.85
	rank	1	3	3	3	2	2	2	2	2	2	5	2	4
Sum rank		10	38	48	52	20	28	22	35	27	32	60	20	50
Mean rank		1	3.8	4.8	5.2	2	2.8	2.2	3.5	2.7	3.2	6	2	5
Total rank		1	8	9	11	2	5	3	7	4	6	12	2	10

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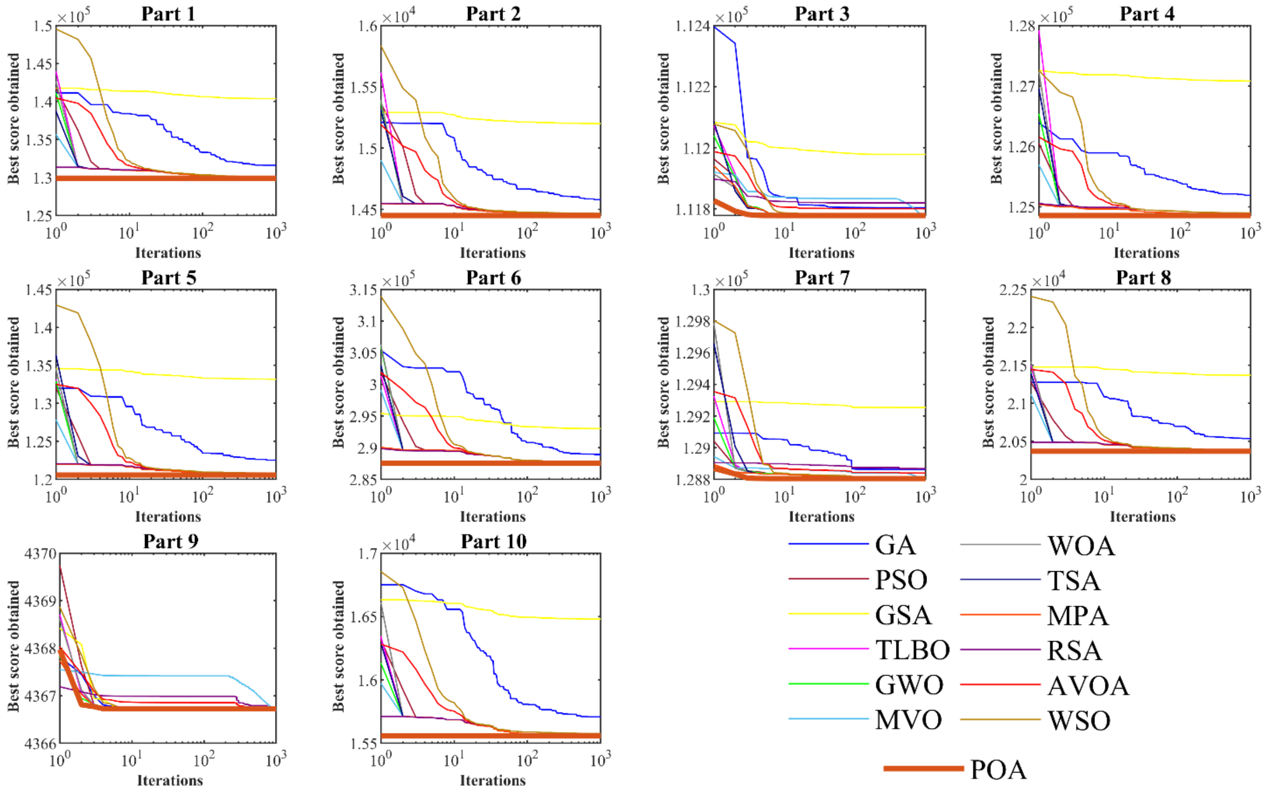

Figure. 2 convergence curves of performance of metaheuristic algorithms in sustainable lot size optimization

The effectiveness of POA in comparison to the other algorithms can be attributed to its unique mechanism of exploration and exploitation, which balances the search for optimal solutions across a complex and dynamic solution space. The hybrid nature of POA, which integrates multiple optimization strategies, allows it to adaptively navigate through local and global optima, enhancing its capability to find more efficient solutions.

The implementation of POA and the comparative algorithms involved rigorous testing on a series of benchmark problems representative of real-world supply chain scenarios. The test problems included varying levels of complexity, demand fluctuations, and constraints related to sustainability criteria such as carbon emissions and resource utilization.

The superior performance of POA is evident in its ability to minimize the total cost more effectively than the other algorithms. This success is likely due to POA's robust search capabilities and its dynamic adjustment mechanisms, which ensure that both cost efficiency and sustainability are simultaneously optimized. This dual focus aligns with modern supply chain management's evolving priorities, where sustainability and economic performance are both critical.

5. Conclusions and future works

In this paper, a new metaheuristic algorithm named Potter Optimization Algorithm (POA) inspired by the pottery process was introduced to deal with Supply Chain Management (SCM) applications. The main source of inspiration in the design of POA is derived from two basic activities in the pottery process: (i) making extensive changes to the pottery materials and (ii) making small precise changes to the produced pottery. POA theory was stated and then mathematically modeled in two phases of exploration and exploitation. The effectiveness of POA on SCM applications was challenged to deal with sustainable lot size optimization including 10 case studies. The optimization results showed that POA has achieved suitable solutions with the ability to manage global and local search as well as balance between exploration and exploitation. In order to measure the quality of POA, the obtained results were compared with twelve competing metaheuristic algorithms. Analysis of the simulation results showed that POA has a superior performance compared to ten competing algorithms by providing better results and getting the rank of the first best optimizer for all ten study cases. The findings of this study are that POA, by providing better results in 100% of case studies,

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has an effective performance to achieve optimization tasks and especially sustainable lot size optimization.

By introducing POA in this study, several research proposals are proposed for further work in the future. Among the most prominent of these proposals are the development of binary and multipurpose versions of POA. In addition, employing POA to handle optimization tasks in various sciences and other real-world applications is one of the other research proposals of this study for further work in the future.

Conflicts of Interest

"The authors declare no conflict of interest."

Author Contributions

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

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