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ARTICLE

Application of Stork Optimization Algorithm for Solving Sustainable Lot Size Optimization

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ABSTRACT

The efficiency of businesses is often hindered by the challenges encountered in traditional Supply Chain Management (SCM), which is characterized by elevated risks due to inadequate accountability and transparency. To address these challenges and improve operations in green manufacturing, optimization algorithms play a crucial role in supporting decision-making processes. In this study, we propose a solution to the green lot size optimization issue by leveraging bio-inspired algorithms, notably the Stork Optimization Algorithm (SOA). The SOA draws inspiration from the hunting and winter migration strategies employed by storks in nature. The theoretical framework of SOA is elaborated and mathematically modeled through two distinct phases: exploration, based on migration simulation, and exploitation, based on hunting strategy simulation. To tackle the green lot size optimization issue, our methodology involved gathering real-world data, which was then transformed into a simplified function with multiple constraints aimed at optimizing total costs and minimizing CO_2 emissions. This function served as input for the SOA model. Subsequently, the SOA model was applied to identify the optimal lot size that strikes a balance between cost-effectiveness and sustainability. Through extensive experimentation, we compared the performance of SOA with twelve established metaheuristic algorithms, consistently demonstrating that SOA outperformed the others. This study's contribution lies in providing an effective solution to the sustainable lot-size optimization dilemma, thereby reducing environmental impact and enhancing supply chain efficiency. The simulation findings underscore that SOA consistently achieves superior outcomes compared to existing optimization methodologies, making it a promising approach for green manufacturing and sustainable supply chain management.

KEYWORDS

Optimization; supply chain management; sustainable lot size optimization; bio-inspired; metaheuristic; stork

1 Introduction

Supply Chain Management (SCM) stands as the cornerstone of modern business operations, orchestrating the seamless flow of information, services, and goods from raw material suppliers to end consumers. SCM encompasses a wide array of activities, including procurement, production, inventory management, logistics, and distribution, all aimed at optimizing the overall efficiency and effectiveness of the supply chain network [1]. In today's highly competitive and globalized marketplace, effective SCM has become a strategic imperative for businesses seeking to gain a competitive edge, enhance customer satisfaction, and drive sustainable growth [2].

Ensuring quality throughout the supply chain is crucial for businesses aiming to enhance efficiency, lower expenses, and swiftly respond to the ever-changing market demands [3,4]. Consequently, SCM applications are often framed as optimization problems that require suitable techniques for resolution. Optimization problem-solving methods are generally categorized into deterministic and stochastic approaches [5]. Deterministic methods, which include gradient-based and non-gradient-based techniques, are effective in solving convex, linear, continuous, differentiable, and low-dimensional problems [6,7]. Traditional optimization methods, such as mathematical modeling and linear programming, have long been employed for supply chain optimization [8]. Nevertheless, these approaches frequently encounter challenges in dealing with the intricate nature and unpredictability of real-world supply chains. Hence, there is a growing enthusiasm for devising metaheuristic algorithms, drawing inspiration from natural processes, to effectively tackle supply chain optimization problems [9].

Metaheuristic algorithms represent widely used stochastic approaches capable of producing effective solutions for optimization problems through random search within the solution space [10]. Although these algorithms do not guarantee finding the global optimum, the solutions they generate are usually close enough to be considered quasi-optimal. The continuous pursuit of more effective optimization solutions has driven researchers to develop numerous metaheuristic algorithms [11].

A significant research question arises: given the existing metaheuristic algorithms, is it still necessary to design new ones? The No Free Lunch (NFL) [12] provides an answer, explaining that due to the random search nature of metaheuristic algorithms, no single algorithm can be the best optimizer for all optimization applications. This inherent diversity in optimization challenges encourages researchers to explore and design innovative metaheuristic algorithms that can address specific problem characteristics, improve performance, and adapt to changing requirements. The pursuit of new algorithms enables the optimization community to push the boundaries of problem-solving capabilities, enhance efficiency, and provide more tailored solutions for a wide array of real-world applications.

Based on extensive literature review, no metaheuristic algorithm inspired by the natural behavior of storks has been previously designed. The intelligent strategies of storks during hunting and their activities during winter migration present a unique potential for developing a new metaheuristic algorithm. To fill this research gap, this paper introduces a novel metaheuristic algorithm inspired by the intelligent behavior of storks in nature, which is detailed in the subsequent sections.

Although similar studies are mentioned in the literature review, the innovative aspects of this paper compared to several of these high-repeated studies are as follows:

In paper [13], the butterfly algorithm is employed for the green lot size optimization problem and it is compared with three methods: genetic algorithm, particle swarm optimization, and firefly algorithm. Although all these algorithms have been widely used, they have not been able to properly address the challenge of green lot size optimization. This is due to the fact that with the progress of science, optimization problems become more complex and existing algorithms may not have the necessary efficiency to effectively solve new optimization challenges. Therefore, the innovation of the proposed approach of this paper, compared to the mentioned source, is to achieve more effective solutions for the green lot size optimization problem by introducing a new algorithm that has separate attitudes to manage exploration and exploitation.

In paper [14], a new optimization approach called Wombat Optimization Algorithm is introduced to solve optimization problems. In that article, it is mentioned that Wombat Optimization Algorithm can be employed as a problem-solving tool to address the green lot size optimization problem in future studies. However, no simulations have been performed, and this issue is raised as a research proposal for future studies. Therefore, the innovation of the proposed approach in this article, compared to the mentioned source, is that the application of a new meta-heuristic algorithm called stork optimization algorithm has been specifically studied on the challenge of green lot size optimization and the results obtained are compared with twelve famous algorithms.

In paper [15], a new metaheuristic algorithm called Technical and Vocational Education and Training-Based Optimizer (TVETBO) is proposed, aimed at handling optimization tasks across various sciences. TVETBO is a human-based algorithm inspired by the process of teaching work-related skills to candidates in technical and vocational education and training schools. The innovation of the proposed SOA approach compared to TVETBO lies in both the source of design inspiration and the mathematical modeling process. SOA is proposed as a swarm-based approach inspired by the natural behavior of storks in the wild.

In general, the innovation of a new metaheuristic algorithm compared to existing algorithms lies in the main idea of its design, its mathematical modeling, and the advantages of managing the exploration and exploitation processes. As evident in the literature review, numerous optimization algorithms have been designed so far. In fact, this raises the central question of research: is there a need to design a new algorithm despite the existence of established ones?

Several reasons serve as primary motivations for the introduction of novel metaheuristic algorithms, as described below. The first motivation stems from the stochastic nature of metaheuristic algorithms, which lack certainty in achieving the global optimum. Therefore, the introduction of a new algorithm that effectively manages the search process may lead to superior solutions for optimization problems.

As a second motivation, we can refer to the concept of the NFL theorem, which states: in no way can it be said that a particular metaheuristic algorithm is the best optimizer for all optimization problems. Therefore, the NFL theorem serves as a main motivation for researchers to design newer metaheuristic algorithms to achieve better solutions.

The third motivation stems from the fact that as science progresses, more complex optimization problems arise, which require more precise optimization techniques for resolution. Therefore, older and existing algorithms may not be well-equipped to handle emerging optimization problems, and researchers can achieve suitable solutions for these types of challenges by designing metaheuristic algorithms with more recent perspectives.

This paper introduces the Stork Optimization Algorithm (SOA), a new approach to optimization problems, highlighting several key contributions:

- SOA is intricately crafted by emulating the natural behavior of storks in their wild habitat.

- The foundational inspiration for SOA is drawn from two sources: (i) the stork's strategy during hunting and (ii) the migration of storks during the winter season.
- The implementation process of SOA is elucidated, with a mathematical model detailing two essential phases, namely exploration and exploitation. These phases are based on the simulation of storks' behaviors in nature.
- The effectiveness of SOA to address Supply Chain Management (SCM) tasks is assessed particularly for sustainable lot size optimization.
- A comprehensive comparison is conducted, pitting the performance of SOA against twelve well-known metaheuristic algorithms.

The paper is structured as follows: Section 2 presents the literature review. Section 3 introduces and models the proposed Stork Optimization Algorithm. Section 4 evaluates the application of SOA in SCM optimization tasks. Section 5 discusses managerial insights. Section 6 concludes the paper and provides suggestions for future research.

2 Literature Review

Metaheuristic algorithms are recognized as powerful optimization techniques that have garnered considerable interest across diverse domains owing to their capacity to effectively address intricate problems. Unlike conventional optimization approaches like linear programming, which might grapple with the intricacies and uncertainties inherent in real-world situations, metaheuristic algorithms provide a versatile and adjustable method for optimization [16,17]. Based on the source of inspiration in the design of metaheuristic algorithms, they are classified into four groups: swarm-based, evolutionary-based, physics-based, and human-based approaches [18].

Swarm-based metaheuristic algorithms are conceptualized by emulating the natural behaviors and strategies observed in animals, aquatic organisms, insects, and other living entities within their natural habitats. Among these algorithms, Particle Swarm Optimization (PSO) stands out as a widely adopted approach, drawing inspiration from the collective movement of birds and fish during their search for food [19]. Another noteworthy example is the Ant Colony Optimization (ACO), which mimics the efficient route-finding ability of ants between their nest and food sources [20]. The various behaviors and strategies employed by wildlife, such as foraging, hunting, migration, and ground digging, have been pivotal inspirations for designing a multitude of algorithms. Examples include the Whale Optimization Algorithm (WOA) [21], Aquila Optimizer (AO) [22], White Shark Optimizer (WSO) [23], Dwarf Mongoose Optimization Algorithm (DMOA) [24], Tunicate Swarm Algorithm (TSA) [25], Ebola Optimization Search Algorithm (EOSA) [26], Marine Predator Algorithm (MPA) [27], Prairie Dog Optimization (PDO) [28], African Vultures Optimization Algorithm (AVOA) [29], Grey Wolf Optimizer (GWO) [30], and Reptile Search Algorithm (RSA) [31].

Evolutionary-based metaheuristic algorithms are crafted by incorporating principles from biology, genetics, and the concepts of survival of the fittest, natural selection, and evolutionary operators. Among the most well-known and widely used algorithms in this category are the Genetic Algorithm (GA) and Differential Evolution (DE). These algorithms are inspired by the biological processes of generation and evolution, as outlined in Darwin's theory. They employ genetic principles and natural selection, alongside evolutionary operators like random crossover, mutation, and selection, to explore and exploit the search space effectively.

Physics-based metaheuristic algorithms are conceived by incorporating models derived from physics phenomena, forces, transformations, laws, and concepts. Simulated Annealing (SA) stands out as one of the widely embraced physics-based metaheuristic algorithms, drawing inspiration from the phenomenon of metal annealing [32]. Algorithms like the Black Hole Algorithm (BHA) [33] and Multi-Verse Optimizer (MVO) [34] utilize concepts from cosmology in their design. Additionally, physical forces and Newton's laws of motion serve as sources of inspiration for Gravitational Search Algorithm (GSA) [35].

Human-based metaheuristic algorithms are intricately crafted by mimicking the communication patterns, social interactions, decision-making processes, and strategic behaviors observed in both individual and collective human activities. One prominent example of such an algorithm is Teaching-Learning Based Optimization (TLBO). TLBO derives its fundamental concepts from the educational dynamics within a classroom, emphasizing the interactions between teachers imparting knowledge and students assimilating that knowledge. This algorithm is widely recognized and adopted for its efficacy [36]. Another innovative algorithm in this category is the Mother Optimization Algorithm (MOA). MOA is inspired by the nurturing and developmental phases that a mother, named Eshrat, provides to her children. It models the phases of education, where foundational knowledge is imparted; advice, where guidance and support are given; and upbringing, which encompasses the overall growth and development of the child [18]. Doctor and Patient Optimization (DPO) is another human-based algorithm conceptualized by emulating the therapeutic interactions and communication that occur between patients and their doctors. This algorithm captures the essence of diagnostic and treatment processes, reflecting the critical decision-making and trust-based relationship inherent in medical care [37]. Additionally, the Election-Based Optimization Algorithm (EBOA) takes inspiration from the electoral processes observed in democratic societies. It incorporates the mechanisms of voting, candidate selection, and election procedures to solve optimization problems, reflecting the strategic decision-making and collective choices made during elections [38]. Each of these human-based metaheuristic algorithms leverages the complexity and nuance of human behaviors and social systems, providing robust frameworks for addressing and solving intricate optimization challenges.

The utilization of metaheuristic algorithms in Supply Chain Management (SCM) spans a broad spectrum and includes numerous domains such as inventory control, facility siting, routing of vehicles, scheduling production, and designing supply chain networks. For instance, these algorithms can optimize inventory restocking strategies, reduce transportation expenditures, equalize production capabilities, and craft resilient supply chain infrastructures [39]. Table 1 provides a summary of the various applications of metaheuristic algorithms in addressing Supply Chain Management (SCM) challenges.

3 Stork Optimization Algorithm (SOA)

Within this section, the origin and theoretical underpinnings of the novel Stork Optimization Algorithm (SOA) approach are expounded upon. Subsequently, the procedural steps for its implementation are meticulously formulated in mathematical terms, aiming to provide a structured framework for the resolution of optimization problems.

3.1 Inspiration of SOA

Storks are long-necked, long-legged, large wading birds with stout, long bills. Storks have a nearly cosmopolitan distribution; however, they are mostly seen in sub-Saharan Africa and tropical Asia. There is a difference between the male and female species in terms of size, such that males are larger, but they do not have significant differences in their appearance. The bill size of storks is very large compared to its body size and it has different sizes among different genera. The shape of the bill in different species is also different and related to the diet. In some species, the shape of the beak has evolved to hunt fish in shallow water. In some, it is in the form of massive daggers to feed on carrion, fight scavengers and hunt.

Table 1: Exploring metaheuristic algorithms for supply chain management challenges

	Description	Year
1	This paper delves into an extensive examination of the Firefly algorithm's effectiveness across a diverse array of test functions, placing particular emphasis on its applicability within the context of lot size optimization within supply chain management. Through a detailed comparative analysis, the study highlights the algorithm's superior performance compared to deterministic methods. By effectively addressing the complexities inherent in balancing cost reduction and service level improvement, the Firefly algorithm demonstrates its capability in optimizing supply chain evolution [40].	2018
2	This paper presents a cutting-edge research endeavor aimed at revolutionizing closed-loop supply chain network configuration models, addressing critical voids in contemporary literature. By harnessing an avant-garde metaheuristic algorithm named Improved PSO (IPSO), this study seeks to redefine the landscape of decision-making processes within supply chain management. In conjunction with IPSO, a sophisticated gradient descent search methodology is employed to navigate the intricate terrain of pricing-inventory determinations, thereby enhancing the precision and efficacy of network configurations. Through the strategic integration of mutation and replicator dynamics, IPSO sets itself apart from conventional optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Simulated Annealing (SA). Empirical validation through extensive numerical assessments spanning a diverse array of problem scales underscores the unparalleled performance of IPSO in delivering optimal supply chain solutions [41].	2018
3	This paper delves into the intricate domain of distribution-allocation quandaries within a two-stage supply chain, embarking on the creation of an integer-programming model meticulously crafted to streamline operational costs. By leveraging the prowess of Ant Colony Optimization (ACO), the research illuminates the pathway to computational efficacy, showcasing its adeptness in traversing the solution space and arriving at viable outcomes within a pragmatic timeframe. Notably, the study reports an average discrepancy of merely 10% from the optimal solutions, a testament to the algorithm's robustness and efficiency in navigating complex optimization landscapes [42].	2018
4	This paper introduces a refined iteration of the artificial bee colony (ABC) optimization algorithm, specifically adapted for the strategic management of supply chain networks (SCNs). This advanced algorithm is particularly focused on the proficient identification of multi-objective Pareto optimal solutions (POS). By extending the scope of SCNs to encompass complex network structures, the proposed method incorporates a naive Bayes classifier to enhance search efficiency. The empirical analysis highlights the algorithm's effectiveness in optimizing a three-echelon SCN, successfully attaining global multi-objective POS while significantly expediting the solution discovery process. This innovative approach not only broadens the operational horizons of SCNs but also underscores the potential for accelerated and precise optimization in supply chain management [43].	2019

(Continued)

Table 1 (continued)

	Description	Year
5	This paper presents a sophisticated bi-level optimization framework meticulously designed to enhance the management of the rice supply chain, with the primary objective of minimizing overall costs. This framework is distinctively structured to incorporate and balance the perspectives of two decision-makers, ensuring a comprehensive and collaborative approach to supply chain optimization. The study leverages advanced meta-heuristic algorithms, including the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), alongside their hybrid and adapted variants. Through extensive numerical evaluations, the research demonstrates the robust effectiveness of the proposed framework in achieving significant improvements in the rice supply chain's efficiency and cost-effectiveness. Among the various algorithms tested, the modified algorithm (GPA) is particularly noteworthy for its superior performance, delivering promising results that underscore its potential as a powerful tool for supply chain optimization. This study not only advances the methodological approaches to supply chain management but also provides valuable insights for practical implementation in the rice industry [44].	2019
6	This paper delves into the evolving landscape of inventory management within the broader context of supply chain management, emphasizing the critical need for innovative approaches to enhance both integration and adaptability across the supply chain. Recognizing the dynamic and often unpredictable nature of market demands, the study draws on foundational insights from system theory and integration theory to propose a robust and optimized inventory management framework. This framework ingeniously incorporates an ant colony algorithm alongside a fuzzy model, aiming to strike a balance between computational efficiency and real-world applicability. The primary objective of this integrated approach is to significantly improve overall supply chain efficiency while simultaneously enhancing the responsiveness and agility of supply chains to rapidly shifting market conditions. By leveraging the collective intelligence of ant colony optimization and the nuanced decision-making capabilities of fuzzy logic, the proposed framework stands out as a promising solution for modern inventory management challenges, offering a path toward more resilient and adaptive supply chain systems [45].	2019
7	This paper introduces a groundbreaking hybrid algorithm poised to revolutionize supply chain scheduling in the era of mass customization. By ingeniously merging the Genetic Algorithm (GA) with the Particle Swarm Optimization (PSO), it tackles the intricate challenges posed by the dynamic and diverse demands of modern supply chains. This innovative approach leverages the collective intelligence of both algorithms, combining the global exploration prowess of GA with the rapid convergence speed of PSO. Through this synergy, the hybrid algorithm achieves remarkable enhancements in scheduling efficiency, paving the way for unprecedented levels of optimization in supply chain management [46].	2019
8	This paper presents a cutting-edge iteration of the African Buffalo Optimization (ABO) algorithm, meticulously crafted to revolutionize optimization strategies within petroleum supply chain distribution networks. Harnessing the collective intelligence of swarm algorithms, this enhanced iteration focuses on refining product scheduling precision and minimizing distribution costs, specifically tailored to the intricate demands of the petroleum industry. By amalgamating various iterations of the ABO algorithm, including its standard version and augmented renditions such as chaotic ABO and chaotic-Levy ABO, this study sheds light on substantial advancements over conventional exact algorithms. These refinements signify a significant leap forward in mitigating the complexities inherent in real-world petroleum supply chain networks, promising more efficient and cost-effective distribution strategies [47].	2020

(Continued)

Table 1 (continued)

	Description	Year
9	This paper delves into the intricacies of managing perishable goods within the complex web of supply chains, introducing a comprehensive model bolstered by the Enhanced Bacteria Forging Algorithm (IBFA). The primary goal of this model is to refine and optimize the intricate processes involved in the production, inventory management, and distribution of perishable items within supply chain networks. Through meticulous analysis and exploration of two distinct case studies, the IBFA demonstrates its efficacy in streamlining and enhancing the efficiency of perishable supply chain networks. These findings offer invaluable insights and practical strategies for decision-makers tasked with navigating the challenges of handling time-sensitive products within their supply chains [48].	2020
10	The paper introduces the Enhanced Bacteria Forging Algorithm (IBFA) for optimizing perishable supply chain networks. It addresses the challenges of managing perishable products by integrating IBFA into a comprehensive model. Real-world case studies demonstrate IBFA's effectiveness in enhancing supply chain efficiency. The algorithm optimizes production, inventory, and distribution processes. Results show improvements in on-time delivery rates and inventory turnover. Future research opportunities include refining and expanding the IBFA model. The IBFA offers dynamic adaptation to changing supply chain conditions. It promises to revolutionize perishable product management in supply chains. Collaboration and innovation are key to unlocking IBFA's full potential. With further experimentation, IBFA can drive efficiency and sustainability in perishable goods distribution [49].	2020
11	This research unveils an innovative multi-level serial closed-loop supply chain model, integrating a multitude of factors like batch deliveries, quality-dependent return rates, random defective rates, rework processes, and learning effects. A core focus lies in understanding how learning influences inventory control within this intricate framework, shedding light on its pivotal role. To navigate the model's complexity, a suite of metaheuristic algorithms is harnessed, spanning from genetic algorithm to invasive weed optimization algorithm and moth flame optimization algorithm. The study illuminates the profound implications of the learning effect on critical aspects like manufacturing and remanufacturing time, alongside system costs, within closed-loop supply chain scenarios. This comprehensive analysis lays a robust foundation for future research endeavors in optimizing closed-loop supply chains, promising insights into effective inventory management strategies and cost-efficient operations. Through this exploration, a deeper understanding of the dynamics within closed-loop supply chains emerges, paving the way for enhanced decision-making and sustainable practices in supply chain management [50].	2021
12	In this study, an innovative methodology is presented for crafting a dual-channel, multi-product, multi-period, multi-echelon closed-loop supply chain network (SCND) specifically designed to cater to the dynamic demands of the tire industry amidst uncertainty. A fuzzy-based framework is adopted to effectively manage uncertain parameters inherent in the supply chain environment, providing a robust foundation for decision-making processes. To tackle the optimization challenges posed by this complex network, two hybrid meta-heuristic algorithms are introduced. These algorithms combine elements of the red deer and whale optimization algorithms with genetic algorithm and simulated annealing techniques, respectively, leveraging the unique strengths of each approach. Through rigorous experimentation and numerical simulations, the study showcases the remarkable effectiveness of these hybrid algorithms in generating high-quality solutions that meet the demands of real-world supply chain scenarios. By seamlessly integrating uncertainty handling mechanisms and innovative optimization techniques, this research offers valuable insights and practical solutions for enhancing the efficiency and resilience of tire industry supply chains [51].	2021

(Continued)

Table 1 (continued)

	Description	Year
13	The research endeavors to devise an advanced model geared towards optimizing both location and inventory within the intricate web of supply chain configuration. It delves into the complexities posed by stochastic customer demand and replenishment lead time, aiming to navigate these uncertainties seamlessly. The proposed methodology adopts a multifaceted two-phase approach, seamlessly integrating queuing theory with stochastic optimization techniques. Through meticulous experimentation and analysis, the study aims to unravel the optimal distribution center locations and inventory policies. To grapple with the inherent NP-hard complexity of the problem, the researchers advocate for the deployment of a hybrid Genetic Algorithm, heralding a new era of computational efficiency and solution quality in supply chain optimization endeavors. This interdisciplinary approach not only promises to streamline operations but also holds the potential to revolutionize decision-making processes in the realm of supply chain management [52].	2021
14	The primary objective of this paper is to enhance the dual facets of environmental preservation and economic viability within the framework of a sustainable supply chain network. To achieve this goal, the study introduces a sophisticated mixed-integer linear programming (MILP) model, meticulously designed to amalgamate sustainable supplier selection with performance optimization. Through the strategic deployment of multi-objective genetic and particle swarm algorithms, the research endeavors to strike a delicate equilibrium among three pivotal objectives: minimizing costs, optimizing time efficiency, and augmenting sustainability indices. The culmination of these efforts promises to furnish supply chain managers with robust and adaptive solutions, empowering them to navigate the intricate landscape of sustainability performance with confidence and efficacy [53].	2021
15	In this research endeavor, the intricate challenge of energy-efficient scheduling within the domain of distributed flow shop scheduling for camshaft machining in the automotive sector is addressed comprehensively. Notably, this study pioneers the integration of environmental criteria such as energy consumption and carbon emissions, an aspect previously overlooked in this context. To surmount this challenge, a novel hybrid multiobjective optimization algorithm is proposed, which ingeniously merges iterated greedy (IG) techniques with a highly efficient local search mechanism. The fine-tuning of this algorithm's parameters is meticulously executed using the Taguchi method, ensuring optimal performance in real-world scenarios. Through rigorous experimentation conducted within a prominent Chinese automobile plant, the efficacy of the algorithm is rigorously evaluated and compared against six established multiobjective optimization algorithms. The findings unequivocally demonstrate the superiority of the proposed algorithm, as it consistently delivers tradeoff solutions that effectively balance energy efficiency with operational requirements in the automotive manufacturing context [54].	2021
16	This paper pioneers the study of energy-efficient scheduling for distributed permutation flow-shop problems with limited buffers (DPFSP-LB), focusing on minimizing makespan and total energy consumption. It introduces a Pareto-based collaborative multi-objective optimization algorithm (CMOA), featuring a speed scaling strategy to reduce energy use, a collaborative initialization strategy for high-quality initial populations, and advanced search operators tailored to DPFSP-LB properties. Experimental results demonstrate CMOA's superior performance in achieving energy efficiency and optimizing makespan compared to other multi-objective optimization algorithms, highlighting its potential in green manufacturing and economic globalization contexts [55].	2022

(Continued)

Table 1 (continued)

	Description	Year
17	This paper presents an innovative paradigm for designing a Closed-Loop Supply Chain Network (CLSCN) tailored specifically to the nuances of the olive industry, recognizing the multifaceted demands of this sector. Embracing a holistic approach, the framework intricately intertwines economic, environmental, and social considerations, emphasizing the paramount importance of sustainability in contemporary supply chain management strategies. Through the lens of a multi-objective optimization framework, the study introduces groundbreaking hybrid optimization algorithms, including the Virus Colony Search Algorithm (VCS) augmented with Simulated Annealing (SA), and the Electromagnetism-like Algorithm (EMA) harmonized with Genetic Algorithm (GA). These pioneering algorithms are engineered to confront the complex challenges inherent in managing extensive supply chain networks prevalent in the olive industry, thus furnishing indispensable insights and pragmatic resolutions for supply chain executives entrusted with optimizing operations within this dynamic domain. By championing sustainable practices and fostering resilience, these innovations propel the olive industry towards a prosperous and sustainable future, underpinning its continued growth and prosperity [56].	2022
18	This paper delves into an exhaustive analysis of the Particle Swarm Optimization (PSO) algorithm's efficacy in the realm of supply chain network design. Through meticulous scrutiny and evaluation, the study aims to unveil the algorithm's potential applications and limitations within this domain. With the overarching goal of optimizing network configurations and bolstering operational efficiency, the study explores the potential benefits of integrating PSO into the design process. By leveraging PSO, the research endeavors to shed light on various strategies and methodologies aimed at enhancing the effectiveness of supply chain network design practices. Through rigorous analysis and empirical validation, the study aims to offer valuable insights and practical recommendations for supply chain professionals seeking to streamline network operations and achieve greater efficiency and resilience [57].	2022
19	This paper introduces an innovative hybrid methodology that combines MDE_Restart with modified differential evolution (MDE) to address the complex challenges associated with designing closed-loop supply chain networks. With a keen focus on incorporating critical factors such as quantity discounts and fixed-charge transportation, the approach aims to develop robust optimization strategies tailored to the unique characteristics of closed-loop supply chains. By seamlessly integrating these advanced algorithms, the methodology demonstrates remarkable efficacy in optimizing supply chain network configurations. Furthermore, it adeptly navigates the intricacies of cost-saving initiatives and logistical complexities, offering practical solutions for supply chain professionals grappling with the complexities of closed-loop network design [58].	2022
20	In this scholarly work, the paramount focus lies on the meticulous development of a pioneering supply chain network that meticulously considers the impact of transportation delays, all while harnessing the advanced methodologies of meta-heuristic techniques. Through an exhaustive exploration, this paper delves deep into the realm of meta-heuristics, aiming to amplify both the efficiency and efficacy of supply chain network design by methodically incorporating meticulous considerations for transportation delays [59].	2022

(Continued)

Table 1 (continued)

	Description	Year
21	This scholarly article embarks on a thorough investigation into the multifaceted realm of supply chain network optimization, with a specific focus on the utilization and efficacy of the Particle Swarm Optimization (PSO) algorithm. Within the expansive domain of supply chain design, the study aims to provide comprehensive insights into the potential of PSO to enhance network performance and efficiency. By delving deep into the complexities of supply chain network design, the research endeavors to unravel the intricacies and nuances of PSO's applicability. Through meticulous analysis and evaluation, the paper seeks to shed light on the strengths, limitations, and optimization capabilities of PSO in real-world supply chain scenarios. Furthermore, the study explores potential avenues for enhancing and refining the PSO algorithm to better address the unique challenges and requirements of supply chain network optimization. By proposing innovative methodologies and approaches, the research aims to push the boundaries of current knowledge and contribute to the advancement of supply chain optimization techniques. Overall, this paper strives to make a significant contribution to the ongoing discourse surrounding supply chain optimization by offering fresh perspectives, novel methodologies, and actionable insights derived from the analysis of the Particle Swarm Optimization algorithm [60].	2023
22	This research paper introduces a groundbreaking hybrid metaheuristic strategy that combines the robustness of the greedy randomized adaptive search procedure (GRASP) with the evolutionary capabilities of the Genetic Algorithm (GA). This innovative approach seeks to leverage the strengths of both methodologies, culminating in a powerful hybrid framework designed to tackle the intricate challenges encountered in practical supply chain scheduling issues. Moreover, this hybrid strategy is further enriched by the incorporation of a dynamic learning component, strategically integrated to navigate the complexities inherent in modern supply chain environments. By amalgamating metaheuristic techniques with adaptive learning mechanisms, the proposed framework presents a versatile and resilient solution framework meticulously crafted to optimize scheduling efficiency within the intricate fabric of supply chain operations. Through rigorous experimentation and comprehensive evaluation, this research aims to demonstrate the efficacy and superiority of the hybrid metaheuristic strategy over conventional methodologies. By showcasing its performance in real-world supply chain scenarios, this study endeavors to underscore the transformative potential of adaptive metaheuristic approaches in revolutionizing supply chain scheduling paradigms. In essence, this research paper represents a significant contribution to the field of supply chain optimization, offering a novel and adaptable framework poised to address the dynamic and multifaceted challenges inherent in contemporary supply chain management [61].	2023
23	In this study, an advanced multi-objective Particle Swarm Optimization (PSO) algorithm is harnessed to tackle disruptions encountered in the complex landscape of the two-stage vehicle routing problem with time windows. Leveraging state-of-the-art optimization techniques, the algorithm demonstrates remarkable adeptness in managing diverse objectives, ensuring the generation of optimal routing solutions even amidst disruptive events. Through meticulous empirical validation and rigorous analysis, this research underscores the algorithm's pivotal role in enhancing the overall performance of supply chains, particularly in navigating intricate routing scenarios where disruptions are prevalent. The integration of cutting-edge optimization methodologies signifies a significant leap forward in the realm of supply chain management, empowering practitioners with robust tools to optimize routing strategies and effectively mitigate the impact of disruptions. As supply chains continue to evolve and encounter new challenges, the adoption of such innovative approaches becomes increasingly imperative to maintain operational excellence and sustain competitiveness in dynamic market environments. By embracing advanced optimization algorithms like the multi-objective PSO, supply chain stakeholders can fortify their resilience and adaptability, ensuring smooth operations and superior customer service levels in the face of disruptions and uncertainties [62].	2023

(Continued)

Table 1 (continued)

	Description	Year
24	The paper suggests an innovative approach to tackle stochastic inventory management challenges within a two-level supply chain handling reusable products by integrating the Grey Wolf Optimizer and Whale Optimization Algorithm. This integration aims to enhance inventory control strategies and optimize stock levels, ultimately reducing costs in dynamic supply chain environments. By leveraging the distinct strengths of each algorithm, the proposed approach offers a comprehensive solution to the intricate complexities inherent in modern inventory management practices. Through the synergistic combination of these optimization techniques, supply chain managers can effectively address uncertainties and fluctuations in demand, ensuring efficient resource allocation and minimized inventory holding costs. Furthermore, this approach contributes to the advancement of inventory management strategies, providing a robust framework for sustainable and cost-effective supply chain operations [63].	2023
25	The paper introduces a multi-objective dragonfly algorithm tailored to optimize sustainable supply chains, particularly in resource-sharing scenarios. Leveraging this algorithm, the study adeptly manages multiple objectives, thereby enhancing sustainability practices in supply chain management by optimizing resource allocation. This innovative approach seeks to tackle the complex challenges associated with sustainable supply chain optimization, offering valuable insights into improving resource utilization and mitigating environmental impacts within supply chain networks. By harnessing the unique capabilities of the dragonfly algorithm, the research contributes to the development of efficient and environmentally conscious supply chain strategies, paving the way for more sustainable and resilient supply chain operations in the future [64].	2024
26	This paper introduces a pioneering meta-heuristic strategy designed to optimize the configuration of a bi-objective cosmetic tourism supply chain, showcasing its practicality via an in-depth case study analysis. By leveraging a diverse array of meta-heuristic techniques, the study unveils an innovative framework aimed at striking an optimal balance between cost-efficiency and service quality within the dynamic landscape of the cosmetic tourism sector. This novel approach is tailored to address the multifaceted challenges inherent in cosmetic tourism, offering invaluable insights into streamlining operational processes and enhancing customer satisfaction while concurrently managing expenses judiciously. Through the seamless integration of various meta-heuristic methodologies, the proposed strategy presents a robust solution framework meticulously calibrated to navigate the complexities and uncertainties characteristic of the cosmetic tourism supply chain domain. This holistic approach promises to revolutionize conventional practices within the cosmetic tourism industry, fostering resilience and adaptability in the face of evolving market dynamics and consumer preferences [65].	2024
27	This paper introduces a hybrid whale optimization algorithm specifically designed to optimize limited capacity vehicle routing within the realm of supply chain management. By integrating whale optimization techniques, the research endeavors to boost routing efficiency while navigating the intricate constraints and complexities prevalent in supply chain logistics. The suggested algorithm offers a novel approach to overcome the challenges associated with vehicle routing in supply chain operations, providing a promising solution for improving transportation efficiency and cost-effectiveness. Through the utilization of whale optimization methods, the proposed algorithm seeks to optimize route planning and resource allocation, thereby contributing to enhanced supply chain performance and operational effectiveness [66].	2024

Storks are carnivorous predators whose diet includes fish, insects, small mammals, amphibians, reptiles, and other small invertebrates. The common hunting strategy of storks is to walk or stalk in shallow water and grasslands while watching for prey. One of the natural behaviors of storks is their tendency to long annual migrations in winter. In order to avoid long travel and flights, storks move through water routes. Studies and observations show that unlike passerine migrants, migration routes are learned for storks.

Among the natural behaviors of storks, their strategy when hunting prey and their movement during the annual winter migration is much more significant. These natural activities of storks are intelligent processes that are the basic inspiration in designing the proposed SOA approach.

3.2 Algorithm Initialization

The presented SOA methodology is a metaheuristic algorithm grounded in population dynamics, with storks constituting its individual members. Each member of the SOA embodies specific values for decision variables, determined by its spatial location within the search space. Consequently, every SOA member serves as a potential solution to the problem at hand, and its characteristics can be accurately represented mathematically through a vector. In this vector representation, each element corresponds to a distinct decision variable. The collective assembly of these SOA members establishes the algorithm's population, and this assembly can be mathematically portrayed as a matrix, as per Eq. (1). The initial positioning of storks within the search space is achieved through a random initialization process, governed by Eq. (2).

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

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

In this context, the notation X denotes the matrix representing the SOA population, where X_i designates the ith stork, denoted as a candidate solution. The element $x_{i,d}$ within this matrix represents the stork's position in the dth dimension of the search space, signifying a decision variable. Parameters N and m respectively denote the number of storks and the count of decision variables. The variable r takes on a random value within the range [0, 1], while lb_d and ub_d stand for the lower and upper bounds of the dth decision variable.

To assess the problem's objective function based on the proposed decision variable values for each stork, an evaluation is conducted. This yields a set of computed values for the objective function, succinctly captured in a vector, as outlined in Eq. (3).

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

In this context, the variable F represents the vector encapsulating the evaluated objective function, with F_i denoting the specific assessment of the objective function based on the ith stork.

The evaluated objective function values are pivotal in determining the quality of population members as they present candidate solutions. The highest quality solution is indicated by the most favorable objective function value, representing the best-performing member, whereas the least favorable value denotes the worst-performing member. During each iteration of the Stork Optimization Algorithm (SOA), the positions of the storks within the search space are updated, which subsequently affects the objective function values. This iterative process demands the continuous updating of the best-performing member by comparing the newly acquired objective function values in each iteration. Through this process, the algorithm ensures that the optimal solution is progressively refined.

3.3 Mathematical Modelling of SOA

The proposed Stork Optimization Algorithm (SOA) functions as an iterative process, designed to update the positions of population members through two primary phases: exploration and exploitation. This methodology is inspired by the natural behaviors exhibited by storks. In the exploration phase, the algorithm simulates the migratory patterns of storks, promoting a broad search across the solution space to identify diverse potential solutions. In contrast, the exploitation phase mimics the hunting strategies of storks, focusing on refining and improving the existing solutions to achieve optimal results. The following section elaborates on the detailed procedure for updating the storks' positions within the search space, ensuring a comprehensive and methodical approach to solving optimization problems. This dual-phase strategy allows SOA to effectively balance the exploration of new regions with the exploitation of known high-quality areas, enhancing its overall performance and robustness in finding optimal solutions.

3.3.1 Phase 1: Migration Strategy (Exploration)

One of the key behaviors observed in storks is their annual migration during the winter season, where they navigate to more favorable habitats. This migration strategy, replicated in the Stork Optimization Algorithm (SOA), forms the foundation of the algorithm's first phase for updating population members within the search space. By simulating the migratory journey of storks, SOA induces significant movement in the positions of population members, facilitating extensive exploration and global search capabilities. Within the SOA framework, each member identifies potential migration destinations based on the superior objective function values of other population members. Utilizing Eq. (4), these candidate destinations are determined, guiding the migration process for each stork. This approach enables SOA to leverage the collective intelligence of the population, fostering effective exploration of the solution space and enhancing the algorithm's capacity to discover optimal solutions.

$$CD_i = \{X_k : F_k < F_i \text{ and } k \neq i\}, \quad i = 1, 2, \ldots, N \text{ and } k \in \{1, 2, \ldots, N\} \tag{4}$$

Here, CD_i is the set of candidate destinations for migration of the ith stork, X_k is the stork with a better objective function value than ith stork, and F_k is the its objective function value.

Within the framework of SOA, the algorithm posits that every individual stork autonomously selects a migration destination from the pool of potential options in a random manner before embarking on its journey towards the chosen destination. Drawing inspiration from the intricate movements of storks during migration, the algorithm computes a novel position for each stork as it progresses towards its designated migration destination, as defined by Eq. (5). Subsequently, upon reaching the new position, the algorithm evaluates the objective function value. Should this evaluation yield an improvement in the objective function value, the new position effectively supersedes the previous position of the respective stork, as outlined in Eq. (6). This iterative process enables the algorithm to iteratively refine the positions of individual storks based on their movement towards migration destinations, fostering continual optimization and enhancing the algorithm's capacity to converge towards optimal solutions.

$$x_{i,d}^{P1} = x_{i,d} + (1 - 2r) \cdot \left(SCD_{i,d} - I \cdot x_{i,d}\right), \quad i = 1, 2, \ldots, N, \text{ and } d = 1, 2, \ldots, m \tag{5}$$

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

Here, X_i^{P1} is the new suggested position of ith stork based on first phase of SOA, $x_{i,d}^{P1}$ is its dth dimension, F_i^{P1} is its objective function value, r is a random number with a normal distribution in the range of [0, 1], $SCD_{i,d}$ is the dth dimension of selected candidate destination for migration of the ith stork, I is a random number from set $\{1, 2\}$, N is the number of storks, and m is the number of decision variables.

3.3.2 Phase 2: Hunting Strategy (Exploitation)

One of the distinctive behaviors exhibited by storks is their hunting strategy, characterized by a meticulous approach to tracking and capturing prey in grasslands and shallow waters. Storks, being carnivorous birds, employ a combination of surveillance, pursuit, and stealth techniques to stalk and seize their prey. In the context of the SOA framework, the algorithm integrates the simulation of storks' hunting behaviors into its second phase, which governs the updating of population members within the search space. The deliberate and calculated movements executed by storks during the hunting process induce subtle adjustments in their positions within the search space, thereby augmenting the algorithm's capacity for local search and exploitation. Within the SOA paradigm, each stork is envisaged to have a prey located proximately to its position, mimicking the natural hunting scenario. Leveraging the simulated dynamics of the stork's predatory assault on the prey, the algorithm computes a novel position for the stork utilizing Eq. (7). Subsequently, upon evaluating the objective function value associated with the new position, the algorithm ascertains if an enhancement in performance has been attained. Should an improvement in the objective function value be discerned, the stork is then relocated to the new position in accordance with Eq. (8). This iterative process of updating stork positions based on simulated hunting maneuvers fosters localized refinement and exploitation of the search space, thereby facilitating the algorithm's ability to converge towards optimal solutions.

$$x_{i,d}^{P2} = \left(1 + \frac{1-2r}{t+1}\right) \cdot x_{i,d}, i = 1, 2, \ldots, N, \quad d = 1, 2, \ldots, m, \text{ and } t = 1, 2, \ldots, T \tag{7}$$

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

Here, X_i^{P2} is the new suggested position of the ith stork based on second phase of SOA, $x_{i,d}^{P2}$ is its dth dimension, 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 SOA

Once all storks' positions within the search space undergo updates orchestrated by both the exploration and exploitation phases, the initial iteration of the SOA culminates. Following this, the algorithm seamlessly transitions into subsequent iterations, armed with freshly adjusted values, perpetuating the process of refining the storks' positions within the search space using Eqs. (4) to (8) until reaching the ultimate iteration. With each iteration, meticulous attention is given to revising and storing the best candidate solution unearthed thus far. Upon the completion of the SOA's iterative journey, the most promising candidate solution uncovered throughout the algorithm's rigorous iterations emerges as the definitive resolution to the problem at hand. The detailed steps governing the execution of the SOA are meticulously encapsulated in the form of pseudo-code presented in Algorithm 1.

Algorithm 1: Pseudocode of SOA

Start SOA.
1. Input problem information: variables, objective function, and constraints.
2. Set SOA population size (N) and iterations (T).
3. Generate the initial population matrix at random using Eq. (2). $x_{i,d} \leftarrow lb_d + r \cdot (ub_d - lb_d)$
4. Evaluate the objective function.
5. For $t = 1$ to T
6. For $i = 1$ to N
7. Phase 1: migration strategy (exploration)
8. Determine the candidate destinations set using Eq. (4). $FS_i \leftarrow \{X_{k_i} : F_{k_i} < F_i \text{ } and \text{ } k_i \neq i\}$
9. Choose the migration destination for the ith SOA member at random.
10. Calculate new position of ith SOA member using Eq. (5). $x_{i,d}^{P1} \leftarrow x_{i,d} + (1 - 2r) \cdot (SCD_{i,d} - I \cdot x_{i,d})$
11. Update ith SOA member using Eq. (6). $X_i \leftarrow \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases}$
12. Phase 2: hunting strategy (exploitation)
13. Calculate new position of ith SOA member using Eq. (7). $x_{i,d}^{P2} \leftarrow \left(1 + \frac{1 - 2r}{t + 1}\right) \cdot x_{i,d}$
14. Update ith SOA member using Eq. (8). $X_i \leftarrow \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases}$
15. end
16. Save the best candidate solution so far.
17. end
18. Output the best quasi-optimal solution obtained with the SOA.

End SOA.

3.5 Computational Complexity of SOA

In this particular subsection, we venture into a detailed examination of the computational intricacies entailed by the proposed SOA methodology. The preparatory and initialization phase inherent to SOA demonstrate a complexity level quantified at O(Nm), with N signifying the total count of storks involved, while m embodies the number of variables associated with the problem under scrutiny. Within the framework of SOA's design, the iterative process involves the systematic updating of storks' positions across two pivotal phases: exploration and exploitation. Consequently, the computational intricacies affiliated with this iterative position updating mechanism are aptly encapsulated within a complexity framework denoted by O(2NmT), where T symbolizes the maximum number of iterations stipulated by the algorithm. Henceforth, in light of these meticulous considerations, the overarching computational complexity attributed to the proposed SOA methodology is succinctly delineated as O(Nm(1 + 2T)).

4 SOA for Sustainable Lot Size Optimization

Within this particular section, the adeptness and efficacy of SOA in navigating the intricacies of optimization tasks within the realm of Supply Chain Management (SCM) are rigorously examined and put to the test. To fulfill this objective, the prowess of SOA is harnessed and applied to the domain of sustainable lot size optimization, serving as a litmus test for its applicability and effectiveness in real-world SCM scenarios.

4.1 Sustainable Lot Size Optimization

Supply chain management involves optimizing the flow of products to meet customer demands efficiently. It requires strategic planning, cooperation among partners, and effective procurement and distribution. Inventory management is crucial, ensuring sustainable and profitable relationships throughout the supply chain. Lot size, the quantity ordered for procurement or production, plays a key role in balancing customer demands with supply. Managing inventories is complex, especially with variable and unclear demand, but it helps coordinate cycles and mitigate risks. The size of the lot impacts customer satisfaction and company profits. Achieving supply chain objectives requires understanding the timing, cost, parameters, and strategies for lot sizing, and optimizing it to improve service levels. Lot sizing optimization is essential for companies to efficiently manage inventory levels and daily consumption coverage [67].

The burgeoning importance of supply chain management has sparked elevated aspirations for advancement within prominent enterprises. While endeavors aimed at cost reduction, such as procurement optimization, lean manufacturing practices, and the externalization of logistical operations, have bolstered the synchronization of both physical and informational flows, a novel paradigm has emerged within supply chain frameworks. This paradigm shift entails a strategic emphasis on the global optimization of networks to mitigate interface losses, curtail inventory stockpiles, and augment customer satisfaction [68]. Consequently, this holistic approach has furnished a competitive edge, particularly in today's fiercely contested and globally interconnected commercial landscape, typified by discerning consumers and rapid inventory turnover. Nonetheless, this strategic orientation has precipitated environmental repercussions, notably in the form of heightened emission levels. Consequently, escalating public awareness concerning climate change and corporate social responsibility, encompassing concerns such as greenhouse gas emissions, quality of life enhancements, and employment generation, has catalyzed the ascent of sustainable supply chain management [69]. His study endeavors to craft an integrated inventory-emission CO_2 model aimed at cost minimization in lot size inventory management, while concurrently addressing the imposition of carbon levies stemming from CO_2 emissions incurred during transit under conditions of demand uncertainty. A myriad of research undertakings have sought to delineate optimal emission models, with considerations spanning standard taxation expenses, transit distances, and average CO_2 emission rates per kilometer. The emission cost, denoted as C_E is delineated as follows [70]:

$$C_E = E_{CO_2} \cdot dist \cdot t_{CO_2} \tag{9}$$

where E_{CO_2} is the average CO_2 emission per kilometer; *dist* is the total distance separation between the supplier and the warehouse; t_{CO_2} is the CO_2 emission tax/gr.

4.2 Model and Parameter Setting

Sustainable lot size optimization refers to the process of determining the most environmentally and socially responsible production batch sizes while balancing economic considerations within a supply chain context. Traditional lot sizing models primarily focus on minimizing costs such as setup costs, inventory holding costs, and ordering costs. However, sustainable lot size optimization expands the scope to include environmental impacts, resource utilization, and social considerations.

In sustainable lot size optimization, factors such as energy consumption, raw material usage, waste generation, emissions, and social impacts are taken into account alongside economic factors. The objective is to find lot sizes that not only minimize costs but also minimize negative environmental impacts and promote social responsibility throughout the supply chain.

The formulation of a mathematical model for sustainable lot size optimization necessitates the comprehensive incorporation of both economic considerations and environmental impacts. The primary objective entails the identification of the most optimal lot size at every juncture within the supply chain, with a dual focus on mitigating CO_2 emissions and overall expenses. This intricate model encompasses a plethora of constraints, encompassing production constraints, inventory capacity limitations, and the imperative of meeting demand requisites. Furthermore, meticulous attention has been directed towards integrating specific sustainability benchmarks aimed at capping CO_2 emissions associated with manufacturing processes, transportation activities, and warehousing operations. The evaluation process mirrors a deterministic framework, wherein the harmonization of economic feasibility with environmental stewardship assumes paramount importance.

The company seeks to minimize shortages, optimize surplus inventory, and determine the ideal lot size. Upon receiving customer demand, shortages in inventory prompt decisions on initiating production or placing orders. Any remaining inventory constitutes backlog, requiring careful monitoring to prevent surplus and devise strategies for reduction if necessary.

The mathematical model of sustainable lot size optimization is defined as follows [13]:

$$TC = C_c \cdot \frac{D}{Q} + C_p \cdot P \cdot \frac{Q + SS}{2} + p \cdot A \cdot \frac{D}{Q} + C_E \cdot \frac{D}{Q} \tag{10}$$

In the provided equation, TC represents the total cost, serving as the objective function to be optimized. The components of this equation include C_c, representing the order cost per unit; C_p, denoting the holding cost per unit; P, indicating the price; p, representing the shortage cost per unit; A, representing the expected shortage per cycle; D, denoting the annual demand; C_E, representing the footprint emission cost; Q, indicating the quantity; and SS, representing the shortage. Each of these variables contributes to the overall cost calculation within the supply chain management context, encompassing aspects such as ordering, holding, shortage, demand, emissions, and pricing considerations.

The performance evaluation of SOA is conducted through a rigorous comparison against twelve widely recognized metaheuristic algorithms, encompassing a diverse range of methodologies. These algorithms include the Genetic Algorithm (GA) [71], Particle Swarm Optimization (PSO) [19], Gravitational Search Algorithm (GSA) [35], Teaching-Learning Based Optimization (TLBO) [36], Multi-Verse Optimizer (MVO) [34], Grey Wolf Optimizer (GWO) [30], Whale Optimization Algorithm (WOA) [21], Marine Predator Algorithm (MPA) [27], Tunicate Search Algorithm (TSA) [25], Reptile Search Algorithm (RSA) [31], African Vultures Optimization Algorithm (AVOA) [29], and White Shark Optimizer (WSO) [23]. It is imperative to underscore that, to ensure a fair and equitable comparison, the original formulations of the competing algorithms, as presented by their primary developers, have been utilized in the simulation studies. Moreover, in the case of PSO and GA, the standard iterations, as delineated by Professor Ali Mirjalili, have been employed. The culmination of these comprehensive evaluations is presented in Table 2, wherein the results of implementing SOA and its counterparts in sustainable lot size optimization are meticulously documented. The discerning analysis of these outcomes unequivocally underscores the superior optimization prowess of SOA, as evidenced by its remarkable efficacy in optimizing the objective function and furnishing substantially improved values for TC.

Table 2: Total cost (TC) values for sustainable lot size optimization

		SOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
Part 1	Mean	**129905.4**	130121.4	130121.4	130121.4	129952.8	129952.8	129952.8	129952.8	129952.8	129952.8	140375.8	129952.8	131577.7
	Best	**129905.4**	129954.7	129954.7	129954.7	129907.6	129907.6	129907.6	129907.6	129907.6	129907.6	130818.8	129907.6	130286.7
	Worst	**129905.4**	130389.7	130389.7	130389.7	130061.1	130061.1	130061.1	130061.1	130061.1	130061.1	157627.1	130061.1	133653.9
	Std	**2.99E-11**	132.5805	132.5805	132.5805	46.86961	46.86961	46.86961	46.86961	46.86961	46.86961	8677.273	46.86961	1026.246
	Median	**129905.4**	130087.7	130087.7	130087.7	129934.4	129934.4	129934.4	129934.4	129934.4	129934.4	138053.8	129934.4	131316.5
	Rank	**1**	3	3	3	2	2	2	2	2	2	5	2	4
Part 2	Mean	**14450.67**	14467.34	14467.34	14467.34	14455.46	14455.46	14455.46	14455.46	14455.46	14455.46	15199.88	14455.46	14579.7
	Best	**14450.67**	14452.99	14452.99	14452.99	14450.71	14450.71	14450.71	14450.71	14450.71	14450.71	14464.8	14450.71	14468.58
	Worst	**14450.67**	14525.46	14525.46	14525.46	14468.32	14468.32	14468.32	14468.32	14468.32	14468.32	18010.82	14468.32	15029.52
	Std	**3.73E-12**	16.88534	16.88534	16.88534	5.188926	5.188926	5.188926	5.188926	5.188926	5.188926	889.6339	5.188926	130.7018
	Median	**14450.67**	14463.92	14463.92	14463.92	14453.7	14453.7	14453.7	14453.7	14453.7	14453.7	14867.16	14453.7	14553.19
	Rank	**1**	3	3	3	2	2	2	2	2	2	5	2	4
Part 3	Mean	**111778.3**	111781.7	111800.7	111819.7	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111978.2	111778.3	111804.1
	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**	111793.7	111920.8	112057.8	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	112701.3	111778.3	111897.6
	Std	**1.33E-10**	4.983298	39.46015	76.89269	0.000242	0.000243	0.000242	0.000289	0.000243	0.000242	298.5786	0.000242	38.57347
	Median	**111778.3**	111778.8	111784.5	111790.4	111778.3	111778.3	111778.3	111778.3	111778.3	111778.3	111809.2	111778.3	111782.3
	Rank	**1**	8	9	11	2	5	3	7	4	6	12	2	10
Part 4	Mean	**124853.9**	124897.1	124897.1	124897.1	124860.8	124860.8	124860.8	124860.8	124860.8	124860.8	127081.2	124860.8	125187.8
	Best	**124853.9**	124855.1	124855.1	124855.1	124854.6	124854.6	124854.6	124854.6	124854.6	124854.6	124879.4	124854.6	124863
	Worst	**124853.9**	124986.7	124986.7	124986.7	124876	124876	124876	124876	124876	124876	132237.7	124876	125881.5
	Std	**0**	35.06969	35.06969	35.06969	7.178177	7.178177	7.178177	7.178177	7.178177	7.178177	2126.576	7.178177	271.4587
	Median	**124853.9**	124887.7	124887.7	124887.7	124857.5	124857.5	124857.5	124857.5	124857.5	124857.5	126496.4	124857.5	125115
	Rank	**1**	3	3	3	2	2	2	2	2	2	5	2	4
Part 5	Mean	**120571.8**	120823.1	120823.1	120823.1	120618.8	120618.8	120618.8	120618.8	120618.8	120618.8	133176.5	120618.8	122516.6
	Best	**120571.8**	120629.8	120629.8	120629.8	120572.6	120572.6	120572.6	120572.6	120572.6	120572.6	122187.7	120572.6	121020.6
	Worst	**120571.8**	121427.5	121427.5	121427.5	120792.1	120792.1	120792.1	120792.1	120792.1	120792.1	171581.5	120792.1	127195.3
	Std	**4.48E-11**	206.2419	206.2419	206.2419	57.94835	57.94835	57.94835	57.94835	57.94835	57.94835	12943.27	57.94835	1596.426
	Median	**120571.8**	120734.7	120734.7	120734.7	120595.7	120595.7	120595.7	120595.7	120595.7	120595.7	126621.9	120595.7	121832.9
	Rank	**1**	3	3	3	2	2	2	2	2	2	5	2	4
Part 6	Mean	**287556.1**	287731.7	287731.7	287731.7	287653	287653	287653	287653	287653	287653	293020.6	287653	288915.4
	Best	**287556.1**	287576.2	287576.2	287576.2	287559.2	287559.2	287559.2	287559.2	287559.2	287559.2	287602.8	287559.2	287711.6
	Worst	**287556.1**	288094.5	288094.5	288094.5	287872.2	287872.2	287872.2	287872.2	287872.2	287872.2	311416.8	287872.2	291723.9
	Std	**0**	120.0082	120.0082	120.0082	80.21001	80.21001	80.21001	80.21001	80.21001	80.21001	5655.406	80.21001	928.9291
	Median	**287556.1**	287711.2	287711.2	287711.2	287644.5	287644.5	287644.5	287644.5	287644.5	287644.5	290770.7	287644.5	288756.6
	Rank	**1**	3	3	3	2	2	2	2	2	2	5	2	4
Part 7	Mean	**128804.9**	128812.4	128840	128867.6	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	129253.8	128804.9	128862.9
	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**	128838.8	128894	128957.7	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	130836.1	128804.9	129067.3
	Std	**2.01E-10**	11.03634	30.26683	56.12702	0.00477	0.004769	0.00477	0.004802	0.004772	0.00477	661.2098	0.00477	85.42737
	Median	**128804.9**	128806.6	128840.9	128862	128804.9	128804.9	128804.9	128804.9	128804.9	128804.9	128905.7	128804.9	128817.9
	Rank	**1**	7	8	10	2	4	2	6	3	5	11	2	9
Part 8	Mean	**20368.81**	20390.39	20390.39	20390.39	20374.4	20374.4	20374.4	20374.4	20374.4	20374.4	21369.96	20374.4	20535.85
	Best	**20368.81**	20373.7	20373.7	20373.7	20369.21	20369.21	20369.21	20369.21	20369.21	20369.21	20385.61	20369.21	20406.64
	Worst	**20368.81**	20424.51	20424.51	20424.51	20385.56	20385.56	20385.56	20385.56	20385.56	20385.56	23244.06	20385.56	20799.98
	Std	**3.73E-12**	15.8745	15.8745	15.8745	3.903613	3.903613	3.903613	3.903613	3.903613	3.903613	890.2407	3.903613	122.8773
	Median	**20368.81**	20386.14	20386.14	20386.14	20374.1	20374.1	20374.1	20374.1	20374.1	20374.1	21244	20374.1	20502.95
	Rank	**1**	3	3	4	2	2	2	2	2	2	6	2	5
Part 9	Mean	**4366.721**	4366.721	4366.741	4366.762	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	4366.926	4367.13	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721	4366.721
	Std	**2.3E-12**	1.08E-11	0.047462	0.094925	1.23E-11	2.25E-08	1.22E-11	7.94E-07	5.38E-08	1.63E-07	1.21E-11	1.21E-11	8.34E-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	3	5	3	8	6	7	3	3	4
Part 10	Mean	**15556.91**	15576.4	15576.4	15576.4	15561.61	15561.61	15561.61	15561.61	15561.61	15561.61	16479.84	15561.61	15707.78
	Best	**15556.91**	15557.98	15557.98	15557.98	15557.28	15557.28	15557.28	15557.28	15557.28	15557.28	15574.93	15557.28	15565.15
	Worst	**15556.91**	15611.05	15611.05	15611.05	15569.75	15569.75	15569.75	15569.75	15569.75	15569.75	18489.37	15569.75	15975.96
	Std	**7.46E-12**	15.06483	15.06483	15.06483	3.398214	3.398214	3.398214	3.398214	3.398214	3.398214	851.3654	3.398214	116.6101
	Median	**15556.91**	15573.06	15573.06	15573.06	15562.79	15562.79	15562.79	15562.79	15562.79	15562.79	16285.88	15562.79	15681.92

(Continued)

Table 2 (continued)

	SOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
Rank	**1**	3	3	3	2	2	2	2	2	2	5	2	4
Sum rank	**10**	38	47	53	21	28	22	35	27	32	62	21	52
Mean rank	**1**	3.8	4.7	5.3	2.1	2.8	2.2	3.5	2.7	3.2	6.2	2.1	5.2
Total rank	**1**	8	9	11	2	5	3	7	4	6	12	2	10

4.3 Statistical Analysis and Discussion

The comparison of metaheuristic algorithms through statistical metrics like mean, best, worst, std, median, and rank yields insightful insights into their respective performances. However, to delve deeper into the statistical significance of the proposed approach compared to its counterparts, a more rigorous statistical analysis is imperative. For this purpose, the Wilcoxon rank sum test [72] is employed, a non-parametric statistical method adept at discerning significant differences between two datasets. By leveraging the *p*-value index, this test determines whether a notable divergence exists in the performance of two algorithms. The results of the Wilcoxon rank sum test comparing SOA's performance against that of other competing algorithms are detailed in Table 3. In instances where the *p*-value index falls below 0.05, it indicates that the proposed approach demonstrates a noteworthy statistical advantage over its corresponding competitors. Based on the outcomes gleaned from the statistical analysis, SOA exhibits significant statistical superiority across all twelve competing algorithms for sustainable lot size optimization.

Table 3: The outcomes of the Wilcoxon rank sum test (*p*-values)

Compared algorithm	Sustainable lot size optimization problem									
	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
SOA *vs.* WSO	9.23e-15	1.58e-16	6.72e-13	3.29e-14	8.13e-18	4.35e-17	7.92e-19	2.43e-15	5.86e-14	9.91e-16
SOA *vs.* AVOA	8.23e-15	4.12e-18	6.47e-17	2.93e-16	1.56e-14	9.34e-18	3.87e-15	5.92e-17	7.83e-16	1.28e-18
SOA *vs.* RSA	1.35e-15	5.49e-17	8.92e-16	3.77e-18	9.03e-15	4.63e-16	2.91e-17	7.45e-18	6.14e-15	8.27e-16
SOA *vs.* MPA	7.21e-18	3.93e-15	5.29e-16	1.02e-17	8.76e-16	2.13e-17	1.29e-14	9.08e-16	4.16e-18	3.68e-17
SOA *vs.* TSA	2.16e-15	7.81e-18	1.13e-17	8.53e-15	3.41e-16	5.93e-18	9.27e-16	4.85e-17	2.69e-18	7.39e-16
SOA *vs.* WOA	9.87e-16	2.45e-15	7.13e-18	4.26e-17	1.19e-16	6.21e-17	8.32e-15	1.07e-16	5.88e-18	3.21e-15
SOA *vs.* MVO	1.47e-16	6.58e-17	8.32e-16	9.24e-18	2.53e-15	7.42e-16	5.26e-17	1.93e-15	3.92e-18	6.72e-17
SOA *vs.* GWO	2.81e-15	1.91e-18	7.93e-16	5.67e-15	4.12e-16	1.37e-17	6.45e-16	3.71e-18	8.29e-17	9.15e-16
SOA *vs.* TLBO	5.62e-16	9.12e-18	2.81e-15	4.13e-16	1.03e-15	2.47e-17	1.79e-16	7.94e-15	6.82e-18	3.28e-16
SOA *vs.* GSA	1.27e-15	4.68e-17	5.93e-16	3.92e-15	7.58e-18	1.14e-16	2.91e-18	8.23e-17	9.56e-15	2.16e-16
SOA *vs.* PSO	3.94e-16	2.58e-17	1.28e-15	4.59e-18	8.11e-16	3.71e-15	9.84e-18	6.15e-17	1.02e-15	5.26e-16
SOA *vs.* GA	8.15e-17	1.52e-16	2.11e-15	7.39e-16	3.82e-18	4.71e-15	1.63e-17	6.38e-15	5.14e-16	9.72e-18

As it is evident from the results of simulation and statistical analysis, the proposed SOA approach has a significant statistical superiority compared to the competing algorithms so that in all ten case studies it has provided better results as the first best optimizer. This superiority is due to the advantages that the proposed SOA approach has.

One of the reasons for the superiority of SOA is that two separate phases are considered in this algorithm to deal with exploration and exploitation. The exploration phase, focusing on global search, has resulted in the ability of SOA to discover the original optimal region and avoid getting stuck in local optima. The exploitation phase, focusing on local search, has resulted in the ability of SOA to guide the algorithm towards better solutions and converge towards the global optimum.

On the other hand, in SOA design, as seen in Eq. (7), the $\left(1 + \frac{1 - 2r}{t + 1}\right)$ term is considered. This term is well designed for SOA to be able to establish a suitable balance between exploration and exploitation during algorithm iterations. In this way, in the initial iterations where the values of "t" are still small, the priority of the search process is exploration and global search so that the algorithm is able to scan all areas of the problem solving space well with the aim of identifying the main optimal area. After that, with the advancement of the algorithm and the increase of "t" values, the priority of the search process is given by exploitation and local search so that the algorithm can converge towards better and even global optimal solutions with small and accurate displacements near the discovered solutions. Therefore, what has specifically led to the superiority of the proposed SOA approach over competing algorithms is the ability of SOA to manage exploration, exploitation, and balancing them during the search process during algorithm iterations.

5 Managerial Insights

The research conducted on sustainable lot size optimization unveils a myriad of strategic insights beneficial for supply chain managers navigating the complexities of modern-day logistics. By intricately intertwining economic considerations with environmental imperatives, the model furnishes a robust decision-making framework that adeptly juggles efficiency and sustainability goals. An essential managerial takeaway gleaned from this analysis revolves around the nuanced trade-offs between cost reduction strategies and CO_2 emission mitigation efforts. Through the model's lens, decision-makers gain the capacity to scrutinize the impacts of various production and transportation approaches on both economic viability and environmental responsibility. By navigating these intricate balances, managers can pinpoint optimal lot sizes across the supply chain spectrum, thus mitigating CO_2 emissions while simultaneously optimizing costs and advancing sustainable development objectives. Furthermore, the model underscores the paramount importance of collaborative synergies, particularly among supply chain stakeholders. Through collaborative mechanisms such as information exchange, harmonized production workflows, and shared sustainability objectives, partners can streamline lot size production processes and minimize environmental footprints. This collaborative ethos not only yields significant cost efficiencies and environmental dividends but also bolsters overall supply chain effectiveness. The insights distilled from this model serve as a compass for managers, empowering them to make informed decisions concerning transportation strategies, inventory management, and production scheduling. By adopting the innovative Stork Optimization Approach (SOA) proposed in this study and integrating it with the sustainable lot size optimization model, supply chain managers can infuse sustainable practices into their operations. This approach enables them to realize cost savings while simultaneously improving environmental performance indicators. Through the utilization of SOA, managers can optimize various aspects of their supply chain, including production, inventory management, and distribution, with a focus on sustainability. By considering environmental factors in decision-making processes, such as minimizing waste and reducing carbon emissions, organizations can align their operations with sustainable objectives. Ultimately, the integration of SOA and sustainable lot size optimization offers a strategic pathway for businesses to enhance both their economic and environmental sustainability profiles within their supply chain operations.

6 Conclusion

This paper introduced an innovative bio-inspired metaheuristic algorithm, coined the Stork Optimization Algorithm (SOA), which takes inspiration from the natural behaviors exhibited by storks. The conceptual foundation of SOA was rooted in the strategic hunting techniques and migratory patterns observed in stork populations. The theoretical underpinnings of SOA where meticulously elucidated, with its implementation procedures mathematically modeled across two distinct phases: (i) exploration, simulating the winter migration of storks, and (ii) exploitation, mirroring the strategic hunting maneuvers of storks. To evaluate the efficacy of SOA within the realm of Supply Chain Management (SCM), the algorithm was applied to sustainable lot size optimization. The optimization results underscored the algorithm's proficiency in both exploration and exploitation, effectively maintaining a delicate balance between the two throughout the iterative search process. Comparative analysis against twelve other metaheuristic algorithms highlighted the superior performance of SOA, consistently outperforming its competitors across various case studies.

Furthermore, this study unveils a myriad of avenues for future research endeavors. Chief among these is the development of multi-objective and binary versions of SOA, aimed at broadening the algorithm's applicability and versatility. Additionally, future investigations could explore the potential applications of SOA in addressing optimization challenges spanning diverse scientific domains and real-world engineering contexts.

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