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Research paper

Swarm intelligence algorithms: a survey of modifications and applications

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Abstract

Swarm Intelligence (SI) is a dynamic subfield of artificial intelligence that draws inspiration from the collective behaviors of natural systems such as ant colonies, bird flocks, and fish schools. This paper provides a comprehensive review of SI algorithms, examining their foundational principles, recent modifications, and applications across diverse domains. Prominent algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Bat Algorithm (BA) are analyzed alongside emerging approaches like Grey Wolf Optimizer (GWO), Zebra Optimization Algorithm (ZOA), and hybrid frameworks. A key focus is placed on algorithmic advancements, in-cluding adaptive inertia weights in PSO, pheromone update mechanisms in ACO, and hybridization techniques such as GWO-PSO and WOA-BA, addressing challenges related to convergence speed, scalability, and robustness against local optima.
This review explores the practical applications of SI algorithms in engineering design, healthcare, robotics, logistics, education, and social media. Detailed performance comparisons reveal the strengths and limitations of each algorithm, supported by empirical results from benchmark problems such as the Traveling Salesman Problem (TSP), pressure vessel design optimization, and radiotherapy planning. Addi-tionally, the study highlights novel algorithms developed between 2020 and 2023, shedding light on their contributions to the field. The paper concludes by identifying current challenges, such as computational overhead and parameter sensitivity, and suggests future directions, including the integration of machine learning, lightweight adaptations for resource-constrained environments, and bio-inspired enhance-ments.

Keywords: *Swarm Intelligence; Algorithm Modifications; Applications; Particle Swarm Optimization; Ant Colony Optimization; Artificial Bee Colony.*

1. Introduction

Swarm Intelligence (SI) algorithms, a subset of artificial intelligence, have gained significant attention due to their ability to solve complex optimization problems by mimicking the collective behavior of social organisms. Inspired by natural systems such as ant colonies, bird flocks, and fish schools, SI algorithms are inherently decentralized and adaptive, allowing them to address high-dimensional, non-linear, and dynamic problems effectively. Over the past decades, SI has proven to be a robust tool for tackling challenges in engineering, healthcare, robotics, logistics, and emerging fields like social media and education [1].
Prominent SI algorithms such as Particle Swarm Optimization (PSO) [2] and Ant Colony Optimization (ACO) [3] have demonstrated remarkable success in real-world applications, including radiotherapy planning, feature selection in disease diagnosis, and autonomous robotics. Recent advancements in the field have introduced innovative algorithms like the Zebra Optimization Algorithm (ZOA) and Spider Wasp Optimizer (SWO), which bring unique mechanisms inspired by animal behaviors to address complex optimization problems. Hybrid approaches, such as GWO-PSO, further extend the capabilities of standalone algorithms by leveraging complementary strengths to achieve superior performance [1].
Despite their success, SI algorithms face several challenges, including premature convergence, parameter sensitivity, and computational inefficiencies in large-scale problems. Researchers have addressed these limitations through various modifications, such as adaptive parameter control, enhanced initialization techniques, and hybridization with other optimization frameworks[4]. These enhancements not only improve performance but also broaden applicability to diverse fields, including sustainable energy systems, personalized medicine, and intelligent urban planning [2].
This paper provides a comprehensive review of SI algorithms, exploring their foundational principles, significant modifications, and diverse applications. Emphasis is placed on recent developments, particularly those emerging between 2020 and 2023, to highlight the current state of the art. Detailed performance comparisons across benchmark problems, including the Traveling Salesman Problem (TSP) and pressure vessel design optimization, are presented to provide practical insights into the strengths and limitations of various algorithms. By synthesizing these findings, this review aims to guide future research and practical implementations in the rapidly evolving field of swarm intelligence.

2. Literature review

Swarm Intelligence (SI) algorithms have evolved significantly over the years, driven by the need to solve complex optimization problems in diverse domains [6].
In 1992, Marco Dorigo introduced the Ant Colony Optimization (ACO) algorithm [1], [6], inspired by the pheromone-based communication observed in ant colonies. ACO has proven effective in solving combinatorial optimization problems such as the Traveling Salesman Problem (TSP) and network routing. The algorithm utilizes a feedback loop where artificial ants deposit pheromones to guide subsequent ants, optimizing search paths over iterations. Applications extend to logistics, scheduling, and bioinformatics [1], [6].
In 1995 Kennedy and Eberhart developed Particle Swarm Optimization (PSO) [2], drawing inspiration from the social behaviors of bird flocking and fish schooling. PSO leverages a population of particles that adjust their positions in the search space based on individual and group experiences. The algorithm has been applied in feature selection, engineering design, and financial modeling, achieving notable success in dynamic and multi-modal environments [3], [5].
In 2005, Karaboga introduced the Artificial Bee Colony (ABC) algorithm [7], mimicking the foraging behavior of honeybees. The algorithm divides bees into employed, onlooker, and scout categories to explore and exploit search spaces effectively. ABC excels in constrained optimization and has been applied to wireless sensor networks, image processing, and scheduling problems [5], [6].
In 2010 Yang introduced the Bat Algorithm (BA)[8, 9], inspired by the echolocation behavior of bats. BA integrates frequency-tuning and velocity adjustments to balance exploration and exploitation. The algorithm has demonstrated high efficiency in solving engineering design problems, feature selection, and energy optimization in smart grids [8].
In 2014 Mirjalili proposed the Grey Wolf Optimizer (GWO) [10], inspired by the hierarchical hunting strategies of grey wolves. GWO utilizes leadership hierarchy and pack dynamics to converge on optimal solutions. It has been widely applied in renewable energy optimization, image segmentation, and mechanical design.
In 2008 Firefly Algorithm (FA) [11], developed by Yang, models the bioluminescent attraction of fireflies to guide search processes. FA has been applied to non-linear optimization, feature selection, and multi-objective problems, demonstrating robustness and scalability.
In 2006 Cat Swarm Optimization (CSO) [13] algorithm was developed by Chu and Tsai, based on the social and solitary behaviors of cats. CSO alternates between seeking and tracing modes to simulate diverse search patterns. Applications include clustering, classification, and robotics path planning, with notable success in high-dimensional problems.
In 2009 Cuckoo Search (CS) Proposed by Yang and Deb [1], inspired by the brood parasitism behavior of cuckoos. The algorithm leverages Lévy flight mechanisms to enhance exploration and convergence in global optimization problems. CS has been successfully applied in data clustering, structural design, and energy optimization .
In 2014, Bansal et al. introduced Spider Monkey Optimization (SMO) [1], inspired by the social division and foraging behavior of spider monkeys. SMO balances exploration and exploitation through a dynamic hierarchical approach. It has been applied to supply chain optimization, robotics, and network routing [17], [18].
In 2020 Slime Mould Algorithm (SMA) Developed Li et al., the Slime Mould Algorithm (SMA) models the oscillatory behavior of slime moulds. SMA demonstrates adaptability in dynamic environments and has been applied to image processing, multi-objective optimization, and environmental monitoring [19], [20].
In 2016 Whale Optimization Algorithm (WOA) Proposed by Mirjalili, Whale Optimization Algorithm (WOA) mimics the bubble-net hunting strategy of humpback whales. WOA has shown strong performance in constrained optimization tasks, including feature selection, engineering design, and machine learning [21], [22].
Recent advancements in swarm intelligence research have highlighted the potential of hybrid approaches that combine the strengths of multiple algorithms to address specific challenges in optimization tasks.
PSO-GWO (Particle Swarm Optimization - Grey Wolf Optimizer) Developed to integrate the social dynamics of PSO with the hierarchical hunting strategies of GWO, this hybrid algorithm has been particularly effective in solving engineering design problems and renewable energy optimization. By leveraging PSO's fast convergence and GWO's exploration capabilities, PSO-GWO achieves a balance between local and global search efficiency [23], [24].
ACO-GDA (Ant Colony Optimization - Great Deluge Algorithm) by Saman M. Almufti [4] ACO-GDA combines the pheromone-based search strategies of ACO with the gradient-based adjustments of the Great Deluge Algorithm. This hybrid excels in solving NP-hard problems like the Traveling Salesman Problem (TSP) and has been widely applied in medical imaging and logistics planning [4].
ABC-PSO (Artificial Bee Colony - Particle Swarm Optimization) By merging the foraging behavior of ABC with the velocity-based adjustments of PSO, ABC-PSO achieves improved convergence rates in high-dimensional search spaces. This hybrid has shown significant success in wireless sensor network optimization and financial modeling [27], [28].
These hybrid approaches exemplify the power of combining complementary strategies from different algorithms, enhancing their ability to address diverse and complex optimization challenges. They represent the forefront of innovation in swarm intelligence, enabling solutions for real-world problems across engineering, healthcare, logistics, and beyond.
Table 1, shows a collections of well-known Swarm Intelligence algorithms details including the inspirations, strengths and limitations

Table 1: Swarm Intelligence Algorithms

Ref.	Algorithm	Biological Inspiration	Strengths	Limitations
[2]	Particle Swarm Optimization (PSO)	Bird flocking and fish schooling	Rapid convergence, simplicity	Premature convergence
[6]	Ant Colony Optimization (ACO)	Ant foraging	Effective in discrete problems	Scalability issues
[7]	Artificial Bee Colony (ABC)	Bee foraging behavior	Balances exploration/exploitation	Parameter sensitivity
[8] [9]	Bat Algorithm (BA)	Echolocation in bats	Adaptive parameter handling	Requires careful tuning
[10]	Grey Wolf Optimizer (GWO)	Hunting strategies of wolves	Simple yet effective	Limited in multi-modal problems
[11]	Firefly Algorithm (FA)	Bioluminescent attraction	Effective in dynamic systems	High computational cost
[12] [13]	Cat Swarm Optimization (CSO)	Feline predatory behavior	Maintains diversity well	Sensitive to initial parameters
[14]	Mayfly Optimization Algorithm (MOA)	Flight and mating behavior of mayflies	Effective in discrete and continuous optimization	Complex parameter handling
[15]	Bald Eagle Search (BES)	Hunting strategies of eagles	Robust and adaptive search	High computational cost
[16]	Black Widow Optimization Algorithm (BWOA)	Mating and lifecycle behavior of black widows	Suitable for combinatorial problems	Prone to local optima

[17]	Dingo Optimization Algorithm (DOA)	Hunting and scavenging behavior of dingoes	Good balance of exploration/exploitation	Requires further validation
[18]	Wild Horse Optimizer (WHO)	Group dynamics of wild horses	High exploration capabilities	Slow convergence in some cases
[19]	Chameleon Swarm Algorithm (CSA)	Adaptive behavior of chameleons	Effective for constrained problems	Parameter sensitivity
[20]	Zebra Optimization Algorithm (ZOA)	Foraging and defense mechanisms of zebras	Good at multi-modal optimization	Limited scalability
[21]	Beluga Whale Optimization (BWO)	Social and predatory behavior of beluga whales	Effective for engineering problems	High computational resources
[22]	Artificial Hummingbird Algorithm (AHA)	Foraging and flight dynamics of hummingbirds	Precise global and local search	Requires advanced parameter tuning
[23]	Dwarf Mongoose Optimization (DMO)	Foraging strategies of mongooses	High convergence speed	Limited validation
[24]	Prairie Dog Optimization (PDO)	Burrowing and foraging behavior of prairie dogs	Robust for engineering design	Prone to stagnation in local optima
[25]	Nutcracker Optimizer Algorithm (NOA)	Food storage behavior of nutcrackers	Effective for multi-objective problems	Complex implementation
[26] [27]	Spider Wasp Optimizer (SWO)	Hunting and nesting strategies of spider wasps	Strong local optimization capabilities	High parameter sensitivity
[28]	Gold Rush Optimizer (GRO)	Gold prospecting strategies	Effective for constrained optimization	Limited scalability
[29]	Crayfish Optimization Algorithm (COA)	Social and competitive behavior of crayfish	Good balance of exploration/exploitation	High computational cost
[30]	Piranha Foraging Optimization Algorithm (PFOA)	Foraging dynamics of piranhas	High accuracy in engineering designs	Prone to premature convergence

3. Fundamentals of swarm intelligence algorithms

Swarm Intelligence (SI) algorithms operate on the principle of decentralized coordination among agents, inspired by the collective behaviors observed in natural systems. These agents interact locally to achieve global objectives, showcasing characteristics such as self-organization, adaptability, and robustness. The following subsections outline the key principles and biological inspirations underlying SI algorithms [4].

3.1. Decentralized agent systems

At the core of SI algorithms is the concept of decentralized agent systems, where simple agents interact with their environment and each other without central control. This decentralized approach mirrors natural phenomena, such as ants leaving pheromone trails to optimize foraging paths or birds coordinating flight patterns to avoid predators. These local interactions enable the system to adapt dynamically to changes in the environment, making SI algorithms particularly effective in dynamic and uncertain problem spaces [3], [4].

3.2. Key characteristics of SI algorithms

Swarm Intelligence systems are defined by the following key characteristics [4]:

- Self-Organization: Agents independently adjust their actions based on local interactions, leading to emergent global behavior.
- Adaptability: The system responds to dynamic changes in the environment, making SI algorithms suitable for real-time optimization problems.
- Robustness: The system maintains functionality even if individual agents fail, ensuring reliability in large-scale optimization tasks.
- Scalability: SI algorithms efficiently handle high-dimensional search spaces due to their distributed nature.

3.4. Algorithmic workflow

The general workflow of SI algorithms involves the following steps [5]:

1) Initialization: A population of agents (solutions) is randomly initialized within the search space.
2) Fitness Evaluation: Each agent's performance is evaluated based on a predefined objective function.
3) Interaction and Update: Agents interact with their neighbors or environment to update their positions or strategies. This step incorporates specific mechanisms, such as velocity updates in PSO or pheromone updates in ACO.
4) Convergence: The algorithm iteratively refines the population until a termination criterion, such as a maximum number of iterations or convergence threshold, is met.

3.3. Categories of SI algorithms

Swarm intelligence algorithms can be broadly categorized based on their biological inspirations [5].
Figure 1. Shows the SI categories include algorithms inspired by animals, insects, and other natural phenomena:

1) Inspired by Animals: This category includes algorithms such as Bird-inspired (e.g., PSO), Lion-inspired (e.g., Lion Optimization Algorithm), Monkey-inspired (e.g., Monkey Search), Bat-inspired (e.g., Bat Algorithm), and Wolf-inspired (e.g., Grey Wolf Optimizer). Other animal-inspired algorithms include Fish, Frog, Cat, Chicken, and Buffalo-based approaches, each mimicking unique behaviors like hunting, foraging, or social interactions [6]
2) Inspired by Insects: These algorithms draw from the behaviors of insects such as Ants (e.g., Ant Colony Optimization), Bees (e.g., Artificial Bee Colony), Fireflies (e.g., Firefly Algorithm), Termites, and Glow-worms (e.g., Glowworm Swarm Optimization). Additional inspirations include Roach, Mosquito, Fruit Fly, Super Bug, Dragonfly, Antlion, and Grasshopper behaviors [5], [6].

3) Other Inspirations: This group encompasses algorithms inspired by less conventional sources, such as Slime (Slime Mould Algorithm), Cuckoo (Cuckoo Search), Dolphin, Beaver, Bacteria (e.g., Bacterial Foraging Optimization), Krill, Moth (e.g., Moth Flame Optimization), and Whale (e.g., Whale Optimization Algorithm) [5].

These categories highlight the diversity and richness of swarm intelligence as a field, emphasizing its ability to adapt biological principles to computational optimization challenges. Table 1, shows the details of some well-known SI algorithms.

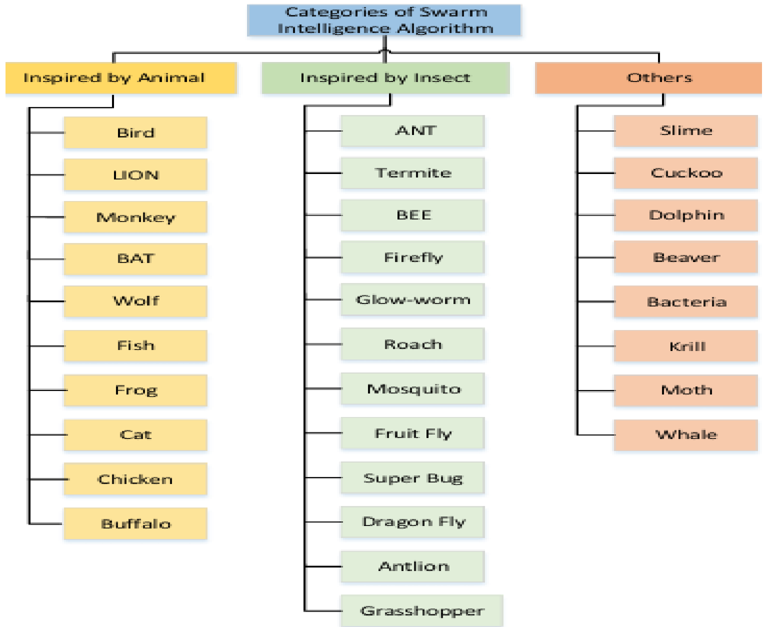

Fig. 1: Swarm Intelligent Categories.

4. Applications of swarm intelligence algorithms

The versatility of Swarm Intelligence (SI) algorithms is evident through their wide-ranging applications across numerous domains. From engineering design and healthcare optimization to robotics and education, these algorithms have consistently demonstrated their ability to address complex, high-dimensional problems effectively [31]. This section highlights key domains where SI algorithms have been applied, detailing their representative applications and associated benefits. A comprehensive summary is provided in the following table:

Table 2: Applications of Swarm Intelligence Algorithms

Domain	Key Algorithms	Representative Applications	Key Benefits	References
Structural Design	ABC, BA, GWO	Truss and beam optimization	Minimized material cost and weight	[32, 33, 34].
Power Systems	PSO, GWO	Load balancing, energy distribution	Cost reduction, improved efficiency	[37, 38, 58]
Healthcare	PSO-GA, ACO-GDA	Feature selection, radiotherapy planning, Drug Discovery	Improved diagnostic accuracy, minimal tissue damage	[39, 40,41, 42, 43, 44, 45, 46,47, 48].
Robotics	ACO, PSO, Dragonfly	Multi-robot coordination, path planning	Collision-free, energy-efficient paths	[24,49, 50].
Transportation	BA, GSO, WOA	Fleet management, traffic scheduling	Reduced delays, cost optimization	[50, 52, 53, 54]
Renewable Energy	WOA, GWO	Solar and wind farm layout optimization	Maximized energy capture efficiency	[35, 36]
Education	ACO, ABC, PSO	Curriculum optimization, student clustering	Enhanced learning outcomes	[60], [61]
Social Media	PSO, FA	Community detection, content recommendation	Improved user interaction	[62], [63]
E-commerce	CS, PSO	Recommendation systems	Improved user engagement	[55, 56, 57]
Image Processing	FA, ACO, ABC	Edge detection, segmentation	Enhanced visual accuracy	[11], [5], [8], [42]

5. Algorithm modifications and enhancements

Algorithmic modifications play a crucial role in adapting swarm intelligence algorithms to tackle real-world optimization challenges effectively. Researchers have developed numerous enhancements to improve convergence rates, scalability, and robustness against local optima.

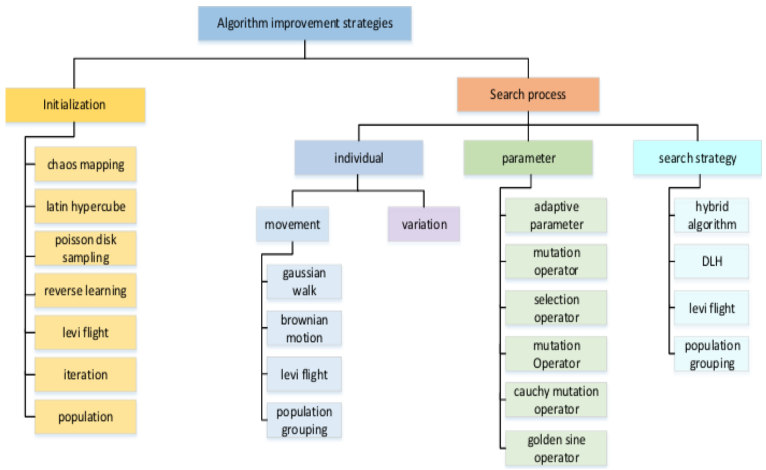

Fig. 2: Enhancement Strategies.

Figure 2 categorizes the various strategies used to improve the performance of algorithms in terms of initialization and search dynamics. It demonstrates the flexibility and adaptability of modern optimization techniques, allowing them to address diverse and complex problem spaces effectively.
Below are significant modifications for key algorithms [5]:

Table 3: Summary of Some SI Algorithm Modifications

Original Algorithm	Algorithm name	Authors	Ref
Ant Colony Optimization (ACO)	AC S-SMTTP AntNet-FS U-TACO Ant-P-solver	Bauer et at Di Caro & Dorigo Saman M. Almufti Solnon	[38]
Artificial Bee Colony (ABC)	Original ABC Hybrid ABC-GA Multi-Objective ABC Hybrid ABC-DE	D. Karaboga A. Singh, P. Singh J. C. Bansal et al. X. B. Zhang, Y. Wang	[36]
Cat Swarm Optimization (CSO)	PCSO CSO Clustering AICSO BBCSO	Tsai et al. Santosa et al. Orouskhani et al. Siqueira et al.	[13]
Lion Algorithm (LA)	MO-ADDOFL ALF-TOHIP M-LionWhale	Satish Chander Ambekar Kolekar Chintalapalli & Ananthula	[64]
Vibrating particles system (VPS)	VPS EVPS MO- VBPSO	Kaveh et al. Patrick et al. Liang Ou et al.	[65], [66]
Grey Wolf Optimizer (GWO)	IGWO CEGWO BGWO	Wen et al. Luo et al. Emary et al.	[67]

This table illustrates modifications across several foundational SI algorithms, showcasing the diversity of enhancements aimed at addressing specific optimization challenges. Each modification incorporates novel features such as hybridization, adaptive control, or enhanced search mechanisms to meet the demands of complex problem spaces effectively.

6. Discussion

Swarm Intelligence (SI) algorithms have shown remarkable versatility in solving a variety of optimization problems, ranging from classical benchmarks like the Traveling Salesman Problem (TSP) to complex real-world applications in engineering, healthcare, and logistics. Algorithms such as ACO and its hybrid variants (e.g., U-TACO) achieve near-optimal solutions for TSP, while PSO and BA excel in reducing material costs for pressure vessel design. Similarly, ABC and GWO provide accurate and computationally efficient solutions for high-dimensional knapsack problems. Despite these strengths, challenges such as premature convergence in standalone algorithms and computational overhead in large-scale problems persist. However, advancements in hybridization, such as PSO-GWO and ACO-GDA, have enhanced adaptability and scalability, enabling these algorithms to address dynamic, multi-modal environments effectively. The practical implications span diverse domains, offering optimized designs in engineering, improved diagnostics in healthcare, and cost-effective solutions in logistics, underscoring their transformative potential in modern problem-solving.

7. Conclusion

Swarm Intelligence (SI) algorithms have emerged as powerful tools for addressing a wide range of optimization problems, leveraging decentralized, nature-inspired mechanisms to achieve robust and scalable solutions. This comprehensive review highlights the foundational principles, recent modifications, and diverse applications of prominent algorithms such as PSO, ACO, ABC, and BA, alongside novel approaches like GWO and ZOA. Performance comparisons across benchmarks and real-world scenarios underline the effectiveness of SI in areas like engineering design, healthcare optimization, and logistics. While challenges such as parameter sensitivity and computational overhead persist, advancements in hybridization and adaptive strategies continue to expand their applicability and efficiency. Future research directions include the integration of machine learning, exploration of lightweight adaptations, and development of bio-inspired enhancements to further strengthen the role of SI in solving complex, dynamic problems. This study provides a foundation for future investigations and practical implementations in this rapidly evolving field.

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