International Journal of Scientific World, 11 (1) (2025) 114-122

International Journal of Scientific World

Website: www.sciencepubco.com/index.php/IJSW
https://doi.org/10.14419/s0sjgq84
Review paper

A review of exploring recent advances in ant colony optimization: applications and improvements

Renjbar Sh. Othman [1, 2] *, Ibrahim Mahmood Ibrahim [3]

[1] *Duhok Polytechnic University, Technical Institute of Amedi, Department of Information Technology, Duhok, Kurdistan Region, Iraq*
[2] *Akre University for Applied Science, Technical College of Informatics-Akre, Department of Information Technology, Akre, Kurdistan Region, Iraq*
[3] *Akre University for Applied Sciences, Technical College of Informatics-Akre, Department of Computer Network and Information Security, Kurdistan Region, Iraq*
**Corresponding author E-mail: renjbar.othman@dpu.edu.krd*

Received: February 19, 2025, Accepted: March 6, 2025, Published: March 20, 2025

Abstract

Inspired by the foraging behavior of ants, the well-known metaheuristic Ant Colony Optimization (ACO) provides strong answers to challenging optimization issues in many spheres. This work investigates current developments in ACO algorithms with an emphasis on hybridization, employing methods including machine learning, adaptive mechanisms, and genetic algorithms to improve performance. Applications such as robotics, telecommunications, healthcare, and logistics show ACO's adaptability in handling path planning, resource allocation, and data optimization. Dynamic pheromone methods, multi-objective optimization, and domain-specific adaptations , which have raised computing efficiency, scalability, and solution quality, have been key advances. Notwithstanding these developments, problems, including parameter sensitivity and real-time adaptation, remain unresolved. Future studies include integrating real-time data, creating scalable adaptive algorithms, and tackling domain-specific restrictions to further increase ACO's relevance. This work emphasizes ACO's possible importance as a fundamental instrument for addressing problems of real-world optimization.

Keywords: *Ant Colony Optimization; Metaheuristics; Path Planning; Hybrid Algorithms; Optimization Techniques*

1. Introduction

Inspired by ant foraging behavior, especially in their food search, Ant Colony Optimization (ACO) has become a well-known metaheuristic method. Originally developed in the early 1992s, ACO has evolved into a flexible instrument for addressing challenging optimization issues in many fields, including logistics, robotics, telecommunications, and bioinformatics [1]. The method works on pheromone deposition, in which synthetic ants travel a solution space, leaving pheromone trails guiding the next ants toward optimal solutions. This group behavior offers a strong basis for addressing combinatorial optimization problems, including the Traveling Salesman Problem (TSP) and vehicle routing concerns, since it reflects the natural process of ants discovering the most effective path to food sources [2] [3].
Recent ACO improvements have focused on increasing its efficiency and applicability using several changes and hybrid approaches. Researchers have looked at multi-objective optimization techniques, allowing Ant Colony Optimization (ACO) to solve problems like cost, time, and quality with numerous conflicting objectives [4][5]. These improvements have significantly reduced processing time and better solution quality, hence establishing ACO as a preferred choice for complex real-world uses. Combining Ant Colony Optimization (ACO) with other optimization techniques, such as particle swarm optimization and genetic algorithms, has generated hybrid models that make use of the benefits of both approaches to achieve improved performance [6 - 8].
ACO's versatility is well shown by its application in several fields. Ant Colony Optimization (ACO) has been applied successfully in logistics to improve supply chain management and routing problems, therefore lowering operating costs and raising efficiency [9- 11]. In robotics, ACO has been utilized for path planning, enabling robots to navigate complex environments while avoiding obstacles [12- 14]. Furthermore, proving its adaptability throughout many issue areas, ACO has been applied in bioinformatics for protein interaction predicting and in telecommunications to improve network routing [15 – 17].
The constant improvement of ACO methods has produced customized variants meant for certain uses. Particularly helpful in situations like traffic control and drone path optimization, the application of dynamic ACO algorithms helps real-time adjustments in response to changing surroundings [18] [19]. The adoption of multi-colony approaches has been proposed to improve exploration capacity and avoid local optima, hence strengthening the general resilience of the algorithm [20] [21]. These innovations reflect the ongoing research efforts to address traditional ACO's limitations and expand its applicability.

In the end, the study of present advancements in Ant Colony Optimization reveals a dynamic and growing discipline that keeps expanding the boundaries of optimization strategies. Its relevance as a strong tool for addressing difficult optimization problems is shown by the integration of ACO with other methods, the creation of variants, and its effective use over numerous sectors. As researchers are developing ACOs and thereby enhancing both theoretical and practical applications, they would gain considerably from such improvements; hence, the ability of ACOs to solve practical problems is still great.
This review aims to explore recent advancements in Ant Colony Optimization (ACO) algorithms, focusing on their hybridization with other techniques, enhanced scalability, and dynamic adaptation mechanisms. The study aims to evaluate ACO's applications in diverse fields such as robotics, telecommunications, and healthcare, while identifying challenges and future directions for improved real-world implementation.
Section 2 outlines the remaining work, providing a brief review of current developments in Ant Colony Optimization, including their uses and enhancements. Together with the most important conclusions, Section 3 shows the results of the review analysis. Section 4 discusses the review study. Section 5 compiles the research findings for future directions and concludes the study.

2. Background theory

Ant Colony Optimization (ACO) is a nature-inspired metaheuristic algorithm that simulates the foraging behavior of ants to solve complex optimization problems. Since its inception, ACO has been widely adopted for applications ranging from network routing to machine scheduling and robotic path planning. Recent advancements in ACO emphasize its expanded applications and significant algorithmic improvements to address computational efficiency, adaptability, and scalability [1].

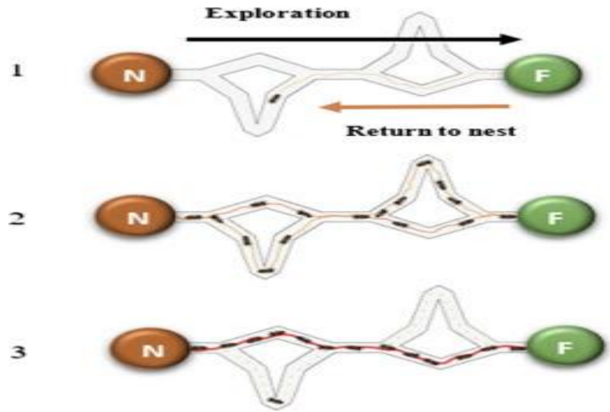

Fig. 1: Choice of the Shortest Path by an Ant Colony. After Dispersing the Pheromone Along Its Course, an Ant Discovers A Food Source (F) and Then Returns to the Nest (N) [22].

2.1. Theoretical foundations

The ACO algorithm is based on indirect communication via pheromones, in which artificial ants iteratively develop solutions and deposit pheromones to instruct future ants. ACO algorithms are distinguished by their positive feedback mechanism, distributed computing, and capacity to generate approximation solutions to NP-hard problems. The algorithm's versatility enables it to combine with other metaheuristics and optimization approaches, increasing its effectiveness [24 – 26].

2.2. Key improvements in ACO algorithms

Hybrid Approaches: Recent years have seen a lot of research on the hybridization of ACO with techniques such as particle swarm optimization (PSO) and genetic algorithms (GA). By integrating the capabilities of many approaches, these hybrids seek to exceed ACO's constraints like delayed processing and premature convergence. For UAV route planning, for example, the merging of ACO with sparrow search has been used to provide improved outcomes in collaborative evolution and pheromone updating techniques [23].
Dynamic Pheromone Strategies: Using adaptive pheromone updates and unequal pheromone distribution will help to raise convergence rates. Such improvements maximize the exploration-exploitation trade-off, which is essential for real-time applications like multi-trip vehicle routing difficulties [26].
Multi-Objective Optimization: Multi-objective ACO versions have become very popular in handling issues with competing objectives, including energy efficiency and work offloading in-vehicle edge computing [25]. These approaches often incorporate Pareto front strategies to balance different optimization criteria effectively.
Algorithmic Speed and Scalability: The computing performance of ACO is more improved in using clustering-based preprocessing and graph reduction methods. For 3D path planning in robotic systems, for instance, multi-algorithm hybrid ant colony optimizers (MAHACO) have shown promise [25].
Domain-Specific Adaptations: Customizing ACO for particular uses has produced creative modifications like enhanced defect diagnosis in milling machines utilizing convolution neural networks mixed with ACO [27], and optimization in healthcare task scheduling leveraging runtime-aware algorithms.

2.3. Expanding applications

The adaptability of ACO is evident in its growing application domains:

- Transportation and Logistics: ACO has proved essential in vehicle routing issues by including dynamic needs and diverse fleet concerns [28].
- Robotics: Multi-objective methods and farthest-point optimization using enhanced ACO algorithms guide robot path planning [29].

- Wireless Networks: ACO maximizes safe path planning and resource allocation in UAV communication networks by use of block-chain architectures [30].
- Healthcare and Edge Computing: Task scheduling in cloud-based healthcare systems evidence ACO's capacity to maximize resource allocation [31].

2.4. Challenges and future directions

ACO still has problems like parameter sensitivity, scalability to bigger datasets, and real-time implementation, notwithstanding recent developments. More strong hybrid algorithms, incorporating machine learning for adaptive parameter tweaking, and improving ACO's applicability in dynamic, real-world contexts are among future fields of research.

3. Literature review

This part offers a thorough review of the body of knowledge already in use, stressing important results, techniques, and gaps pertinent to the project. It provides the theoretical basis and places the present research in the larger scholarly debate. This part points out topics of additional research to progress knowledge of the issue:

Particularly for the Traveling Salesman Problem (TSP), Y. Liu and Cao in 2020 presented an upgraded Ant Colony Optimization (ACO) algorithm using the Levy flight to boost solution diversity and efficiency. Although the study mostly concentrates on TSP benchmarks, showing notable performance improvements and needing 42% fewer iterations than Max-min ACO and surpassing other state-of-the-art solvers. This restriction limits its application range and leaves scalability to unknown challenging real-world issues void. Future studies could stretch the Levy ACO to several real-world optimization problems and include adaptive parameter tweaking to improve scalability and resilience over several domains, so overcoming this restriction [32].

Presenting an Adaptive Ant Colony Algorithm (AACO) for global path planning in autonomous cars, Y. Li et al. in 2021 showed notable increases in path quality, convergence speed, and resilience in stationary situations. Its main restriction, though, is its emphasis on stationary settings, which limits its efficacy in dynamic, real-world situations, including moving impediments. Future studies could improve AACO by including real-time obstacle recognition and predictive motion planning, therefore allowing the algorithm to dynamically change to fit changing surroundings and increase its practical relevance [33].

González et al. in 2022, using multi-colony and asynchronous distributed techniques to improve efficiency and scalability, introduced a new parallel Ant Colony Optimization (ACO) framework intended for High-Performance Computing (HPC) scenarios. Although it shows notable performance gains, especially in solving challenging problems like the Traveling Salesman Problem (TSP), a drawback is that the framework may need considerable tuning for cases or different HPC architectures, restricting its general relevance. Developing adaptive tuning mechanisms and automated configuration tools could help to accomplish this by facilitating optimization and lowering the demand for hand adjustments, thereby improving the usability of the framework in several situations [34].

In 2021 Dahan et al. developed the EFACO - Enhanced Flying Ant Colony Optimization algorithm, which uses a multi-pheromone distribution technique and an efficient adjacent selection process to improve QoS-aware web service composition. By addressing both exploration and exploitation, this method is claimed to suitably handle the combinatorial optimization problem of online service selection in terms of QoS criteria, including cost, response time, availability, and dependability. In 13 out of 22 datasets connected to the problem, EFACO is shown to be more efficient than current methods, hence, the suggested solution helps to reach improved quality of services. Still, it should be remembered that a limited flying ant process does result in a loss in solution quality. Future research may use adaptive parameters to be able to control the execution of the algorithm depending on the feedback obtained to enhance solution quality and execution efficiency [35].

Zhang, Pu, and Si, in 2021, using non-uniform starting pheromone distribution and a pheromone diffusion model to maximize exploration and lower convergence difficulties, proposed an Adaptive Improved Ant Colony System (AIACSE) for mobile robot path planning. Although the method exhibits better effectiveness in stationary contexts, its emphasis on these conditions limits it and calls for more study for dynamic situations. Integrating real-time sensor data and adaptive learning techniques would help the AIACSE to constantly modify its path planning in response to changing surroundings, hence increasing its relevance in useful contexts [36].

In 2020, Ding et al.. proposed an Improved Ant Colony Algorithm (IMACA) for best band selection in remotely sensed hyperspectral images. Incorporating a pre-filter and an adaptive information update strategy helps the method improve convergence and population diversity, hence enhancing the basic Ant Colony Algorithm (ACA). Using three public databases, Indian Pines, Pavia University, and Botswana, the methodology assesses performance. Reaching the best overall classification accuracy, the method often beats benchmarks. Crucially, IMACA-BS improves classification performance far more than conventional techniques. The fact that the process of parameter optimization in this work is labor-intensive and time-consuming indicates the need for more effective techniques. Using automated parameter tuning techniques, including evolutionary algorithms or Bayesian optimization, could help to simplify the optimization process [37].

In 2022 Manogaran et al. presented a fitness-based ant colony optimization (FACO) method meant to improve electric vehicle (EV) driving range. Using a two-phase model for both conditional route finding and sustained traversing, depending on the FACO method while maximizing route efficiency, the algorithm emphasizes reducing travel time and energy usage. Important findings show that FACO retains 7.15% of charge, increases driving distance by 28.58%, and lowers power depletion by 51.99%, thereby improving routing performance. The research ignores the incorporation of real-time traffic data, which can improve the routing efficiency of electric cars even more. Future studies should include real-time traffic data and dynamic charging station availability into the FACO algorithm to improve the routing efficiency of electric vehicles, hence enabling adaptive route optimization depending on current conditions [38].

H. Wang, Zhang, and Dong in 2022, investigated an enhanced Ant Colony Optimization (ACO) method for path planning of Unmanned Surface Vehicles (USVs) combined with an Immune Algorithm (IA). The IA-IACO model improves optimization efficiency depending on methods including pheromone generation and change of transition probability. Convergence speed and global path planning efficacy show notable increases in the algorithm. One of the significant outcomes is the effective simulation demonstrating the superiority of the algorithm in useful applications. The study does not, however, assess the performance of the algorithm in highly dynamic settings, thus restricting its relevance. Future studies should include adaptive methods to properly manage dynamic situations during path planning for USVs, thereby increasing the applicability of the algorithm [39].

Liang and Wang in 2020, Depending on the method applied to address the traveling salesman problem (TSP), presented a hybrid method combining the Genetic Algorithm (GA) and Ant Colony Optimization Algorithm (ACOA) to maximize marine investigation path planning. In studies of marine resources, the model greatly increases efficiency and lowers expenses. The significant outcome shows that this hybrid strategy, which shows better resilience and solution quality than conventional techniques, clearly finds ideal routes for research vessels. The generalizability of the findings may be affected, therefore, by a restriction of this study whereby the complexity of many marine ecosystems may not be entirely explained. Future studies should include real-world marine environmental factors and limitations in the model to increase its resilience and generalizability, hence improving the applicability of the method [40].

X. Chen et al., in 2020, investigated, utilizing Ant Colony Optimization (ACO) approaches, the AI-empowered path selection in Wireless Sensor Networks (WSNs). It groups models into stationary and mobile networks and describes several ACO techniques meant to maximize data flow. One of the main outcomes is the thorough review of ACO techniques that noticeably improve WSN performance. The report does not, however, include a thorough comparison of many ACO approaches. Extensive comparative studies and empirical evaluations of ACO techniques should be part of future studies to improve their usability and efficacy in practical situations [41].

In 2021, Imtiaz et al. suggested the Multi-Layer Ant Colony Optimization (MLACO) method. It uses Kernel K-means (KKM) and Ratio Cut (RC), depending on the approach as objective functions. Three big-scale datasets allow the model to show efficiency. Based on measures including modularity and Normalized Mutual Information (NMI), the approach beats current techniques. One significant outcome shows its better performance in both synthetic and actual networks. The effect of different network architectures on the performance of the algorithm is not, therefore, thoroughly discussed in this work. Future studies should investigate the algorithm's adaptability across various network configurations and apply dynamic changes depending on network features to improve its robustness [42].

Sangeetha et al., in 2021, proposed the Green Ant Colony Optimization (GDGACO) algorithm intended for effective path planning in dynamic 3D environments. It combines Octrees for effective spatial representation and uses a gain function-based pheromone augmentation method to maximize energy use. With thorough simulations confirming its efficacy, the method shows considerable increases in path length, calculation time, and energy efficiency when compared to conventional approaches. Its main emphasis on energy efficiency, which could overlook other crucial factors like real-time adaptation and scalability in complicated situations, limits us, though. Future studies could combine adaptive mechanisms and scalability elements addressing real-time environmental changes and challenging barrier scenarios to surpass the GDGACO algorithm [43].

In 2021 Tabrizi, Reza, and Jameii developed a nanite drug delivery adaptive algorithm combining Ant Colony Optimization (ACO) methods with Reinforcement Learning. This concept aims to improve autonomous path planning for nanites such that their navigation efficiency is much raised, and path lengths are shortened. The ability of the method to recalculate optimal pathways in real-time improves decision-making accuracy in dynamic medical environments using its capacity. The paper does not, however, thoroughly address the scalability of the algorithm in more complicated and larger biological systems, therefore perhaps influencing its real-world application. Aiming for higher scalability in intricate biological systems, future studies should try to develop adaptive algorithms using multi-layered models and real-time data [44].

Gong et al. in 2022, using grid mapping and self-adaptive parameters, presented a Parallel Self-Adaptive Ant Colony Optimization Algorithm (PSAACO) for UAV path planning in Cloud IoT. Depending on the method, it uses parallel computing together with inversion and insertion operators to improve efficiency. An important model is the dynamic Floyd algorithm for no-fly zone avoidance. Particularly in complicated contexts, the major outcome shows that PSAACO drastically lowers energy usage and completion time compared to current methods. The study does not, however, really investigate real-time adaptation in fast-changing environments. Including machine learning methods for dynamic course alterations depending on environmental changes would help to increase real-time flexibility and hence operational efficiency of the UAV [45].

Kalantari, Ebrahimnejad, and Motameni 2020 put forward a dynamic software rejuvenation method meant to reduce software aging in online services. To improve server choice and availability, depending on the technique it combines Ant Colony Optimization (ACO) with Gravitational Emulsion Local Search (GELS). The method emphasizes finding ideal rejuvenation times to reduce failure rates. One significant outcome showed a 28% drop-in failure rates relative to current approaches. This work does not, however, address the fundamental reasons for software aging, which might continue even with efforts at rejuvenation. Regular maintenance and root cause investigation, along with improved monitoring and load balancing, help greatly reduce software aging problems in online services [46].

Wu et al. in 2022, proposed the Modified Adaptive Ant Colony Optimization Algorithm (MAACO), hence improving conventional ACO methods for mobile robot path planning. It uses an unequal initial pheromone distribution to maximize search efficiency, modulates state transition probability, and uses a heuristic method, including orientation information to increase convergence speed. Tested in five stationary and one dynamic situation, the model shows notable gains over 13 current methods, including shorter path lengths and fewer twists. The main finding shows a 22.2% decrease in turn times relative to the best current approaches. The restrictions, however, include a dearth of thorough testing in extremely dynamic settings, which might compromise MAACO's resilience. Future studies should concentrate on thorough testing in many highly dynamic environments and real-world scenarios to evaluate MAACO's adaptability and efficiency, strengthening its robustness [47].

In 2020, Mendonça et al., emphasizing swarm robotics concepts, presented a Multi-Robot System (MRS) for victim rescue missions. Using a Fuzzy Logic Controller (FLC), a Dynamic Fuzzy Cognitive Map (DFCM), and DFCM with Ant Colony Optimization (DFCM-ACO) models depending on the method. To assess efficiency, the algorithms run through real-life situations. Important findings reveal that DFCM-based methods maintain performance while using less processing time and traveling lesser distances. The fact that this study depends on simulated environments limits it since they might not completely reflect the complexity of the real world. Future studies should combine physical testing in several settings with simulation to better depict difficult conditions in victim rescue operations, hence mastering real-world applicability [48].

Jiang et al. (2020) proposed for the best path seeking and control of mobile robots in different situations a hybridized Advanced Sine-Cosine Algorithm (ASCA) and Advanced Ant Colony Optimization (AACO). Based on the approach, the models improve navigation by using real-time obstacle detection. The method chooses optimum standpoints and efficiently determines the worldwide best locations for robots. An interesting outcome shows a 10.21% increase in path length efficiency over current techniques. The scalability of the suggested methods in bigger or more complicated environments is not thoroughly discussed in the work, though. Adaptive algorithms for better scalability in challenging contexts should be developed in the next studies [49].

In 2021, Thirugnanasambandam et al. 2021 investigated a new method for Document Information Retrieval (DIR) based on fuzzy C-means clustering and ant colony optimization. Based on these methods, the suggested model intelligibly searches clusters to extract pertinent information and efficiently preprocesses documents. Retention efficiency across small, medium, and large document sizes showed notable increases under the method. The study's restriction, however, is in its reliance on the quality of the input data, which might influence general performance. Using data quality assessment techniques could help to improve the preprocessing step [50].

In 2020, Luo et al., depending on methods that improve search efficiency and convergence speed, presented an enhanced ant colony optimization algorithm for mobile robot path planning. The method avoids local optima by using pseudo-random path selection models and unequal starting pheromone distribution. Deadlock is addressed using a dynamic punishment approach, therefore improving the worldwide search capability. The complexity of the study, which can impede real-time implementations, is its drawback, though. One possible fix is to streamline the method for quicker running without sacrificing its efficiency [51].

Z. Li et al. (n.d. in 2022) investigated a Floyd-based improved ant colony algorithm for mobile robot path planning. This approach uses a multi-objective optimization model including path length, safety, and energy consumption. The method uses a fallback approach to direct ants and raises pheromone levels, therefore enhancing path quality and convergence speed. The effective reduction of local optima and path length by quadratic B-spline optimization is one of the significant outcomes. The study might, however, lack thorough practical testing of the suggested model. Using simulations in various surroundings could help one overcome issues by verifying the resilience of the method [52].

Onan in 2023, proposed the SRL-ACO framework to improve training sets for NLP models by use of Semantic Role Labeling (SRL) and Ant Colony Optimization (ACO). SRL detects semantic roles depending on the method, while ACO generates fresh phrases, therefore enhancing models such as classifiers for sentiment analysis and sarcasm detection. One of the significant outcomes is the shown performance increase over seven text classification challenges. The study might, however, lack a thorough assessment across several languages and circumstances. Future studies should incorporate a greater spectrum of datasets and languages to demonstrate the universal efficacy of the framework and help to address this [53].

In 2020, Yi et al. proposed the use of an enhanced Ant Colony Algorithm to optimize tasks in distributed Cyber-Physical Systems (CPS). Based on this approach, a task management model is suggested to improve the efficiency of resource allocation. The method uses adaptive mechanisms to achieve higher convergence speed and adaptability, thereby improving task scheduling quality and local search capacity. The study's shortcomings, meanwhile, include a dearth of thorough real-world application testing to support the efficacy of the suggested methodology. By doing such tests across different CPS contexts, the effectiveness of the model would be improved through insightful validation and validation for more enhancement [54].

S. Li et al., in 2022, suggested a concept of tourism route optimization concentrated on raising tourist attraction income and satisfaction. For efficient data processing, depending on the method, it makes use of random sampling and hierarchical clustering. Improved by a bacterial foraging algorithm, the models include a knowledge-based hybrid Ant Colony Algorithm. One significant outcome of this work is the efficacy of the method in identifying the best options for different travel preferences. Nevertheless, the restrictions include a possible lack of relevance in practical situations resulting from simplistic presumptions. Including real-world factors such as seasonal variations and different visitor behavior in the next models, could improve their practical relevance and efficiency [55].

In 2021, Zhang et al. presented EACSPGO, a hybrid method for mobile robot path planning to combine a local optimization algorithm grounded on geometric features with improved ant colony optimization strategies. Among the models are an unequal starting allocation method and a simplified pheromone diffusion model. The significant outcome reveals that in terms of adaptability, stability, and convergence speed, EACSPGO beats conventional methods. One drawback of complicated ecosystems is possible processing overhead. I believe that future studies should concentrate on maximizing the computing efficiency of the method to overcome this restriction even more [56].

Table 1 summarizes advancements in Ant Colony Optimization (ACO) algorithms, focusing on diverse applications such as robotic path planning, logistics optimization, healthcare scheduling, and hyperspectral image processing. It outlines key methods like hybrid algorithms, dynamic pheromone strategies, and multi-objective optimization, highlighting improvements in efficiency, scalability, and solution quality. Despite these advancements, challenges such as parameter sensitivity, lack of real-time adaptation, and dataset dependency persist. Future directions emphasize real-time data integration, automated parameter tuning, and enhancing generalizability for dynamic, large-scale problems. The table showcases ACO's versatility and its evolving role in solving complex optimization tasks.

Table 1: Comparative Summary Table of Ant Colony Optimization (ACO) Algorithms: Algorithms, Research Focus, Applied Techniques, Key Findings, Limitations, and Future Work Directions Across Diverse Domains

Ref. No., Year	Algorithms	Research Focus	Methods/Techniques	Key Findings/Outcomes	Limitations	Future Work Recommendations
[32]. In 2020	Levy-ACO	Enhancing TSP optimization	Levy flight-enhanced ACO	Improved solution diversity and efficiency, 42% fewer iterations vs. Max-min ACO	Limited to TSP benchmarks; scalability for real-world issues unknown	Extend Levy ACO to real-world problems, including adaptive parameter tuning
[33]. In 2021	Adaptive Ant Colony (AACO)	Path planning for autonomous vehicles	Adaptive mechanism for stationary environments	Improved path quality, convergence speed, and resilience	Limited to stationary conditions; not applicable to dynamic scenarios	Integrate real-time obstacle recognition and predictive motion planning
[34]. In 2022	Parallel ACO	High-performance computing	Multi-colony, asynchronous distributed framework	Improved scalability and efficiency in solving complex problems like TSP	Requires significant tuning for specific HPC architectures	Develop adaptive tuning mechanisms and automated configuration tools
[35]. In 2021	EFACO	QoS-aware web service composition	Multi-pheromone distribution and efficient selection	Improved QoS performance in service selection	Limited flying ant process impacts solution quality	Use adaptive parameters for better control and improved solution quality
[36]. In 2021	Adaptive Improved ACS	Robot path planning	Non-uniform starting pheromones, diffusion model	Better effectiveness in stationary conditions	Focused only on stationary conditions; lacks dynamic scenario application	Incorporate real-time sensor data and adaptive learning techniques
[37]. In 2020	IMACA	Band selection for hyperspectral imagery	Pre-filter, adaptive info update	Enhanced convergence and diversity, superior classification accuracy	Parameter optimization is labor-intensive	Employ automated parameter tuning like evolutionary or Bayesian methods
[38]. In 2022	FACO	Route optimization for electric vehicles	Two-phase conditional route finding	Improved driving range, energy use, and efficiency	No incorporation of real-time traffic data	Add real-time traffic data and dynamic charging station availability
[39]. In 2022	IA-IACO	USV path planning	Immune algorithm integrated with ACO	Enhanced convergence speed and planning efficacy	No testing in highly dynamic settings	Incorporate adaptive methods for better handling of dynamic scenarios

[40]. In 2020	Hybrid GA-ACO	Marine investigation path planning	Genetic algorithm with ACO	Improved efficiency and cost reduction	Lacks generalizability for complex marine ecosystems	Include real-world marine environmental factors
[41]. In 2020	ACO Variants	Path selection in wireless sensor networks	Review of stationary and mobile network techniques	Improved WSN performance	Lack of extensive comparative studies	Perform comparative studies and empirical evaluations
[42]. In 2021	MLACO	Community detection in networks	Kernel K-means, Ratio Cut	Superior performance in synthetic and real-world networks	Limited discussion on adaptability across diverse network configurations	Explore adaptability across various network structures
[43]. In 2021	GDGACO	Path planning in 3D dynamic environments	Octrees and gain-based pheromone augmentation	Increased energy efficiency and shorter path lengths	Limited focus on real-time adaptation and scalability	Combine adaptive mechanisms to address real-time environmental changes
[44]. In 2021	ACO with Reinforcement Learning	Nanite drug delivery path planning	Real-time recalculation capability	Improved navigation efficiency in medical environments	Scalability in larger biological systems not thoroughly explored	Develop scalable algorithms using multi-layered models and real-time data
[45]. In 2022	PSAACO	UAV path planning in Cloud IoT	Grid mapping, self-adaptive parameters	Reduced energy usage and completion time	Lack of real-time adaptation	Integrate machine learning for dynamic course alterations
[46]. In 2020	ACO with GELS	Software rejuvenation	Dynamic rejuvenation schedules	Reduced failure rates in online services	No focus on the root causes of software aging	Combine rejuvenation with root cause analysis and improved monitoring
[47]. In 2022	MAACO	Mobile robot path planning	Unequal pheromone distribution, heuristic method	Shorter paths, reduced twists	Insufficient testing in highly dynamic environments	Conduct testing in dynamic real-world scenarios
[48]. In 2020	DFCM-ACO	Multi-robot rescue missions	Dynamic fuzzy cognitive map	Better performance with less processing time	Dependence on simulated environments	Combine physical testing with simulations for better real-world applicability
[49]. In 2020	ASCA-ACO	Mobile robot navigation	Advanced sine-cosine with ACO	Improved navigation efficiency	Scalability for larger environments not addressed	Focus on scalable adaptive algorithms for complex scenarios
[50]. In 2021	Fuzzy C-means with ACO	Document information retrieval	Cluster-based intelligent preprocessing	Increased retention efficiency	Relies on input data quality	Integrate data quality assessment techniques
[51]. In 2020	Enhanced ACO	Mobile robot path planning	Pseudo-random path selection	Improved search efficiency and global search capability	High complexity affects real-time implementation	Simplify methods for faster execution without losing efficiency
[52]. In 2022	Floyd-based ACO	Mobile robot path planning	Multi-objective optimization model	Better path quality and convergence speed	Lack of thorough practical testing	Use diverse simulations to verify model resilience
[53]. In 2023	SRL-ACO	Text augmentation for NLP	Semantic role labeling and ACO	Improved performance across text classification tasks	Limited assessment across languages and contexts	Expand to more datasets and languages
[54]. In 2020	ACO with Adaptive Mechanisms	Cyber-Physical Systems task optimization	Adaptive scheduling for efficiency	Enhanced convergence speed and task scheduling quality	Insufficient real-world application testing	Validate across different CPS contexts
[55]. In 2022	Hybrid ACO with BFA	Tourism route optimization	Knowledge-based hybrid algorithm	Improved tourist satisfaction and income	Simplistic assumptions affect real-world relevance	Incorporate real-world factors like seasonal variations
[56]. In 2021	EACSPGO	Mobile robot path planning	Geometric feature-based local optimization	Superior adaptability, stability, and convergence speed	Processing overhead in complex ecosystems	Optimize computing efficiency for complex environments

4. Discussion

The advancements in Ant Colony Optimization (ACO) have significantly enhanced its performance and applicability across various domains. Liu and Cao (2020) introduced a Levy-ACO algorithm, which utilizes Levy flights to improve solution diversity and efficiency, achieving 42% fewer iterations compared to Max-min ACO for the Traveling Salesman Problem (TSP). However, its focus on benchmark problems limits its scalability to real-world applications, necessitating future research on adaptive parameter tuning. Similarly, Li et al. (2021) developed the Adaptive Ant Colony Algorithm (AACO) for autonomous vehicle path planning, demonstrating improved path quality and resilience in stationary environments. This method's limitation lies in its lack of adaptation to dynamic scenarios, suggesting a need for real-time obstacle recognition and motion prediction.

In the realm of high-performance computing, González et al. (2022) proposed a Parallel ACO framework using multi-colony and asynchronous distributed techniques, achieving notable scalability and efficiency improvements. However, the framework's dependency on specific HPC architectures poses challenges for broader applicability. Adaptive tuning mechanisms and automated configuration tools are recommended for further enhancement. Dahan et al. (2021) developed EFACO for QoS-aware web service composition, leveraging multi-pheromone strategies for improved service selection. Despite its success, the limited flying ant process affects solution quality, highlighting the need for adaptive control to balance exploration and exploitation.

For robotics, Zhang et al. (2021) introduced the Adaptive Improved ACS (AIACSE) with a non-uniform starting pheromone distribution, enhancing robot path planning in stationary conditions. Its applicability to dynamic environments is limited, calling for integration with real-time sensor data and adaptive learning. Ding et al. (2020) proposed IMACA for hyperspectral image band selection, utilizing prefilters and adaptive information updates for superior classification accuracy. However, the labor-intensive parameter optimization process necessitates automated techniques such as evolutionary algorithms.

In energy-efficient transportation, Manogaran et al. (2022) presented the FACO algorithm for electric vehicle routing, improving energy usage and driving range. The exclusion of real-time traffic data limits its practical relevance, suggesting future integration of dynamic traffic and charging station availability. Wang et al. (2022) developed the IA-IACO model for unmanned surface vehicle path planning, combining immune algorithms with ACO for enhanced convergence. This method's performance in highly dynamic settings remains untested, pointing to opportunities for adaptive strategies to manage environmental variations. Liang and Wang (2020) combined Genetic Algorithms with ACO for marine investigation path planning, demonstrating efficiency and cost reductions. However, its generalizability to complex marine ecosystems requires further exploration of environmental factors.

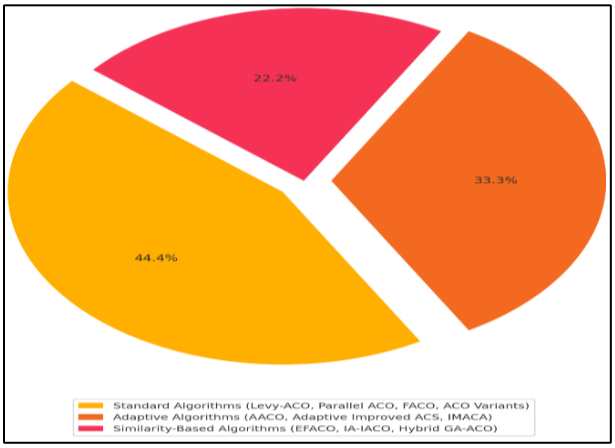

Fig. 2: Distribution of Ant Colony Optimization (ACO) Algorithms with Algorithm Name.

Figure 2 illustrates the distribution of Ant Colony Optimization (ACO) algorithms, highlighting their grouping into Standard Algorithms, Adaptive Algorithms, and Similarity-Based Algorithms. Standard Algorithms, including Levy-ACO, Parallel ACO, FACO, and ACO Variants, dominate with 44.4%, reflecting their foundational role in optimization studies. Adaptive Algorithms, such as AACO, Adaptive Improved ACS, and IMACA, account for 33.3%, showcasing their importance in dynamic and scalable applications. Lastly, Similarity-Based Algorithms, which include EFACO, IA-IACO, and Hybrid GA-ACO, represent 22.2%, emphasizing their hybrid and domain-specific enhancements. This distribution underscores the evolving focus on adaptability and hybrid approaches to address complex, real-world challenges.

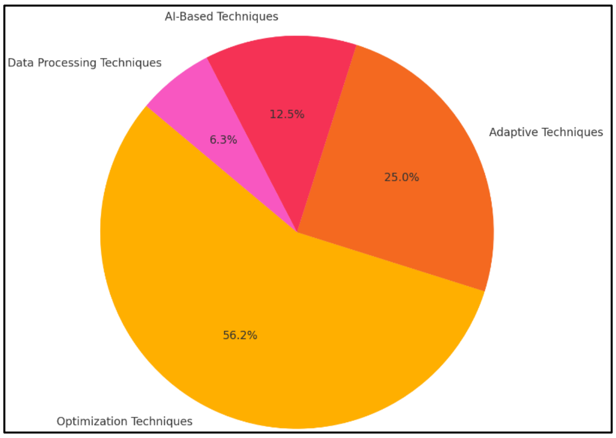

Fig. 3: Revised Distribution of Methodology / Techniques in ACO Algorithms.

Figure 3 illustrates the distribution of merged methodologies and techniques in ACO algorithms. Optimization Techniques are the most prominent, comprising 56.3%, emphasizing their importance in enhancing algorithmic efficiency. Adaptive Techniques follow at 25.0%, reflecting the growing focus on dynamic and scalable solutions. AI-based techniques account for 12.5%, highlighting their role in hybrid approaches. Finally, Data Processing Techniques represent 6.3%, showcasing their application in pre-processing tasks. This distribution reveals the dominance of traditional optimization methods while highlighting the gradual adoption of adaptive and AI-driven methodologies.

Finally, these studies collectively underscore the continuous evolution of ACO, showcasing innovative solutions while identifying areas for future research to overcome existing limitations.

5. Conclusion

To conclude, Ant Colony Optimization (ACO) continues to demonstrate significant advancements in addressing complex optimization problems across domains such as robotics, logistics, and telecommunications. Statistical improvements highlight its efficacy, with the Levy-ACO achieving a 42% reduction in iterations for the Traveling Salesman Problem, fitness-based ACO enhancing electric vehicle driving range by 28.58% and reducing power depletion by 51.99%, and Modified Adaptive ACO cutting robot turn times by 22.2%. Additionally, the Parallel Self-Adaptive ACO improved energy efficiency and completion times in UAV path planning, while the Improved Ant Colony Algorithm enhanced classification accuracy in hyperspectral imaging. These advancements underscore the adaptability and efficiency of ACO algorithms. However, challenges such as parameter sensitivity, scalability, and real-time adaptation remain. Future research is poised to integrate dynamic data processing, automated parameter tuning, and hybridization with machine learning to further enhance scalability and performance. Overall, ACO continues to be a robust and evolving solution for real-world optimization challenges, with a promising trajectory for innovation.

References

[1] M. Dorigo and T. Stützle, Handbook of Metaheuristics; Ant colony optimization: Overview and recent advances, vol. 272. 2019. https://doi.org/10.1007/978-3-319-91086-4_10.

[2] Z. Zheng, "Improved ant colony-based algorithm for solving traveling salesmen problem," Appl. Comput. Eng., vol. 10, no. 1, pp. 265–271, 2023, https://doi.org/10.54254/2755-2721/10/20230191.

[3] M. Mavrovouniotis, S. Yang, M. Van, C. Li, and M. Polycarpou, "Ant colony optimization algorithms for dynamic optimization: A case study of the dynamic travelling salesperson problem [Research Frontier]," IEEE Comput. Intell. Mag., vol. 15, no. 1, pp. 52–63, 2020, https://doi.org/10.1109/MCI.2019.2954644.

[4] R. He, X. Wei, and N. Hassan, "Multi-objective performance optimization of ORC cycle based on improved ant colony algorithm," Open Phys., vol. 17, no. 1, pp. 48–59, 2019, https://doi.org/10.1515/phys-2019-0006.

[5] S. Z. Zhou, Z. H. Zhan, Z. G. Chen, S. Kwong, and J. Zhang, "A Multi-Objective Ant Colony System Algorithm for Airline Crew Rostering Problem with Fairness and Satisfaction," IEEE Trans. Intell. Transp. Syst., vol. 22, no. 11, pp. 6784–6798, 2021, https://doi.org/10.1109/TITS.2020.2994779.

[6] M. Liu, X. You, X. Yu, and S. Liu, "KL Divergence-Based Pheromone Fusion for Heterogeneous Multi-Colony Ant Optimization," IEEE Access, vol. 7, pp. 152646–152657, 2019, https://doi.org/10.1109/ACCESS.2019.2948395.

[7] X. F. Yu, L. W. Yu, M. Q. Zheng, J. H. Lu, and L. Zhang, "Firefly algorithm and ant colony algorithm to optimize the traveling salesman problem," J. Phys. Conf. Ser., vol. 2253, no. 1, 2022, https://doi.org/10.1088/1742-6596/2253/1/012010.

[8] W. Ashour, R. Muqat, and H. Al-Talli, "Optimization of Traveling Salesman Problem based on Adaptive Affinity Propagation and Ant Colony Algorithms," Int. J. Comput. Appl., vol. 181, no. 29, pp. 25–31, 2018, https://doi.org/10.5120/ijca2018918147.

[9] T. Nurcahyadi and C. Blum, "Adding negative learning to ant colony optimization: A comprehensive study," Mathematics, vol. 9, no. 4, pp. 1–23, 2021, https://doi.org/10.3390/math9040361.

[10] Y. Wang, "Inventory Path Optimization of VMI Large Logistics Enterprises Based on Ant Colony Algorithm," Mob. Inf. Syst., vol. 2022, 2022, https://doi.org/10.1155/2022/5186552.

[11] X. Bian and J. Tian, "The Construction of Intelligent Supply Chain System for Agricultural Products Based on Improved Ant Colony Algorithm," Mob. Inf. Syst., vol. 2022, 2022, https://doi.org/10.1155/2022/5643304.

[12] S. Ulusam Seçkiner, A. Shumye, and S. Geçer, "Minimizing Solid Waste Collection Routes Using Ant Colony Algorithm: A Case Study in Gaziantep District," J. Transp. Logist., vol. 6, no. 1, pp. 29–47, 2021, https://doi.org/10.26650/JTL.2021.894265.

[13] Y. Tan, J. Ouyang, Z. Zhang, Y. Lao, and P. Wen, "Path planning for spot welding robots based on improved ant colony algorithm," Robotica, vol. 41, no. 3, pp. 926–938, 2023, https://doi.org/10.1017/S026357472200114X.

[14] J. Chen, J. Yang, and Z. Sui, "Path planning of escort robot based on improved ant colony algorithm," SPIE-Intl Soc Optical Eng, Oct. 2022, p. 29. https://doi.org/10.1117/12.2652708.

[15] Y. Xu, Q. Jin, and Y. Zhang, "A path planning method for mobile robots incorporating artificial potential field method and ant colony algorithm," in International Conference on Automation Control, Algorithm, and Intelligent Bionics (ACAIB 2023), S. Ladaci and S. Kaswan, Eds., SPIE, Aug. 2023, p. 101. https://doi.org/10.1117/12.2686536.

[16] A. R. Purnajaya, "Ant Colony Optimization for Prediction of Compound-Protein Interactions," J. Appl. Informatics Comput., vol. 3, no. 2, pp. 38–41, 2019, https://doi.org/10.30871/jaic.v3i2.1639.

[17] T. Minh Ngo, "Business Applications of Optimisation Theory: Ant Colony Optimization and Selected Applications in Manufacturing," Int. J. Res. Commer. Manag. Stud., vol. 05, no. 04, pp. 183–193, 2023, https://doi.org/10.38193/IJRCMS.2023.5412.

[18] Z. Guo, J. Duan, W. Zheng, and W. Yang, "Drone track planning method based on an improved ant colony algorithm for the task of measuring mobile signal strength," vol. 12916, no. Icsipc, p. 11, 2023, https://doi.org/10.1117/12.3004647.

[19] L. F. de Mingo López, N. Gómez Blas, and C. Morales Lucas, "Ant colony systems optimization applied to BNF grammars rule derivation (ACORD algorithm)," Soft Comput., vol. 24, no. 5, pp. 3141–3154, 2020, https://doi.org/10.1007/s00500-020-04670-9.

[20] M. Beschi et al., "Optimal robot motion planning of redundant robots in machining and additive manufacturing applications," Electron., vol. 8, no. 12, 2019, https://doi.org/10.3390/electronics8121437.

[21] F. Huang, H. Wang, J. Gu, and Q. Sun, "Ant colony optimization approach based on precedence constraint matrix for flexible process planning," J. Eng. Res., vol. 8, no. 1, pp. 272–293, 2020, https://doi.org/10.36909/jer.v8i1.4024.

[22] A. Hemmati-Sarapardeh, A. Larestani, M. Nait Amar, and S. Hajirezaie, "Training and optimization algorithms," in Applications of Artificial Intelligence Techniques in the Petroleum Industry, Elsevier, 2020, pp. 51–78. https://doi.org/10.1016/B978-0-12-818680-0.00003-5.

[23] Y. Tian, J. Zhang, Q. Wang, S. Liu, Z. Guo, and H. Zhang, "Application of Hybrid Algorithm Based on Ant Colony Optimization and Sparrow Search in UAV Path Planning," Int. J. Comput. Intell. Syst., vol. 17, no. 1, p. 286, Nov. 2024, https://doi.org/10.1007/s44196-024-00652-z.

[24] C. Cheng, L. Zhai, Y. Jia, X. Zhu, and Y. Li, "Volunteer vehicle assisted dependent task offloading based on ant colony optimization algorithm in vehicular edge computing," Veh. Commun., vol. 50, p. 100849, Dec. 2024, https://doi.org/10.1016/j.vehcom.2024.100849.

[25] G. Hu, F. Huang, B. Shu, and G. Wei, "MAHACO: Multi-algorithm hybrid ant colony optimizer for 3D path planning of a group of UAVs," Inf. Sci. (Ny)., vol). ,94, p. 121714, Mar. 2025, https://doi.org/10.1016/j.ins.2024.121714.

[26] B. Farah, An Ant Colony Optimization Algorithm for a Vehicle Routing Problem with Heterogeneous Fleet, Mixed Backhauls, and Time Windows, vol. 1, no. 1. Association for Computing Machinery, 2009. https://doi.org/10.3182/20090603-3-RU-2001.00257.

[27] N. Ullah, M. Umar, J.-Y. Kim, and J.-M. Kim, "Enhanced Fault Diagnosis in Milling Machines Using CWT Image Augmentation and Ant Colony Optimized AlexNet," Sensors, vol. 24, no. 23, p. 7466, Nov. 2024, https://doi.org/10.3390/s24237466.

[28] Y. Wang, M. Gou, S. Luo, J. Fan, and H. Wang, "The multi-depot pickup and delivery vehicle routing problem with time windows and dynamic demands," Eng. Appl. Artif. Intell., vol. 139, p. 109700, Jan. 2025, https://doi.org/10.1016/j.engappai.2024.109700.

[29] S. Wu, A. Dong, Q. Li, W. Wei, Y. Zhang, and Z. Ye, "Application of ant colony optimization algorithm based on farthest point optimization and multi-objective strategy in robot path planning," Appl. Soft Comput., vol. 167, p. 112433, Dec. 2024, https://doi.org/10.1016/j.asoc.2024.112433.

[30] S. Aggarwal, I. Budhiraja, S. Garg, G. Kaddoum, B. J. Choi, and M. S. Hossain, "A blockchain-based secure path planning in UAVs communication network," Alexandria Eng. J., vol. 113, pp. 451–460, Feb. 2025, https://doi.org/10.1016/j.aej.2024.10.078.

[31] R. Behmanesh, I. Rahimi, M. Zandieh, and A. H. Gandomi, "Advanced Ant Colony Optimization in Healthcare Scheduling," in Evolutionary Computation in Scheduling, Wiley, 2020, pp. 37–72. https://doi.org/10.1002/9781119574293.ch3.

[32] Y. Liu and B. Cao, "A Novel Ant Colony Optimization Algorithm with Levy Flight," IEEE Access, vol. 8, pp. 67205–67213, 2020, https://doi.org/10.1109/ACCESS.2020.2985498.

[33] Y. Li, Y. Ming, Z. Zhang, W. Yan, and K. Wang, "An Adaptive Ant Colony Algorithm for Autonomous Vehicles Global Path Planning," in Proceedings of the 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design, CSCWD 2021, Institute of Electrical and Electronics Engineers Inc., May 2021, pp. 1117–1122. https://doi.org/10.1109/CSCWD49262.2021.9437682.

[34] P. González, R. R. Osorio, X. C. Pardo, J. R. Banga, and R. Doallo, "An efficient ant colony optimization framework for HPC environments," Appl. Soft Comput., vol. 114, Jan. 2022, https://doi.org/10.1016/j.asoc.2021.108058.

[35] F. Dahan, K. El Hindi, A. Ghoneim, and H. Alsalman, "An Enhanced Ant Colony Optimization Based Algorithm to Solve QoS-Aware Web Service Composition," IEEE Access, vol. 9, pp. 34098–34111, 2021, https://doi.org/10.1109/ACCESS.2021.3061738.

[36] S. Zhang, J. Pu, and Y. Si, "An Adaptive Improved Ant Colony System Based on Population Information Entropy for Path Planning of Mobile Robot," IEEE Access, vol. 9, pp. 24933–24945, 2021, https://doi.org/10.1109/ACCESS.2021.3056651.

[37] X. Ding et al., "An Improved Ant Colony Algorithm for Optimized Band Selection of Hyperspectral Remotely Sensed Imagery," IEEE Access, vol. 8, pp. 25789–25799, 2020, https://doi.org/10.1109/ACCESS.2020.2971327.

[38] G. Manogaran, P. M. Shakeel, V. Priyan R, N. Chilamkurti, and A. Srivastava, "Ant colony optimization-induced route optimization for enhancing driving range of electric vehicles," Int. J. Commun. Syst., vol. 35, no. 12, Aug. 2022, https://doi.org/10.1002/dac.3964.

[39] H. Wang, J. Zhang, and J. Dong, "Application of ant colony and immune combined optimization algorithm in path planning of unmanned craft," AIP Adv., vol. 12, no. 2, Feb. 2022, https://doi.org/10.1063/5.0077858.

[40] Y. Liang and L. Wang, "Applying genetic algorithm and ant colony optimization algorithm into marine investigation path planning model," Soft Comput., vol. 24, no. 11, pp. 8199–8210, Jun. 2020, https://doi.org/10.1007/s00500-019-04414-4.

[41] X. Chen et al., "Artificial intelligence-empowered path selection: A survey of ant colony optimization for static and mobile sensor networks," IEEE Access, vol. 8, pp. 71497–71511, 2020, https://doi.org/10.1109/ACCESS.2020.2984329.

[42] Z. B. Imtiaz, A. Manzoor, S. ul Islam, M. A. Judge, K. K. R. Choo, and J. J. P. C. Rodrigues, "Discovering communities from disjoint complex networks using Multi-Layer Ant Colony Optimization," Futur. Gener. Comput. Syst., vol. 115, pp. 659–670, Feb. 2021, https://doi.org/10.1016/j.future.2020.10.004.

[43] V. Sangeetha, R. Krishankumar, K. S. Ravichandran, and S. Kar, "Energy-efficient green ant colony optimization for path planning in dynamic 3D environments," Soft Comput., vol. 25, no. 6, pp. 4749–4769, Mar. 2021, https://doi.org/10.1007/s00500-020-05483-6.

[44] S. P. H. P. Tabrizi, A. Reza, and S. M. Jameii, "Enhanced path planning for automated nanites drug delivery based on reinforcement learning and polymorphic improved ant colony optimization," J. Supercomput., vol. 77, no. 7, pp. 6714–6733, Jul. 2021, https://doi.org/10.1007/s11227-020-03559-6.

[45] Y. Gong, K. Chen, T. Niu, and Y. Liu, "Grid-Based coverage path planning with NFZ avoidance for UAV using parallel self-adaptive ant colony optimization algorithm in cloud IoT," J. Cloud Comput., vol. 11, no. 1, Dec. 2022, https://doi.org/10.1186/s13677-022-00298-2.

[46] K. R. Kalantari, A. Ebrahimnejad, and H. Motameni, "Efficient improved ant colony optimisation algorithm for dynamic software rejuvenation in web services," IET Softw., vol. 14, no. 4, pp. 369–376, Aug. 2020, https://doi.org/10.1049/iet-sen.2019.0018.

[47] L. Wu, X. Huang, J. Cui, C. Liu, and W. Xiao, "Modified Adaptive Ant Colony Optimization Algorithm and Its Application for Solving Path Planning of Mobile Robot," 2022. https://doi.org/10.1016/j.eswa.2022.119410.

[48] M. Mendonça, R. H. C. Palácios, E. I. Papageorgiou, and L. Botoni De Souza, "Multi-robot exploration using Dynamic Fuzzy Cognitive Maps and Ant Colony Optimization," 2020. https://doi.org/10.1109/FUZZ48607.2020.9177814.

[49] X. Jiang, Z. Lin, T. He, X. Ma, S. Ma, and S. Li, "Optimal Path Finding with Beetle Antennae Search Algorithm by Using Ant Colony Optimization Initialization and Different Searching Strategies," IEEE Access, vol. 8, pp. 15459–15471, 2020, https://doi.org/10.1109/ACCESS.2020.2965579.

[50] K. Thirugnanasambandam, R. Anitha, V. Enireddy, R. S. Raghav, D. K. Anguraj, and A. Arivunambi, "Pattern mining technique derived ant colony optimization for document information retrieval," J. Ambient Intell. Humaniz. Comput., 2021, https://doi.org/10.1007/s12652-020-02760-y.

[51] Q. Luo, H. Wang, Y. Zheng, and J. He, "Research on path planning of mobile robot based on improved ant colony algorithm," Neural Comput. Appl., vol. 32, no. 6, pp. 1555–1566, Mar. 2020, https://doi.org/10.1007/s00521-019-04172-2.

[52] Z. Li, Z. Tian, J. Zhao, and B. Wang, "Research on smooth path planning method based on improved ant colony algorithm optimized by Floyd algorithm."

[53] A. Onan, "SRL-ACO: A text augmentation framework based on semantic role labeling and ant colony optimization," J. King Saud Univ. - Comput. Inf. Sci., vol. 35, no. 7, Jul. 2023, https://doi.org/10.1016/j.jksuci.2023.101611.

[54] N. Yi, J. Xu, L. Yan, and L. Huang, "Task optimization and scheduling of distributed cyber–physical system based on improved ant colony algorithm," Futur. Gener. Comput. Syst., vol. 109, pp. 134–148, Aug. 2020, https://doi.org/10.1016/j.future.2020.03.051.

[55] S. Li, T. Luo, L. Wang, L. Xing, and T. Ren, "Tourism route optimization based on improved knowledge ant colony algorithm," Complex Intell. Syst., vol. 8, no. 5, pp. 3973–3988, Oct. 2022, https://doi.org/10.1007/s40747-021-00635-z.

[56] S. Zhang, J. Pu, Y. Si, and L. Sun, "Path planning for mobile robot using an enhanced ant colony optimization and path geometric optimization," Int. J. Adv. Robot. Syst., vol. 18, no. 3, 2021, https://doi.org/10.1177/17298814211019222.