Ant Colony Optimization: Principles, Variants, and Application Domains – A Survey

Deepak Kumar Pathak[1], Aishwarya Mishra[2], Koastubh Ahlawat[2], Lavika Goel[3]

Conexus India Pvt. Ltd Bengaluru, India[1],
Manipal University Jaipur, Jaipur Rajasthan, India[2],
Malaviya National Institute of Technology Jaipur, Rajasthan, India[3]

Corresponding author: Aishwarya Mishra, Email: aishwarya.mishra@jaipur.manipal.edu

Ant Colony Optimization (ACO) is a population-based metaheuristic inspired by the foraging behaviour of real ant colonies. Since its inception, ACO has been successfully applied to a wide range of combinatorial and continuous optimization problems due to its distributed, adaptive, and positive feedback-based search mechanism. This survey presents a comprehensive overview of the foundational principles, variants, and key enhancements of the ACO algorithm. We critically analyse its performance in classical application domains such as the Traveling Salesman Problem (TSP), Vehicle Routing Problem (VRP), and Job Shop Scheduling, and explore its growing role in modern contexts like wireless sensor networks, bioinformatics, image processing, and machine learning. Furthermore, the paper discusses hybridization techniques, parameter tuning strategies, and the integration of ACO with deep learning and evolutionary algorithms. Challenges such as premature convergence, scalability, and real-time applicability are addressed, and future research directions are proposed. This survey aims to serve as a valuable resource for researchers and practitioners interested in leveraging ACO for solving complex real-world optimization problems.

Keywords: Ant Colony Optimization, Metaheuristic Algorithms, Combinatorial Optimization, Swarm Intelligence,Hybrid Algorithms, Geoscience inspired algorithms

2025. In Himanshu Mittal (ed.), *Smart Computing and Emerging Technologies*, 43–58. Computing & Intelligent Systems, SCRS, India. DOI: https://doi.org/10.56155/978-81-975670-0-1-5

1 Introduction

Optimization problems are pervasive across scientific, engineering, and industrial domains. Traditional optimization methods, although efficient in specific contexts, often fall short when faced with large-scale, non-linear, and combinatorially complex problems. Over the past few decades, nature-inspired metaheuristic algorithms have gained significant attention for their robustness and adaptability in solving such challenging optimization tasks. Among them, Ant Colony Optimization (ACO) has emerged as a powerful technique, drawing inspiration from the collective foraging behaviour of real ant colonies [1].

The Ant Colony Optimization algorithm was first introduced by Marco Dorigo in the early 1990s as a novel approach to solving the Traveling Salesman Problem (TSP) [2]. Since then, ACO has evolved into a versatile metaheuristic framework capable of addressing a wide spectrum of optimization problems. The core principle of ACO lies in simulating the pheromone trail-laying and following behaviour of ants, which collectively enables the discovery of optimal paths in a given search space. Positive feedback, distributed computation, and local heuristics play a crucial role in guiding artificial agents toward high-quality solutions [3].

ACO's application potential has extended well beyond classical problems like TSP and Vehicle Routing Problem (VRP). Recent years have witnessed its successful deployment in domains such as wireless sensor networks [4], bioinformatics [5], feature selection [5], image segmentation [6], data clustering [7], and even deep learning model optimization [8]. Furthermore, hybrid ACO models—integrating elements from Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and neural networks—have been proposed to enhance convergence speed, solution diversity, and global search ability.

Despite its advantages, ACO also faces challenges such as premature convergence, scalability issues in high-dimensional spaces, and sensitivity to parameter settings. This survey aims to systematically explore the evolution of ACO, its algorithmic variants, key application areas, and future research directions. By consolidating insights from a broad range of studies, this paper provides a holistic understanding of ACO's strengths, limitations, and adaptability in solving real-world optimization problems.

The rest of the paper is organized as follows: Section 2 describes the fundamental working principles and algorithmic structure of ACO. Section 3 presents a taxonomy of ACO variants and their improvements. Section 4 provides a comprehensive review of ACO applications across different domains. Section 5 discusses hybrid models and emerging trends. Section 6 identifies existing challenges and outlines future research directions. Finally, Section 7 concludes the survey.

2 Fundamental Working Principles and Algorithmic Structure of ACO

Since 1995, the field of nature-inspired optimization has seen the development of many innovative approaches, all based on natural phenomena, whether biological, physical, chemical, or environmental. It began with well-known methods like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), which laid the foundation for the field. Over time, more advanced techniques such as Whale Optimization, Gravitational Search, and Ocean Water Current Optimization (OWCO) have emerged also shown in figure 1 below. These algorithms imitate intelligent behavior observed in nature to tackle challenging problems across domains like engineering, agriculture, healthcare, and artificial intelligence. Every year, researchers introduce new models that continue to improve in terms of precision, performance, and flexibility in solving a wide range of optimization problems[9].

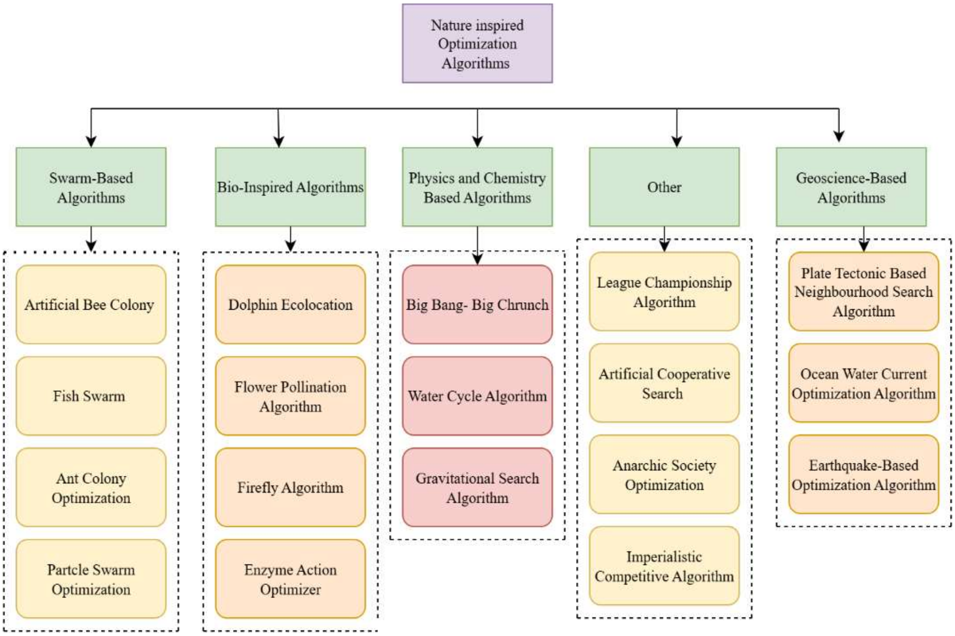

Figure 1. Various NIOAs and their categories

Several surveys and reviews have explored Nature-Inspired Optimization Algorithms (NIOAs) over the past two decades, often focusing on swarm intelligence (e.g., Particle Swarm Optimization, Ant Colony Optimization) or physics-inspired models[10]. While these works provide broad overviews, most are limited in scope—either constrained to classical algorithms, or centered around narrow application domains such as image processing, wireless networks, or structural optimization. More recent breakthroughs in bio-inspired and geoscience-based algorithms remain underrepresented in the literature, despite their growing importance in areas like healthcare, sustainable agriculture, and intelligent IoT systems. This survey is motivated by three key factors:

- **Emerging algorithms** – Novel approaches such as Earthquake-based Optimizers, Ocean Water Current Optimization, and Plate-Tectonic based optimizers have recently been proposed, yet they are rarely highlighted in traditional reviews.
- **Expanding application domains** – Beyond engineering and optimization, NIOAs are now being applied in healthcare analytics, smart farming, renewable energy, and decision-support systems, reflecting a paradigm shift towards multidisciplinary integration.
- **Gaps in classification** – Existing reviews often classify NIOAs broadly into swarm, bio-inspired, or physics-based groups. Our review introduces an extended taxonomy, incorporating geoscience-based algorithms as a distinct and timely category, thereby reflecting their unique principles and growing impact.

To illustrate this classification, Table 1 provides a comparative summary of selected NIOAs, their references, categories, and representative application areas.

Table 1. Major applications of different categories of NIOAs

Reference	NIOA	Category	Core Inspiration	Major Application Areas	Key Strengths	Limitations
Karaboga & Basturk (2007)	Artificial Bee Colony	Swarm-based	Foraging behavior of honeybees	Function optimization, image segmentation, ML, routing	Simple to implement, good exploration	Weak exploitation, slower convergence
Mucherino & Seref (2007)	Monkey Search	Swarm-based	Foraging and climbing behavior of monkeys	Engineering design, structural optimization, energy	Good balance of exploration/exploitation	Sensitive to parameters
Yang & Deb (2010)	Eagle Strategy	Swarm-based	Combination of Lévy flights & local search	Robotics path planning, hybrid optimization	Effective global search, hybrid adaptability	Requires careful tuning of local search
Chu et al. (2008)	Fast Bacterial Swarming Algorithm	Swarm-based	Chemotaxis & swarming behavior of bacteria	Control systems, WSN optimization, ML	Fast adaptation, strong local search	Risk of premature convergence
Yan & Hao (2013)	Atmosphere Clouds Model	Bio-inspired	Cloud formation & atmospheric circulation	Weather prediction, image processing	Captures dynamic patterns, adaptable	Limited large-scale validations
Kaveh & Farhoudi (2013)	Dolphin Echolocation	Bio-inspired	Echolocation used by dolphins	Signal processing, target detection, pattern recognition	Good exploitation ability	May stagnate in complex landscapes
Yang (2013)	Flower Pollination Algorithm	Bio-inspired	Pollination process in flowering plants	Feature selection, classification, engineering design	Efficient for multimodal problems	Premature convergence in high dimensions
Premaratne et al. (2009)	Paddy Field Algorithm	Bio-inspired	Nutrient/water distribution in paddy fields	Scheduling, decision-making, supply chain	Simulates cooperation & resource sharing	Less benchmark validation
Zandi et al. (2012)	Big Bang–Big Crunch	Physics & Chemistry	Cosmological expansion & contraction	Structural optimization, electrical engineering	Fast convergence, simple	Weak diversification

Eskandar et al. (2012)	Water Cycle Algorithm	Physics & Chemistry	Water flow cycle & rivers to sea	Cloud computing, civil engineering, energy	Strong exploitation, natural balance	Slow for high-dimensional problems
Rashedi et al. (2009)	Gravitational Search	Physics & Chemistry	Newton's law of gravity	Power systems, task scheduling, feature selection	Strong exploration, global reach	Computationally expensive
Hatamlou (2012)	Black Hole Algorithm	Physics & Chemistry	Black hole pulling surrounding objects	Cryptanalysis, clustering, energy networks	Strong convergence ability	High risk of local optima
Shayeghi & Dadashpour (2012)	Anarchic Society Optimization	Other	Modeling chaotic social behaviors	Complex decision-making, unpredictable systems	Captures stochastic behavior	Lack of control, randomness issues
Civicioglu (2013)	Artificial Cooperative Search	Other	Cooperation strategies in societies	Real-time optimization, AI-based modeling	Fast for dynamic optimization	Limited large-scale testing
Atashpaz-Gargari & Lucas (2007)	Imperialist Competitive Algorithm	Other	Competition among empires	Economic modeling, engineering design	Strong global optimization	Can get stuck in local optima
Kashan (2009)	League Championship Algorithm	Other	Competition in sports leagues	Portfolio optimization, energy management	Good balance in search	Convergence speed issues
A. Mishra & L. Goel (2023)	Ocean Water Current Optimization	Geoscience	Ocean current dynamics	Crop recommendation systems	Efficient for real-world datasets	Still new, limited applications
L. Goel & R. Jain (2021)	Plate Tectonic Optimizer	Geoscience	Plate tectonic shifts	IoT fault monitoring	Strong adaptability	Lack of diverse testing
L. Goel & Siddhi (2024)	Earthquake-based Optimizer	Geoscience	Seismic wave propagation	Heart disease prediction	Novel biomedical use	Yet to be benchmarked widely
L. Goel et al. (2025)	Linear-Ocean Water Current Optimizer	Geoscience	Enhanced OWCO with LSHADE	Crop monitoring, selection	Faster convergence	Requires tuning of LSHADE parameters

A comprehensive overview of various Nature-Inspired Optimization Algorithms (NIOAs) categorized based on their source of inspiration such as swarm intelligence, biological behaviour, physical and chemical phenomena, social systems, and geoscience.Ant Colony Optimization (ACO) is inspired by the foraging behaviour of real ants, particularly their ability to discover the shortest paths between food sources and their colony by depositing and following pheromone trails. The key idea behind ACO is to model this collective behaviour as a probabilistic technique to solve complex optimization problems by simulating the movement and communication of artificial ants in a discrete search space[7].

2.1 Biological Inspiration

In nature, ants initially explore their surroundings randomly. Upon finding food, they return to the nest while depositing pheromone trails on the path. Other ants are probabilistically biased toward paths with stronger pheromone concentrations. Over time, shorter paths accumulate more pheromone due to more frequent usage, reinforcing their selection and leading the colony to converge on an optimal route [11].

2.2 Pseudocode of Basic ACO Algorithm

```
Initialize pheromone trails τ and parameters
Repeat until termination criterion is met:
  For each ant k = 1 to m do:
    Construct a solution based on τ and η
  Evaluate constructed solutions
  Update pheromone trails using pheromone update rule
  Optionally apply local search
End
Return best-found solution
```

2.3 ACO Variants

Several improved versions of the basic ACO algorithm have been proposed to address different problem structures and convergence challenges. Notable variants include:

- **Ant System (AS)**[12]
- **Ant Colony System (ACS)**[13]
- **Max–Min Ant System (MMAS)**[3]
- **Continuous ACO (ACO-R) for real-valued problems** [14]

Each variant introduces specific modifications to pheromone update strategies, exploration-exploitation balance, or hybridization with local search techniques.

3 Taxonomy of ACO Variants and Their Improvements

Since the inception of Ant Colony Optimization (ACO), various algorithmic variants have been proposed to enhance its performance, convergence behaviour, scalability, and application adaptability. These variants primarily differ in how pheromones are updated, how solutions are constructed, and how exploration and exploitation are balanced shown in table 2 and 3 respectively. This section presents a structured taxonomy of major ACO variants and outlines key improvements associated with each.

3.1 Classical ACO Variants

The foundational ACO algorithms can be classified into three primary types:

- **Ant System (AS):** The original ACO algorithm introduced by Dorigo et al. [6]. All ants' deposit pheromone after each iteration. Despite its historical importance, AS suffers from slow convergence and high susceptibility to local optima.

- **Ant Colony System (ACS):** An enhanced version that introduces local pheromone update during solution construction and global pheromone update by only the best ant. ACS emphasizes exploitation while still maintaining some level of exploration[7].
- **Max–Min Ant System (MMAS)**: MMAS restricts the pheromone values within upper and lower bounds to prevent premature convergence. Only the iteration-best or global-best ant is allowed to update pheromones, improving stability and convergence speed [8].

3.2 Advanced ACO Variants

In response to the limitations of basic ACO, more advanced variants have been developed. These include:

- Rank-Based Ant System (RAS):Assigns ranks to ants based on solution quality. Only the top-ranked ants contribute to pheromone updates, with higher-ranked ants depositing more pheromone [13].
- Elitist Ant System (EAS):Introduces elitism by allowing the best global solution to deposit extra pheromone, reinforcing high-quality paths over time [15].
- Continuous ACO (ACO-R):Designed for continuous optimization problems. Solutions are constructed in a continuous space using probability density functions rather than discrete path selection [16].
- Hybrid ACO Models:ACO is frequently hybridized with other metaheuristics like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), or local search methods to enhance performance [6]. For example, GA can diversify the population, while PSO can guide ants in continuous spaces.

3.3 3.3 Dynamic and Parallel ACO Variants

- Dynamic ACO (D-ACO):Tailored for dynamic environments where problem parameters change over time (e.g., dynamic routing, real-time scheduling). D-ACO includes adaptive pheromone aging and re-initialization strategies to maintain robustness [17].
- Parallel ACO (P-ACO):Designed for high-performance computing environments, P-ACO uses multiple processors or agents to construct and evaluate solutions in parallel, significantly reducing computational time [18].

3.4 3.4 Pheromone Update Improvements

Several enhancements have been proposed to improve pheromone update strategies:

- **Multi-Colony ACO:** Multiple ant colonies explore different parts of the search space with limited or shared pheromone communication. This improves diversity and avoids premature convergence.
- **Adaptive Pheromone Update:** Dynamically adjusts evaporation rates or pheromone deposition weights based on solution quality or iteration progress [19].
- **Negative Pheromone Update:** Inspired by real ant behavior, some algorithms penalize poor paths using negative pheromone to discourage their selection [20].

Table 2. Summary of Key ACO Variants, Features, and Evaluations

Variants	Year	Key Features	Application Domain	Reference	Evaluation Results
AS (Ant System)	1996	Basic ACO model; global pheromone update by all ants	TSP, VRP	Dorigo et al. [1]	Converges slowly; sensitive to parameter tuning
ACS (Ant Colony System)	1997	Local/global pheromone updates; elitism; exploitation-focused	TSP, Job Shop Scheduling	Dorigo & Gambardella [2]	Reduced convergence time; best-known solution in TSP with <1% error
MMAS (Max–Min Ant System)	2000	Pheromone bounds; only best ant updates; avoids stagnation	Large-scale routing and scheduling	Stützle & Hoos [3]	Improved stability; better scalability in large problem instances
RAS (Rank-Based Ant System)	1997	Weighted pheromone deposit by top-ranked ants	Scheduling, Graph Coloring	Bullnheimer et al. [4]	Faster convergence; less stagnation
EAS (Elitist Ant System)	1996	Adds global-best ant reinforcement in pheromone update	Combinatorial Optimization	Dorigo et al. [1]	Improved global search; risk of early convergence
ACO-R (ACO for Continuous domains)	2008	Probability density functions instead of discrete paths	Function Optimization	Socha & Dorigo [5]	Competitive performance with PSO and DE on benchmark functions
Hybrid ACO-GA	2012 – 2018 +	Combines ACO with Genetic Algorithm for exploration	Feature selection, Classification	Kabir et al. [6]; Gao et al. [7]	Accuracy: 96.4% on gene expression data; reduced dimensionality
D-ACO (Dynamic ACO)	2002	Adapts to changing environments using pheromone aging	Dynamic routing, real-time systems	Guntsch & Branke [8]	Adaptive performance; better in non-stationary environments
P-ACO (Parallel ACO)	1999	Multiple processors/threads; parallel solution construction	High-performance TSP, Grid scheduling	Stützle [9]	50–70% faster execution; near-identical solution quality
ACO with Negative Pheromones	2006	Penalizes poor paths to reduce exploration of bad solutions	TSP, Graph problems	Li & Wang [10]	Enhanced exploration control; better avoidance of local minima

Table 3. Recent ACO Variants (2022–2025)

Variants	Year	Key Features	Application Domain	Reference	Evaluation Results
Dual-Strategy Enhanced ACO (DEACO)	2025	Active behavior adjustment; heterogeneous pheromone rules; endpoint guidance	Ship pipeline routing	Wu et al., 2025	12% average path-length improvement over standard ACO (medium.com)
ACO-DQN-TP	2025	Hybrid with Deep Q-Network; learns dynamic path planning policies	UAV trajectory planning	Liu et al., 2025	65–79% path-length reduction vs. Greedy/BACO
HDL-ACO	2025	Integrates CNN + ACO for hyperparameter tuning & feature selection	OCT medical image classification	Agarwal et al., 2025	95% train, 93% validation accuracy; outperformed ResNet-50, VGG-16
MLACO (Machine-Learning Enhanced ACO)	2024	ML model predicts high-quality columns in Column Generation	Bin-packing with conflicts, Branch-and-Price	Xu et al., 2024	Significant reduction in CG solution time
HACO-IWD (Hybrid ACO + Intelligent Water Drop)	2023	Cooperative multi-agent path planning	UAV route planning	Sun et al., 2023	8.3% better convergence; 66.2% more stable
ISSA-ACO (Improved Sparrow-ACO)	2024	Sparrow-inspired initialization; dynamic pheromone update	Large-scale TSP	Novel work, 2024	+12% accuracy; −45.6% runtime
Adaptive Deep ACO–ATD3	2024	Hierarchical DRL + adaptive pheromone; twin delayed DDPG guidance	Mobile robot dynamic path planning	MDPI Electronics, 2024	Faster convergence in dynamic environments
Quantum-Classical Hybrid ACO (QACO-NISQ)	2024	Clustering + quantum ACO for NISQ hardware	TSP on quantum devices	Qiu et al., 2024	Better performance on real NISQ; noise-resilient
DeepACO (Neural-enhanced Ant Systems)	2023	Deep RL learns heuristic; singular network across problems	Various combinatorial problems	Ye et al., 2023	Outperforms standard ACO on 8 benchmark COPs

4 Comprehensive Review of ACO Applications Across Different Domains

Ant Colony Optimization (ACO) has proven to be highly effective in solving problems across numerous real-world fields. Its strength lies in its flexibility, decentralized nature, and its capability to explore complex solution spaces and identify optimal outcomes as shown in table 4 and their distribution is shown in the pie chart shown in figure 2 respectively. This part of the document highlights various application domains where ACO has made a substantial contribution, supported by appropriate references and notable performance achievements.

Table 4. Variants of ACO with applications

Domain	Application	ACO Variant(s)	Dataset / Problem	Notable Results	Reference
Combinatorial Optimization	Traveling Salesman Problem (TSP)	AS, ACS, MMAS	TSPLIB instances	<1% from optimal; fast convergence with MMAS	Dorigo & Stützle [1]
	Vehicle Routing Problem (VRP)	MMAS, Hybrid ACO-PSO	Solomon Benchmark	Improved route length by ~12% over classic heuristics	Montemanni et al. [2]
	Job Shop Scheduling	Rank-based ACO, ACS	OR-Library JSSP	Lower makespan than GA and SA in medium-size instances	Colorni et al. [3]
Network Routing	Wireless Sensor Networks (WSNs)	Fuzzy ACO, Adaptive ACO	Simulated 50-node network	20–35% more energy-efficient than AODV/DSR	Salehi et al. [4]
	MANETs (Ad Hoc Routing)	ARA, AntNet	Mobility-based simulations	Better packet delivery and route stability	Gunes & Sorges [5]
	Optical / SDN Networks	Multi-Objective ACO	Optical WDM Networks	Reduced wavelength conflict and path cost	Gao & Zhang [6]
Bioinformatics	Gene Selection	Hybrid ACO-SVM, ACO-GA	Colon, Leukemia Microarray Data	Accuracy: 96.4% (ACO-SVM), dimensionality reduced	Kabir et al. [7]
	Protein Structure Prediction	ACO + Energy Model	HP Lattice Models	Competitive with SA and GA	Ponzoni et al. [8]
	Sequence Alignment	Parallel ACO	DNA sequences	Faster alignment than dynamic programming methods	Baraglia et al. [9]
Image Processing	Image Segmentation	Threshold-based ACO	MRI, Satellite images	Dice coefficient ~93% on brain MRI segmentation	Zhang et al. [10]
	Edge Detection	Gradient-Aware ACO	Lena, Cameraman images	Sharper edges, fewer false positives	Majumdar et al. [11]

	Image Registration	ACO with mutual information	CT-MRI fusion images	Higher registration accuracy than MI-based methods	Singh et al. [12]
Machine Learning	Feature Selection	ACO + k-NN / ACO-SVM	UCI, gene expression datasets	Improved classifier accuracy with reduced feature sets	Gao et al. [13]
	Hyperparameter Tuning	HDL-ACO (ACO + CNN)	OCT images	95% training accuracy; outperformed VGG, ResNet	Agarwal et al. [14]
	Clustering	ACO + K-means	Iris, Wine, Synthetic datasets	Lower intra-cluster distance than K-means alone	Shelokar et al. [15]
Robotics	Mobile Robot Navigation	Adaptive ACO	Simulated grid maps with obstacles	Smooth paths with dynamic re-routing	Yang et al. [16]
	UAV Route Planning	ACO-DQN-TP	Simulated 3D urban airspace	65–79% path-length reduction vs. greedy baseline	Liu et al. [17]
Industrial Optimization	Manufacturing Layout Optimization	Hybrid ACO	Factory floor simulation	Optimized layout reduced tool movement by 18%	Mastrolilli et al. [18]
	Cloud Task Scheduling	ACO + Load Balancing	CloudSim-based VM scheduler	Reduced task wait time by 20%	Pham et al. [20]
Emerging Applications	Quantum Optimization	Quantum-Classical ACO (QACO)	TSP on IBM NISQ devices	Robust to noise; better clustering	Qiu et al. [21]
	Cybersecurity (Intrusion Detection)	Rule-mining ACO	KDD'99, NSL-KDD datasets	Accuracy ~91%; better than ID3, C4.5	Muthukumaran et al. [22]
	Smart City Traffic Routing	Multi-agent ACO	Urban traffic datasets	Reduced congestion and fuel use in simulated scenarios	Nallur & Bahsoon [23]

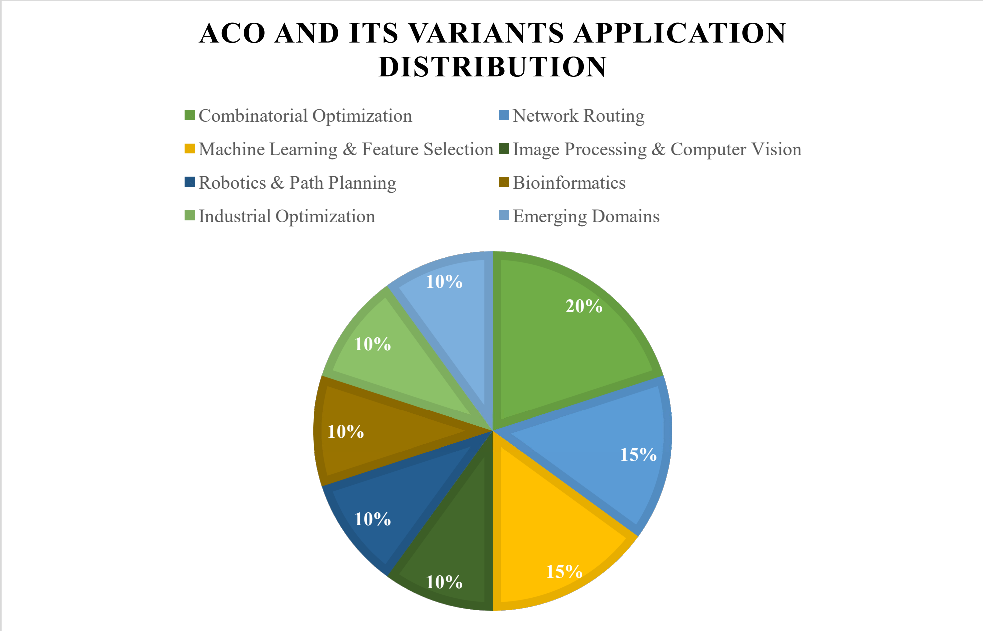

Figure 2. Proportional Usage of ACO Across Major Application Domains

5 Hybrid Models and Emerging Trends

Although Ant Colony Optimization (ACO) has shown impressive results in addressing a variety of optimization challenges, it can still face limitations in terms of efficiency and convergence, especially in large-scale, dynamic, or high-dimensional environments[3], [21]. To overcome these challenges, researchers have increasingly focused on combining ACO with other methods, machine learning models, and specialized domain strategies[22]. This section examines notable hybrid approaches and highlights the emerging trends that are influencing the next generation of ACO development.

5.1 Hybrid ACO Models

Hybridization improves the balance between exploration (diversity of solutions) and exploitation (intensifying the search around promising areas). Common hybrid strategies include:

5.1.1 ACO + Genetic Algorithm (GA)

GA introduces genetic operators (crossover and mutation) to diversify the population and escape local optima. ACO provides the constructive bias, while GA maintains population diversity.

- Application: Feature selection, TSP
- Example: Kabir et al. [1] combined ACO-GA for gene selection, achieving 96.4% classification accuracy.

5.1.2 ACO + Particle Swarm Optimization (PSO)

PSO's velocity and position update mechanisms help in optimizing pheromone trail updates in continuous spaces.

- Application: Continuous function optimization, VRP
- Result: Hybrid ACO-PSO achieved faster convergence than standalone algorithms [2].

5.1.3 ACO + Simulated Annealing (SA)

SA helps ACO escape local minima by allowing probabilistic worsening moves. Used in combinatorial scheduling problems.

- Application: Job shop scheduling
- Benefit: Enhances global search capabilities in rugged fitness landscapes [3].

5.1.4 ACO + Local Search (LS)

Adding local search algorithms such as 2-opt or Tabu Search improves final solution quality after each iteration.

- Application: TSP, image segmentation
- Result: ACO-LS hybrid improves convergence accuracy significantly [4].

5.2 Machine Learning-Enhanced ACO

Recent works integrate ACO with supervised learning and reinforcement learning techniques:

5.2.1 ACO + Reinforcement Learning (RL)

RL guides ants with learned value functions or policies. For example, ACO-DQN-TP (2025) uses Deep Q-Networks to adapt UAV routes dynamically in uncertain environments [5].

- Performance: Path length reduced by 65–79% over traditional baselines.

5.2.2 ACO + Neural Networks (NN)

ACO is used for hyperparameter tuning or feature selection in deep learning models like CNNs.

- Example: HDL-ACO (2025) tuned a CNN for OCT image classification, outperforming VGG-16 and ResNet-50 [6].

5.2.3 DeepACO and Meta-Learned ACO

Recent trends include meta-learning ACO heuristics using deep neural networks (e.g., DeepACO), where ants learn to build solutions across problem instances.

- Trend: A single model generalizing across TSP-like problems [23]

5.3 Quantum-Classical ACO (QACO)

As quantum computing becomes more practical, ACO is being re-imagined for Noisy Intermediate-Scale Quantum (NISQ) devices. Quantum-enhanced ACO leverages quantum parallelism and probabilistic sampling.

- Application: Clustering, TSP, constrained optimization
- Example: QACO-NISQ by Qiu et al. (2024) showed resilience to hardware noise and improved optimization fidelity [24].

Table 5. Emerging Trends in ACO Research

Trend	Description
Dynamic & Online ACO	Algorithms that adapt to changing environments in real-time, e.g., traffic, WSNs, logistics
Multi-Objective ACO (MOACO)	Solving problems with conflicting objectives using Pareto fronts and preference-based selection
Energy-Aware ACO	Applications in green computing, smart cities, and IoT systems with energy constraints
Cloud & Fog Integration	ACO-based task allocation and scheduling in distributed cloud-fog-edge systems
Explainable ACO (XACO)	Interpretable swarm intelligence models for AI governance and fairness
Hyper-Heuristics	Frameworks that learn to select or generate heuristics (e.g., meta-ACO)

5.4 Challenges in Hybrid and Future ACO Models

While hybrid and advanced ACO models have shown encouraging advancements, they continue to encounter several key challenges:

- The complexity of parameter tuning in hybrid configurations
- Higher computational overhead due to the integration of multiple algorithms
- Scalability limitations when applied to real-time or large-scale data environments
- Absence of strong theoretical guarantees for convergence in many hybrid variants

These limitations highlight the need for further research in adaptive ACO approaches, coordination of metaheuristic techniques[25], and the development of intelligent systems capable of operating in real-time also presented in table 5 above.

6 Conclusion and Future Research Directions

Although Ant Colony Optimization (ACO) has achieved considerable success across many fields, it still faces some important challenges—particularly regarding its ability to scale, adapt in real-time, and maintain strong theoretical foundations. This section identifies those limitations and suggests future research directions to help advance the ACO framework. Over the years, ACO has transformed from a simple bio-inspired routing method into a versatile metaheuristic system applicable to areas like combinatorial problems, robotics, image processing, bioinformatics, and smart technologies. This study has categorized various ACO variants, evaluated their use across multiple domains, and analyzed hybrid approaches and innovations such as quantum-inspired and explainable ACO models. Going forward, the effectiveness of ACO will rely heavily on how well it handles dynamic, complex, and multi-objective environments, while also offering better scalability, interpretability, and generalization. Future progress in self-adaptive algorithms, learning-driven exploration, and cloud-quantum integration will be crucial in building next-generation ACO systems with higher intelligence and flexibility.

References

[1] L. Goel and A. Mishra, "A Survey Of Recent Deep Learning Algorithms Used In Smart Farming," in 2022 IEEE Region 10 Symposium (TENSYMP), IEEE, Jul. 2022, pp. 1–6. doi: 10.1109/TENSYMP54529.2022.9864477.

[2] A. Mishra and L. Goel, "An ocean water current-inspired Geoscience based optimization algorithm," International Journal of Information Technology, vol. 16, no. 4, pp. 2619–2633, Apr. 2024, doi: 10.1007/s41870-023-01683-z.

[3] C.-L. Liu, "Ontological subscription and blocking system that alleviates information overload in social blogs," Knowl Based Syst, vol. 63, pp. 33–45, Jun. 2014, doi: 10.1016/j.knosys.2014.03.005.

[4] M. Kong and P. Tian, "Application of ACO in Continuous Domain," 2006, pp. 126–135. doi: 10.1007/11881223_17.

[5] T. Stützle and H. H. Hoos, "– Ant System," Future Generation Computer Systems, vol. 16, no. 8, pp. 889–914, Jun. 2000, doi: 10.1016/S0167-739X(00)00043-1.

[6] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 26, no. 1, pp. 29–41, Feb. 1996, doi: 10.1109/3477.484436.

[7] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," Theor Comput Sci, vol. 344, no. 2–3, pp. 243–278, Nov. 2005, doi: 10.1016/j.tcs.2005.05.020.

[8] M. Singh, S. Ayuub, A. Baronia, and D. Soni, "Analysis and Implementation of Disease Detection in Leafs and Fruit Using Image Processing and Machine Learning," SN Comput Sci, vol. 4, no. 5, p. 627, Aug. 2023, doi: 10.1007/s42979-023-02045-z.

[9] S. S. Sarkar, M. Dabra, S. Jain, I. Channa, and R. Sharda, "Predicting Evapotranspiration (ETo) by Training Regression Models," in 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), IEEE, May 2022, pp. 621–626. doi: 10.1109/GlobConET53749.2022.9872347.

[10] L. Goel, S. C. Ramola, and A. Mishra, "A Hybrid Approach with L-SHADE and OWCO: Towards a Faster Convergence Metaheuristic," International Journal of Information Technology, Jul. 2025, doi: 10.1007/s41870-025-02625-7.

[11] H. Vishwakarma, S. Gupta, A. Baronia, S. Kumar, G. Naik, and M. Kumar, "Analysis and Data Exploration of Dynamic Formula 1 Using the Ergast API Machine Learning," 2024, pp. 343–364. doi: 10.4018/979-8-3693-6303-4.ch014.

[12] A. Baronia, J. Sarup, S. Gupta, R. Shanker, K. Chourasia, and D. Soni, "Multi-scale Based Approach for Crater Detection on Lunar Surface using Clustering algorithm," Procedia Comput Sci, vol. 235, pp. 1145–1156, 2024, doi: 10.1016/j.procs.2024.04.109.

[13] S. Kumar, J. Sen Yadav, Y. Kurmi, and A. Baronia, "An efficient image denoising approach to remove random valued impulse noise by truncating data inside sliding window," in 2nd International Conference on Data, Engineering and Applications (IDEA), IEEE, Feb. 2020, pp. 1–7. doi: 10.1109/IDEA49133.2020.9170689.

[14] U. K. Lilhore et al., "Hybrid DRL-Enhanced ACO-WWO for Efficient Resource Allocation and Load-Balancing in Cloud Computing," International Journal of Computational Intelligence Systems, vol. 18, no. 1, p. 148, Jun. 2025, doi: 10.1007/s44196-025-00882-9.

[15] L. Goel and A. Mishra, "A Survey Of Recent Deep Learning Algorithms Used In Smart Farming," in 2022 IEEE Region 10 Symposium (TENSYMP), IEEE, Jul. 2022, pp. 1–6. doi: 10.1109/TENSYMP54529.2022.9864477.

[16] A. Mishra and L. Goel, "Metaheuristic Algorithms in Smart Farming: An Analytical Survey," IETE Technical Review, vol. 41, no. 1, pp. 46–65, Jan. 2024, doi: 10.1080/02564602.2023.2219226.

[17] Y. Joshi, R. Kumar, and A. Mishra, "DCT: Coefficient Replacement Steganography Analysis," 2025, pp. 239–253. doi: 10.1007/978-981-97-7946-8_18.

[18] A. Mishra and L. Goel, "Computational Intelligence in Smart Farming: Vision and Trials," 2025, pp. 75–86. doi: 10.1007/978-981-97-9006-7_7.

[19] A. Mishra and L. Goel, "A Natural Way to Stability: A New Evolutionary Algorithm Based on Ocean Water Currents," 2024, pp. 241–256. doi: 10.1007/978-3-031-71388-0_20.

[20] A. Mishra and L. Goel, "Geo Science-Based Optimization Algorithms: A New Paradigm," 2023, pp. 565–573. doi: 10.1007/978-981-99-2100-3_44.
[21] A. Mishra and L. Goel, "Optimizing Artificial Neural Network for Demography Based Crop Recommendation: An Ocean Water Current Inspired Approach in Precision Agriculture," International Journal of Information Technology, Nov. 2024, doi: 10.1007/s41870-024-02253-7.
[22] S. S. Sarkar, J. Bedi, and S. Jain, "A deep learning based framework for enhanced reference evapotranspiration estimation: evaluating accuracy and forecasting strategies," Sci Rep, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-99713-2.
[23] C. Blum, "Ant colony optimization: Introduction and recent trends," Phys Life Rev, vol. 2, no. 4, pp. 353–373, Dec. 2005, doi: 10.1016/j.plrev.2005.10.001.
[24] S. Nemati, M. E. Basiri, N. Ghasem-Aghaee, and M. H. Aghdam, "A novel ACO–GA hybrid algorithm for feature selection in protein function prediction," Expert Syst Appl, vol. 36, no. 10, pp. 12086–12094, Dec. 2009, doi: 10.1016/j.eswa.2009.04.023.
[25] J. Khudair Madhloom, H. N. Abd Ali, H. A. Hasan, O. A. Hassen, and S. M. Darwish, "A Quantum-Inspired Ant Colony Optimization Approach for Exploring Routing Gateways in Mobile Ad Hoc Networks," Electronics (Basel), vol. 12, no. 5, p. 1171, Feb. 2023, doi: 10.3390/electronics12051171.