

**REVIEW ARTICLE** 



# State-of-the-Art Advances and Emerging Challenges in UAV Routing Optimization: A Comprehensive Review

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### **Abstract**

This literature review offers an in-depth overview of recent advances in routing optimization for Unmanned Aerial Vehicles (UAVs), a field central to improving the performance, reliability, and flexibility of UAV systems. The review is organized into five categories: (1) multi-objective mission planning, (2) algorithmic design and optimization techniques, (3) energy efficiency and resource allocation, (4) communication protocols and network management, and (5) context-specific applications and environmental adaptability. The review highlights methodological progress and algorithmic approaches developed to balance competing demands such as mission energy use, and communication effectiveness, stability. Emphasis is placed on techniques that aim to extend UAV network longevity through effective energy strategies and on the creation of robust communication frameworks to support dependable data exchange. The study also considers how routing methods are being adapted to accommodate dynamic operational environments and varying external conditions. By drawing together insights from these areas, the review provides a comprehensive perspective on the current state of UAV routing optimization and identifies pressing challenges and directions for future research, with a focus on developing more adaptive and intelligent routing solutions.

**Keywords**: unmanned aerial vehicle, routing optimization, multi-objective mission planning, energy efficiency, communication protocols, environmental adaptation.

### 1 Introduction

In the rapidly evolving landscape of Unmanned Aerial Vehicle (UAV) technology, the optimization of routing strategies has emerged as a critical area of research. With the advent of the low-altitude economy—a



**Submitted:** 30 May 2025 **Accepted:** 18 July 2025 **Published:** 31 July 2025

Vol. 1, No. 1, 2025.

6 10.62762/TSSR.2025.423261

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### Citation

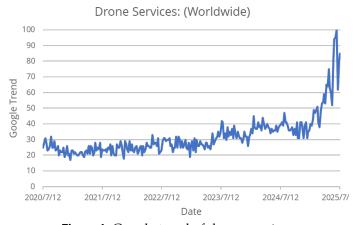
Gao, K., Qu, J., Zhang, G., Zhang, W., Liu, B., Gao, Y., & Wu, D. (2025). State-of-the-Art Advances and Emerging Challenges in UAV Routing Optimization: A Comprehensive Review. *ICCK Transactions on Systems Safety and Reliability*, 1(1), 43–62.



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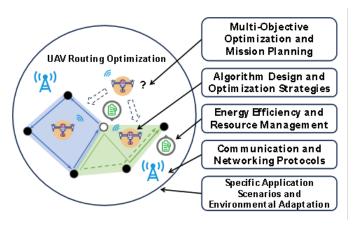
burgeoning sector driven by the integration of development of the low-altitude economy. UAVs into commercial, logistics, emergency response, environmental monitoring, and urban air mobility applications—the need for efficient and intelligent UAV routing has become more urgent than ever.

According to the drone services market data from Fortune Business Insights, the global drone services market was valued at USD 24.12 billion in 2024 and is projected to reach USD 32.08 billion in 2025. Figure 1 presents the Google Trends data on drone-related topics, showing a slow increase over the past five years with an accelerated growth in the past year. We also searched the Web of Science database and identified 2,423 related publications based on relevant topic searches, of which 1,784 (73.6%) were published after 2020. Considering market size data, user-level search trends, and research output, UAV Routing Optimization stands out as a significant topic, warranting a comprehensive review of its recent developments.



**Figure 1.** Google trend of drone services.

The intricate interplay between UAV dynamics, mission objectives, regulatory requirements, airspace traffic, and environmental constraints necessitates a sophisticated approach to routing that ensures operational efficiency, safety, reliability, This literature review aims to adaptability |31|. provide a structured analysis of the existing body of work in UAV routing optimization, dissecting the multifaceted challenges faced by this rapidly It explores a wide range of advancing field. innovative solutions proposed by researchers worldwide, spanning classical algorithmic approaches, metaheuristics, and emerging AI-driven methods. Through this synthesis, the review contributes to a clearer understanding of the state-of-the-art and helps identify key directions for future research within the broader context of supporting the sustainable



**Figure 2.** Five categories: An illustration.

Consistent with the [43] and [44], the review is systematically organized into five thematic categories, each addressing a specific aspect of UAV routing optimization (see Figure 2 for an illustration). Specifically, all reviewed literature are classified into five categories corresponding to the strategic, tactical, operational, technical, and practical levels. Each classification, its corresponding level, and key focus are summarized in Table 1.

The first category, multi-objective optimization and mission planning, delves into the complex task of balancing multiple objectives such as time efficiency, energy conservation, and mission success within the context of UAV swarms and various operational The second category, algorithm design scenarios. and optimization strategies, demonstrates the diverse array of algorithms and heuristics developed to tackle the routing challenges, drawing inspiration from nature and computational intelligence. *Energy* efficiency and resource management, the third category, focuses on the critical issue of conserving energy and managing resources, particularly in the context of data collection and transmission in UAV networks. The fourth category, communication and networking protocols, examines the design and enhancement of communication protocols that underpin the reliable and efficient data exchange in UAV networks. Lastly, specific application scenarios and environmental adaptation, the fifth category, explores the tailored routing strategies for specialized operational contexts, such as disaster monitoring and military operations, and the environmental factors that significantly impact routing decisions.

We also understand that there may be overlaps among the five categories. For example, some studies may involve both multi-objective optimization and practical



applications, meaning they could fall under both Category 1 and Category 5. To clarify this, we provide Table A1 in the appendix, which shows the multiple categories associated with each paper and identifies its primary category. We also include Table A2 to illustrate how the classification would change if Category 5 were merged into Categories 1–4. In addition, we provide Table A3 to review the various performance metrics used in different studies, and Table A4 to review the types of algorithms employed across the literature.

This comprehensive review not only synthesizes the current state of knowledge but also identifies gaps and potential future directions in UAV routing optimization. By examining the collective efforts of researchers in these distinct yet interconnected areas, this review aims to contribute to the ongoing discourse and inspire further advancements in the field. The novelty and contributions are summarized as follows:

- 1. Comprehensive approach: This paper diverges from the typical focus on isolated components of UAV systems found in existing reviews, instead adopting a holistic approach to analyze the system in its entirety. This broad perspective facilitates a nuanced understanding of the intricate interdependencies and complexities that are crucial for maintaining robust and resilient UAV networks.
- 2. Cutting-edge research and industry insights: By focusing on the latest publications in the past years, this review captures the most recent research findings and industry practices. This contemporary focus ensures that the insights provided are current and reflective of the evolving landscape of UAV operations, as well as the new challenges and opportunities in urban transit.

3. Identification of knowledge gaps: The paper provides actionable recommendations for future research to address the identified limitations and enhance the body of knowledge in UAV routing optimization. The findings serve as a valuable resource for researchers and offer practical guidance for UAV operators and policymakers, contributing to the enhancement of UAV system performance, resilience, and the development of sustainable urban transportation solutions.

The remainder of this paper is structured as follows. Section 2 reviews existing works. Section 3 summarizes knowledge gaps. Section 4 concludes.

### 2 Existing Literature on Routing Optimization of UAVs

To provide a comprehensive and structured overview of the UAV routing optimization field, it is essential to categorize the vast array of research into distinct yet interrelated themes. This approach not only clarifies the unique challenges and objectives addressed by each category but also highlights the synergies between them, fostering a holistic understanding of the field. The following sections are meticulously organized to reflect the multifaceted nature of UAV routing optimization:

Multi-objective optimization and mission planning: This category is fundamental as it tackles the intricate task of harmonizing multiple, often competing, objectives within UAV operations. The research here aims to develop sophisticated strategies that not only ensure mission success but also optimize for efficiency, energy conservation, and risk management. By addressing the complexity of balancing these objectives, this category contributes to the operational efficiency and adaptability of UAV networks.

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Category	Level	Focus
Multi-objective Optimization and Mission Planning	Strategic	Sets the overall UAV mission framework and high-level goals from a global, long-term perspective
Algorithm Design and Optimization Strategies	Tactical	Selects or develops specific methods to achieve strategic goals; represents tactical planning
Energy Efficiency and Resource Management	Operational	Focuses on endurance and resource scheduling during routine UAV flights; an operational level
Communication and Networking Protocols	Technical	Provides the data-link and networking support that ensures reliable and efficient UAV networking
Specific Application Scenarios and Environmental Adaptation	Practical	Tailors solutions to real-world use cases, handling environment-specific adaptations

**Table 1.** Mapping between category and levels.

Algorithm design and optimization strategies: The development of advanced algorithms is a cornerstone of UAV routing optimization. This category focuses on creating and refining computational methods that can effectively tackle the intricate routing problems inherent to UAV networks. The algorithms and heuristics developed in this area are designed to enhance decision-making processes, reduce computational time, and improve the overall performance of UAV systems.

Energy efficiency and resource management: Given the energy constraints of UAVs, this category is dedicated to the critical issue of energy conservation and resource allocation. Research in this area seeks to prolong the operational lifespan of UAV networks by minimizing energy consumption and optimizing resource usage. The findings contribute to the sustainability and cost-effectiveness of UAV operations, which are essential for their widespread adoption.

Communication and networking protocols: Effective communication is vital for the coordination and data exchange within UAV networks. This category addresses the development of robust and efficient communication protocols that can withstand the dynamic and often unpredictable nature of UAV environments. The research here ensures that UAVs can reliably transmit and receive information, which is crucial for their safe and effective operation.

Specific application scenarios and environmental adaptation: UAVs are employed in a diverse range of applications, each with unique operational contexts and environmental challenges. This category explores tailored routing strategies that can adapt to specific scenarios, such as search and rescue, agricultural monitoring, or urban surveillance. The research in this area enhances the versatility and resilience of UAV networks, ensuring they can effectively respond to a variety of real-world demands.

Organizing the literature along these thematic lines helps clarify distinct research trajectories while also highlighting their interrelated nature. Each theme represents an essential aspect of the broader UAV routing optimization landscape, and together they form a foundation for advancing UAV networks that are efficient, robust, and responsive to diverse operational demands and environmental contexts. Now we present the review on each category in turn.

## 2.1 Multi-Objective Optimization and Mission Planning

This research category focuses on the complex challenge of optimizing UAV routing to balance multiple objectives such as time efficiency, energy conservation, and mission success [22, 49]. [9] made a notable contribution to sustainable UAV operations by proposing a multi-objective green routing problem aimed at minimizing both operational costs and environmental impact. Notwithstanding its contribution, the study is constrained by assumptions regarding environmental metrics and the feasibility of implementing the proposed solution in real-world applications. [51] developed a methodology for cooperative route planning among multiple UAVs to facilitate fine-resolution 3D building model reconstruction. This work is particularly valuable for domains such as urban planning, architecture, and disaster management, where detailed 3D representations are essential. Yet its reliance on precise sensor data and the inherent coordination complexity among UAVs may limit its scalability and robustness in dynamic environments.

More recently, [2] introduced an innovative approach that synergistically optimizes topology control and routing for UAV swarms in crowd surveillance tasks. While the approach is forward-looking and impactful, its applicability may be limited by the assumption of predictable crowd dynamics and relatively stable environmental conditions. addressed reconnaissance missions through a multi-objective orienteering problem that incorporates time-dependent rewards and multiple connection points. A notable merit of this study is its attempt to balance mission efficiency with resource consumption. However, the intricate nature of the model poses significant challenges for real-time application, especially in rapidly changing operational contexts. [38] employed a hybrid optimization approach for routing and scheduling in UAV-assisted delivery systems, targeting improvements in efficiency and While this work advances practical delivery applications, its assumptions regarding the operational environment may narrow its relevance across varied real-world conditions.

Subsequently, [30] enriched the field by proposing a bi-objective routing framework for UAVs operating in continuous space, effectively addressing trade-offs between competing mission goals. Despite the model's sophistication, its computational intensity could hinder real-world deployment, particularly in

resource-constrained settings. Finally, [15] tackled post-disaster humanitarian logistics by developing algorithms for two-echelon vehicle and UAV routing problems. Their work makes a significant impact on disaster response by improving resource allocation and delivery strategies. Yet, its reliance on specific disaster scenarios and assumptions about data availability may constrain its generalizability to broader disaster contexts.

In the similar vein, [11] proposed a multi-stage control strategy for IoT-enabled unmanned vehicle detection, [12] performed spatiotemporal resilience analysis of IoT-enabled unmanned system-of-systems, and [13] developed an IoUT-enhanced cooperative control scheme for AUVs—collectively advancing autonomous coordination while highlighting practical deployment and communication challenges.

Overall, the methodological approaches in this field can be grouped into three broad categories: first, formal multi-objective optimization frameworks mathematical programming employ graph-theoretic models under largely assumptions to balance efficiency, cost, environmental impact; second, application-driven strategies—such as cooperative route planning or hybrid scheduling—tailored to specific contexts like 3D reconstruction, last-mile delivery, or crowd surveillance, which prioritize practical feasibility and domain relevance; and third, integrated dynamic systems approaches that embed routing within larger frameworks-such as swarm topology control or two-tier disaster relief logistics—to enhance real-time responsiveness and robustness under uncertainty. While the first two categories offer high theoretical precision and targeted performance, they often suffer from computational complexity or strong environmental assumptions that limit large-scale deployment; the third category better reflects operational realities but lacks a unified evaluation framework and cross-scenario generalizability. Moving forward, establishing a common simulationor agent-based benchmarking platform would enable systematic comparisons of these methods across diverse operational conditions, thereby guiding both algorithm selection and real-world implementation.

### 2.2 Algorithm Design and Optimization Strategies

This research category encompasses a diverse array of studies that propose and dissect novel algorithms and heuristics for UAV routing, drawing inspiration from the natural world and other computational

strategies [19]. [29] addressed the multi-UAV routing challenge under distance constraints, with a particular emphasis on forest fire detection. By utilizing a metaheuristic that combines simulated annealing and local search, the study aimed to refine routing optimization. However, the computational complexity of the proposed algorithm may pose challenges for real-time applications due to its resource-intensive nature.

More recently, [6] explored dynamic UAV routing amid fluctuating time windows—a critical capability for emergency response, surveillance, and logistics. While this approach delivers flexibility, it rests on assumptions about environmental stability and mission homogeneity that may not hold across all UAV applications. Meanwhile, [4] introduced a bio-inspired routing algorithm for UAV-assisted vehicular delay-tolerant networks in urban environments. Although this method enhances data delivery, its reliance on specific urban traffic patterns calls for broader empirical validation. [18] then contributed LB-OPAR, a load-balanced, optimized, predictive, and adaptive protocol for cooperative UAV networks. A notable strength of this work is its dynamic routing adjustments, yet its efficacy hinges on the precision of predictive models—a vulnerability in highly unpredictable settings.

Recently, [3] proposed an intelligent routing approach for UAV-IoT networks based on blockchain technology, aiming to bolster the security and reliability of data transmission. This work marks a significant step towards integrating UAVs with IoT systems. However, the complexity and resource demands of implementing blockchain in resource-constrained UAV environments may present scalability and performance challenges. [40] contributed to the field by proposing an adaptive large neighborhood search algorithm to optimize UAV routing with recharging, which could enhance the operational range and efficiency However, the study's limitations may involve the assumptions made about the recharging infrastructure and the adaptability of the algorithm to different operational environments. [14] presented BMUDF, a hybrid bio-inspired model for fault-aware By employing Destination-aware UAV routing. Fan-shaped clustering, the model enhances the resilience of UAV networks against faults. The model's applicability may be limited by its reliance on specific clustering techniques, which may not be universally effective across all UAV network types or fault

scenarios. [39] developed an opportunistic routing strategy for UAVs in emergency communication, constrained by considerations of connectivity and collision. This research bolsters the robustness of emergency communication networks in disaster scenarios. However, the strategy's effectiveness may be contingent on specific environmental conditions and the predictability of UAV movements, which may not always align with real emergency situations.

[41] proposed a reinforcement learning-based cluster routing scheme for multi-UAV networks, featuring dynamic path planning. This work contributes to the evolution of UAV network routing by incorporating adaptive learning techniques. The computational complexity and resource demands of implementing reinforcement learning algorithms may present challenges, particularly in resource-constrained UAV systems. [37] introduced the K-means online-learning routing protocol (K-MORP) for UAV adhoc networks, designed to enhance routing efficiency through an adaptive learning mechanism. The protocol's performance may be influenced by the initial K-means clustering, which could be a limiting factor if the initial assumptions do not accurately reflect the network's actual conditions.

Another key tactical concern in UAV routing is safety, which may involve both unintentional and intentional attacks, such as communication failures and cyberattacks. [20] addressed UAV communication failures by using deep reinforcement learning to maintain reliable backhaul links under node failures, ensuring end-to-end connectivity despite hardware faults or attacks. [25] adapt an adaptive routing algorithms called shuffled frog leaping algorithm to improve resilience by dynamically adjusting UAV paths based on energy, latency, and network changes.

[50] reviewed a wide range of cyberattacks targeting UAV routing and coordination, including spoofing, jamming, ADS-B manipulation, and TCAS-induced collisions, along with corresponding defense mechanisms and future mitigation strategies. Meanwhile, [21] constructed a deep learning-based intrusion detection system and offered promising solutions for enhancing UAV routing security under adversarial threats.

Across these studies, three overarching methodological strands emerge: first, heuristic and metaheuristic frameworks—often combining techniques like simulated annealing, local search, or large-neighborhood search—that excel at refining

static routing under defined constraints (e.g., distance limits or scheduled recharging) but tend to be computationally intensive and sensitive to infrastructure assumptions; second, bio-inspired and graph-theoretic heuristics (including clustering and opportunistic link selection) tailored to specific domains such as urban data delivery, fault-aware networks, or emergency communications—these methods offer lightweight, context-driven solutions yet may struggle with generalizability beyond their target scenarios; and third, adaptive and learning-based protocols—ranging from predictive load-balanced routing to reinforcement learning and online K-means clustering—that promise real-time responsiveness and resilience in dynamic IoT or multi-UAV swarm environments but incur significant resource demands and hinge on the fidelity of environmental or traffic models. Collectively, the trade-offs among computational cost, domain specificity, and adaptability underscore the need for a unified benchmarking framework to systematically evaluate each approach's performance across varied operational settings.

### 2.3 Energy Efficiency and Resource Management

This research category centers on the critical challenge of optimizing energy use and resource allocation in UAV networks, particularly for data collection and transmission. Notwithstanding its valuable insights, [42] proposed a routing strategy that accounts for weather variability and battery constraints, yet its reliability may be undermined by inaccuracies in forecast models and simplified assumptions about energy consumption patterns. Meanwhile, [24] designed an energy-efficient routing protocol for UAV-assisted Wireless Sensor Networks, which strategically orchestrates data gathering to prolong network lifespan; however, its real-world applicability hinges on the specific performance characteristics of sensors and UAV platforms, which can vary significantly across deployments.

More recently, [17] introduced a federated learning framework with mobile aggregators, employing a block-coordinate-descent algorithm to jointly optimize energy expenditure and model accuracy—a notable merit, although its effectiveness depends on stable connectivity and may degrade under network volatility. Furthermore, [8] devised the CEHEAT framework that integrates cognitive IoT with autonomous aerial computing to boost energy efficiency, convergence speed, and scalability in smart

healthcare systems; yet, its real-time performance could be challenged by the overhead of heterogeneous device integration and onboard processing demands. Collectively, these studies underscore both the promise and practical hurdles of energy-aware UAV networking, emphasizing the need for robust forecasting methods, realistic hardware benchmarks, and adaptive algorithmic solutions to achieve sustainable, large-scale deployments.

Across these studies, three primary methodological paradigms emerge in energy-aware UAV networking. The first leverages environment-informed routing models that incorporate exogenous factors—such as weather forecasts and battery constraints—to mission reliability, yet they remain susceptible to forecasting errors and simplified consumption assumptions. The second employs protocol-level optimizations within static sensor strategically tailoring flight paths to minimize energy expenditure during data collection, although their real-world efficacy depends heavily on the heterogeneous performance of sensors and UAV hardware. The third integrates computational frameworks—ranging from federated learning with mobile aggregators cognitive-IoT-enabled aerial computing—to jointly balance energy use and system objectives like model accuracy or responsiveness; these approaches promise dynamic adaptability and scalability, they introduce complexity in connectivity requirements and onboard processing Methodologically, the contrast lies in the trade-offs between model fidelity versus operational robustness, hardware-specific tuning versus algorithmic generality, and static optimization versus real-time adaptability—underscoring the need for unified benchmarks that can systematically evaluate energy-efficiency strategies across varied UAV platforms and application scenarios.

### 2.4 Communication and Networking Protocols

This research category is devoted to the meticulous design and enhancement of communication protocols for UAV networks, with a focus on ensuring efficient and reliable data transmission. Notwithstanding its urban focus, [28] introduced an intelligent routing protocol that leverages UAV assistance within VANETs to bolster connectivity and reduce delays in cityscapes—yet its real-world deployment may be hampered by the challenges of integrating aerial nodes into existing infrastructure and managing

the added network complexity. Meanwhile, [7] proposed GeoUAVs, a geocast protocol tailored for expansive UAV fleets, which is particularly relevant for disaster response, surveillance, and military missions; however, the fleet's dynamic topology and the necessity for robust adaptation mechanisms raise practical implementation concerns.

In a similar vein, [1] enhanced mmWave-based wireless networks by incorporating UAVs into routing decisions, offering substantial gains in high-frequency, short-range performance—but the integration with legacy network infrastructures and the continual adaptation to UAV mobility patterns remain open issues. Furthermore, [33] devised a Geographic Position-based Hopless Opportunistic Routing approach to streamline UAV communication; although it promises greater efficiency, its underlying assumptions about flight dynamics and environmental stability may not fully capture field realities. Concurrently, [5] optimized UAV placement and routing based on traffic patterns to improve throughput, yet the unpredictability of live traffic and ever-changing aerial conditions could undermine the accuracy of its predictive models. Moreover, [26] advanced a data-driven planning model for UAV-IoT routing that harnesses analytics for decision-making; still, its reliance on consistent data availability and ideal operational scenarios may limit transferability to diverse IoT deployments.

More recently, [36] provided a comprehensive survey of AI-enabled UAV routing protocols, thereby mapping emerging trends and challenges—although, as a review, it does not contribute novel empirical findings. Building on this, [27] tackled FANET interference by combining power control with routing optimization to boost throughput, yet its success hinges on precise topology awareness and agile adaptation to UAV movement. Finally, [48] developed an optimal routing and scheduling framework for UAV delivery services that can markedly enhance efficiency and reduce transit times; nonetheless, the assumptions underpinning typical delivery scenarios and the framework's scalability in complex, large-scale operations warrant further scrutiny.

Across these studies, three broad methodological themes emerge in the pursuit of robust UAV communication protocols. The first involves the seamless integration of aerial nodes into existing network infrastructures—be it urban vehicular networks or mmWave systems—where the primary

challenge lies in maintaining connectivity and low latency despite dynamic UAV mobility, yet practical deployment is often constrained by added complexity and legacy compatibility issues. second theme centers on domain-specific routing heuristics—ranging from geocast strategies for large UAV fleets to geographic or opportunistic forwarding schemes—that excel at tailoring data dissemination to mission requirements (e.g., disaster relief or surveillance) but may struggle with generalization when faced with unpredictable topology changes or environmental variability. The third thread leverages data-driven and AI-enabled frameworks, including traffic-aware placement, interference-aware power control, and even federated survey syntheses, which promise adaptive, throughput-optimized performance; however, these approaches frequently hinge on accurate real-time analytics, comprehensive topology knowledge, and scalable processing capabilities. Collectively, the trade-offs among integration complexity, scenario specificity, and algorithmic adaptability underscore the pressing need for unified evaluation platforms to systematically benchmark protocol performance across diverse UAV networking scenarios.

# 2.5 Specific Application Scenarios and Environmental Adaptation

This category of research delves into the nuanced realm of UAV routing, examining specific operational contexts such as disaster monitoring and military operations, and the environmental factors that influence routing strategies. Notably, [23] made a valuable contribution to the field by addressing the problem of UAV route planning for aerial photography in the presence of interval uncertainties; however, the study's assumptions about the nature of those uncertainties and the robustness of the proposed approach in handling a wide range of real-world scenarios may limit its general applicability. Meanwhile, [46] presented a solution approach for the location and routing problem specific to UAVs, which is crucial for enhancing operational efficiency and mission effectiveness; yet the assumptions made about the operational environment and the scalability of the solution to different types of UAV missions could pose challenges.

Subsequently, [52] conducted a comprehensive investigation into the optimal strategies for UAVs engaged in both visiting and transportation tasks, thereby significantly contributing methods to enhance

mission efficiency; nonetheless, its applicability may be restricted by its assumptions about operational conditions, which may not be universally valid in diverse real-world scenarios. In a follow-up, [53] and [47] explored optimal UAV mission execution strategies—particularly for tasks involving target engagement—while considering the defense range of targets and the potential for mission aborts or successful strikes; still, those insights may be constrained by assumptions regarding the predictability of target defense parameters. Furthermore, [34] shifted focus to multi-objective routing optimization for mobile charging vehicles that support UAV power supply, advancing the development of efficient charging strategies to ensure uninterrupted operations; however, its assumptions about charging vehicle mobility patterns and UAV power consumption may not fully capture variability in real-world settings.

More recently, [35] tackled the challenge of multi-UAV routing to maximize surveillance data collection while managing idleness and latency constraints, offering a routing strategy that balances UAV activity with data-collection efficiency; but its assumptions about the surveillance environment and UAV behavior may not hold in more dynamic or complex operations. Likewise, [32] contributed an adaptive conflict-resolution strategy for multi-UAV 4D route optimization using a stochastic fractal search algorithm, which is important for improving safety and efficiency in crowded airspaces; yet the computational complexity and scalability of the algorithm remain open issues for larger fleets. Finally, [45] presented a method for discrete space-based route planning for rotary-wing UAV formations in urban environments—a pivotal advancement for surveillance, emergency response, and logistics—although its assumptions about urban structures and UAV behavior may not fully encompass the dynamic nature of real-world cities. Similarly, [16] introduced a neural network-based heuristic for routing UAVs in landslide monitoring scenarios, addressing a team orienteering problem with mandatory visits to specific locations; however, reliance on neural networks could demand substantial computational resources, potentially limiting feasibility in environments with constrained processing capabilities.

The reviewed studies collectively reveal a spectrum of methodological approaches tailored to distinct UAV mission profiles and environmental complexities.



On one end, deterministic and robust optimization techniques address interval uncertainties and static location-routing requirements, delivering precise plans for tasks like aerial imaging but relying heavily on simplifying assumptions that may not hold under real-world variability. Moving beyond single-vehicle scenarios, multi-objective formulations and mobile-charging strategies integrate power logistics with mission routing to support sustained operations, though they introduce dependency on charging infrastructure patterns and consume significant computational resources. In high-stakes contexts—such as surveillance over expansive or congested airspaces—adaptive conflict-resolution and discrete-space planning methods emphasize safety and coverage, yet often grapple with algorithmic complexity and scalability when fleet sizes or environmental dynamics grow. Finally, data-driven and learning-based heuristics (including neural and fractal-search models) promise real-time adaptability and resilience against unforeseen conditions, even as their performance hinges on reliable data inputs and onboard processing capacity. These contrasts underscore a fundamental trade-off between model fidelity and operational robustness, highlighting the need for cross-scenario benchmarks that can systematically evaluate each approach's scalability, adaptability, and resource demands.

### 3 Research Gaps

After reviewing the literature in five different (but related) fields, we have identified some research gaps and hope to inspire more cutting-edge research in this direction. We have summarized the gaps in each field in Figure 3. Interested readers can refer to the detailed descriptions of each gap from left to right. Additionally, we use different colors to categorize the various types of gaps: green boxes represent gaps related to environmental factors, gray boxes indicate gaps related to data, yellow boxes signify gaps related to machine learning, and uncolored boxes denote gaps related to extensions within a specific subfield.

# 3.1 Multi-Objective Optimization and Mission Planning

Research gaps in multi-objective optimization and mission planning for UAVs:

• Environmental metrics and sustainability: There is a gap in the comprehensive understanding and integration of various environmental metrics into UAV mission

- planning. Future research should explore a broader range of sustainability indicators and their impact on UAV operations.
- Operational environment assumptions: Previous assumptions about the operational environment may limit the generalizability of their findings. Research should consider a wider range of environmental conditions and constraints to enhance the applicability of routing and scheduling solutions.
- Predictability of dynamic environments: The unpredictability of crowd dynamics poses a significant challenge. Future studies should focus on adaptive algorithms that can respond to dynamic changes in the operational environment.
- Computational resources and efficiency: The computational complexity may be a barrier for practical use. There is a gap in developing computationally efficient algorithms that can balance multiple objectives without excessive resource consumption.
- Adaptive learning and machine learning: There is a potential for leveraging machine learning and adaptive learning techniques to improve UAV routing and mission planning. Research in this area could lead to more intelligent UAV systems capable of autonomously optimizing their operations based on past experiences and real-time data.
- Model complexity and practical implementation: The complexity of the model may hinder its practical application. There is a need for simplified models that can be effectively implemented in real-world UAV operations.
- **Disaster response logistics**: The generalizability of their algorithms to different disaster scenarios is uncertain. Future research should aim to develop more flexible and adaptable routing solutions that can be applied to various disaster contexts.
- Integration with other systems: There is a gap in research on how UAV routing and mission planning can be integrated with other systems, such as ground-based logistics, communication networks, and emergency response infrastructure. Future studies should explore interdisciplinary approaches to enhance the overall efficiency and effectiveness of UAV operations in complex environments.

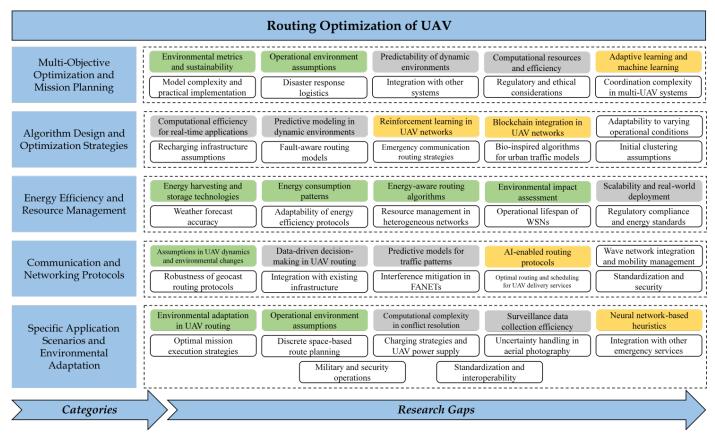


Figure 3. Categories and research gaps in routing optimization of UAVs.

- Regulatory and ethical considerations: With the
  increasing use of UAVs in various applications,
  there is a need for research that addresses
  the regulatory and ethical implications of UAV
  operations. This includes privacy concerns, safety
  regulations, and the ethical use of UAVs in
  sensitive areas.
- Coordination complexity in multi-UAV systems: The complexity of coordinating multiple UAVs remains a challenge. Research is needed to develop more efficient algorithms for real-time coordination and communication among UAVs in various mission scenarios.

These research gaps highlight the need for continued innovation and exploration in the field of UAV routing and mission planning to address the challenges posed by dynamic environments, computational demands, and the integration of UAVs into broader systems.

# **3.2** Algorithm Design and Optimization Strategies Research gaps in algorithm design and optimization

strategies for UAV routing:

• Computational efficiency for real-time applications: The computational complexity may limit its real-time application. There is a need for

- more efficient algorithms that can provide quick solutions without compromising optimization quality.
- Predictive modeling in dynamic environments: The effectiveness relies on accurate predictive models. There is a gap in developing robust predictive models that can handle the unpredictability of UAV operational environments.
- Reinforcement learning in UAV networks: The computational complexity and resource demands may be challenging for UAV systems. There is a need for lightweight reinforcement learning algorithms suitable for UAV networks.
- Blockchain integration in UAV networks: The complexity and resource demands may challenge its scalability. Research is needed to optimize blockchain integration for resource-constrained UAV systems.
- Adaptability to varying operational conditions: The adaptability of the routing strategy to different UAV missions and conditions requires further investigation. Research should explore algorithms that can dynamically adjust to



changes in operational environments and mission requirements.

- Recharging infrastructure assumptions: The assumptions about recharging infrastructure may not hold in all scenarios. Further research should consider diverse recharging infrastructures and their impact on routing optimization.
- Fault-aware routing models: The reliance on specific clustering techniques may limit its universal effectiveness. There is a gap in developing fault-aware routing models that can adapt to various network types and fault scenarios.
- Emergency communication routing strategies:
   The effectiveness depends on environmental conditions and UAV movement predictability.

   Research should focus on strategies that can operate effectively in unpredictable emergency situations.
- Bio-inspired algorithms for urban traffic models: The specificity to certain urban traffic models may limit its broader applicability. Future research should aim to validate and adapt these algorithms to various urban scenarios.
- **Initial clustering assumptions**: The performance may be influenced by the initial K-means clustering. Research should explore methods to improve the accuracy of initial clustering or develop adaptive clustering mechanisms.

These research gaps highlight the need for further development of efficient, adaptive, and fault-tolerant algorithms for UAV routing. The integration of advanced computational techniques, such as machine learning and bio-inspired models, with practical considerations of UAV operations is essential for addressing these challenges.

### 3.3 Energy Efficiency and Resource Management

Research gaps in energy efficiency and resource management for UAV networks:

• Energy harvesting and storage technologies: As UAVs and WSNs become more energy-efficient, the integration of energy harvesting technologies (e.g., solar, wind) and advanced energy storage solutions could further enhance their operational capabilities. Research in this area could lead to more sustainable and self-sufficient UAV networks.

- Energy consumption patterns: A need for a deeper understanding of energy consumption patterns in UAVs. Future research should focus on developing more precise models of energy usage to optimize routing strategies for various UAV missions.
- Energy-aware routing algorithms: There is a need for the development of energy-aware routing algorithms that can dynamically adjust to the energy levels of UAVs and sensors. These algorithms should consider the trade-offs between energy conservation and mission objectives, such as data collection frequency and transmission quality.
- Environmental impact assessment: While energy efficiency is crucial, the overall environmental impact of UAV operations, including emissions and noise pollution, should also be considered. Research should evaluate the environmental footprint of UAV networks and develop strategies to minimize their impact.
- Scalability and real-world deployment: The scalability of energy efficiency protocols to larger networks and their real-world deployment is a significant research gap. Studies should focus on the practical challenges of implementing energy-efficient strategies in diverse and complex operational environments.
- Weather forecast accuracy: The accuracy of weather forecasts and their integration into UAV routing algorithms is an area that requires further research to improve the reliability of UAV operations in dynamic weather conditions.
- Adaptability of energy efficiency protocols: The adaptability of previous protocols to different sensor and UAV capabilities is a research gap. Studies should explore how to tailor energy efficiency strategies to the specific characteristics of the UAV-WSN system.
- Resource management in heterogeneous networks: UAV networks often operate in conjunction with other systems, such as IoT devices and traditional communication networks. Research is needed to develop resource management strategies that consider the heterogeneity of these systems and optimize energy usage across the entire network.
- Operational lifespan of WSNs: There is a

gap in understanding how different operational scenarios, such as varying sensor densities and UAV flight paths, impact the overall energy efficiency and lifespan of the network.

• Regulatory compliance and energy standards: As UAV technology advances, there is a need for research that addresses the regulatory compliance and development of energy standards for UAV operations. This includes understanding the implications of energy regulations on UAV design and operation.

Addressing these research gaps will be essential for the development of energy-efficient UAV networks that can operate effectively and sustainably in various applications, from logistics and surveillance to environmental monitoring and disaster response.

### 3.4 Communication and Networking Protocols

Research gaps in communication and networking protocols for UAV networks:

- Assumptions in UAV dynamics and environmental changes: The assumptions made may not fully capture real-world complexities. Research is needed to develop protocols that can adapt to the unpredictability of UAV dynamics and environmental conditions.
- Data-driven decision-making in UAV routing: The assumptions regarding operational conditions and data availability need to be validated against real-world IoT environments to ensure the effectiveness of data-driven routing strategies.
- Predictive models for traffic patterns: The unpredictability of real-time traffic poses a challenge. There is a gap in developing more accurate predictive models for traffic patterns in dynamic aerial environments.
- AI-enabled routing protocols: There is a need for original research that explores the integration of AI and machine learning techniques into UAV communication protocols to enhance decision-making and adaptability.
- Wave network integration and mobility management: The practical integration and mobility management of UAVs in these networks present significant challenges. Future work should explore strategies for effective UAV integration and mobility control.

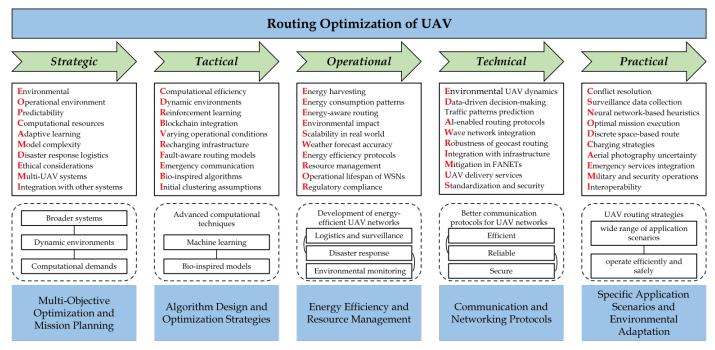
- Robustness of geocast routing protocols: The practical implementation challenges, such as adapting to the dynamic nature of UAV fleets, need to be addressed. Research should focus on developing more robust geocast protocols that can handle the variability of UAV operations.
- Integration with existing infrastructure: The challenge of integrating UAVs into existing VANET infrastructures and managing increased network complexity requires further research to ensure seamless and efficient operation.
- Interference mitigation in FANETs: The effectiveness depends on accurate network topology knowledge. Research should focus on developing adaptive strategies that can manage interference in the dynamic UAV environment.
- Optimal routing and scheduling for UAV delivery services: The scalability of the solution to real-world complexities is a concern. Future research should address the scalability and adaptability of routing and scheduling frameworks to various delivery scenarios.
- Standardization and security: There is a need for research on standardizing communication protocols for UAV networks and ensuring their security. This includes developing protocols that can resist potential cyber threats and ensuring the integrity and confidentiality of data transmission.

Addressing these research gaps will help in the development of more efficient, reliable, and secure communication protocols for UAV networks, enabling their effective deployment in various applications and environments.

# 3.5 Specific Application Scenarios and Environmental Adaptation

Research gaps in specific application scenarios and environmental adaptation for UAV routing:

- Environmental adaptation in UAV routing: There is a need for research that focuses on developing UAV routing strategies that can adapt to various environmental factors, such as weather conditions, terrain features, and potential hazards.
- Operational environment assumptions: The scalability of the approach to various missions and environments is a research gap. Studies should explore the adaptability of routing strategies to different operational contexts.



**Figure 4.** Guiding trajectory for future research.

- Computational complexity in conflict resolution: The computational complexity and scalability of the algorithm to larger UAV fleets and complex scenarios require further investigation.
- Surveillance data collection efficiency: The study's assumptions about the surveillance environment and UAV behavior need to be validated in more dynamic or complex settings.
- Neural network-based heuristics: The reliance on neural networks and computational resources should be addressed, especially for operational environments with limited capabilities.
- Optimal mission execution strategies: Research is needed to validate these strategies across diverse operational conditions and to develop methods for handling unpredictable scenarios.
- **Discrete space-based route planning**: The assumptions about urban structures and UAV behavior should be tested against the dynamic nature of real-world urban environments.
- Charging strategies and UAV power supply: The assumptions about charging vehicle mobility and UAV power consumption should be tested against real-world variability.
- Uncertainty handling in aerial photography:
   Further research is needed to develop more robust approaches that can handle a broader range of

uncertainties and real-world scenarios.

- Integration with other emergency services: UAV routing strategies for disaster monitoring and response should be integrated with other emergency services and infrastructure to enhance overall operational efficiency and effectiveness.
- Military and security operations: Specific research is needed to develop routing strategies for UAVs in military and security contexts, considering the unique challenges and requirements of these operations, such as stealth, electronic warfare, and mission-specific objectives.
- Standardization and interoperability: There is a gap in research on standardizing UAV routing strategies across different applications and environments to ensure interoperability and ease of integration with existing systems.

The research gaps and potential works for all five categories are summarized in Figure 4. Addressing these research gaps will enable the development of more effective and adaptable UAV routing strategies for a wide range of application scenarios, ensuring that UAVs can operate efficiently and safely in diverse and challenging environments.

### 4 Conclusions

This comprehensive review examines the current advance of UAV routing strategies, with particular attention to application-specific scenarios and environmental adaptability, set against the backdrop of the emerging low-altitude economy. As UAVs become increasingly integrated into domains such as logistics, surveillance, environmental monitoring, and emergency response, optimizing their routing capabilities is critical to unlocking the full potential of this expanding sector. By analyzing recent advancements in multi-objective optimization, algorithm development, communication protocols, and energy and resource management, this review identifies both progress and persistent gaps in literature.

Recent studies have proposed various methods to address competing objectives in UAV routing, including mission success, energy conservation, and time efficiency. However, many of these approaches remain constrained by assumptions about environmental conditions, algorithmic complexity, or limited real-world validation. Although heuristic and bio-inspired algorithms have shown promise, their computational demands and scalability challenges hinder practical deployment. Similarly, while communication protocols have been developed to enhance data transmission, concerns remain regarding their adaptability and security in complex settings. Energy optimization and resource management continue to be essential topics, particularly in the context of extending UAV autonomy, yet robust solutions remain limited. Finally, routing strategies tailored to specific applications—such as disaster response or urban monitoring—demonstrate potential but require further development to handle uncertainty and dynamic operational conditions. Collectively, these findings underscore the need for more adaptable, efficient, and secure routing solutions capable of supporting UAVs across diverse and evolving scenarios.

In summary, although UAV routing strategies have advanced considerably, significant research challenges remain. Future work should emphasize the design of flexible and intelligent algorithms capable of real-time adaptation, while also integrating insights from artificial intelligence, machine learning, and environmental science. As the low-altitude economy continues to grow, interdisciplinary approaches will be vital to driving innovation and addressing the complex demands of next-generation UAV applications.

### **Data Availability Statement**

Data will be made available on request.

### **Funding**

The work was supported by the National Natural Science Foundation of China under Grant 72001027, the Postdoctoral Foundation of China under Grant 2021M693331, and the Fundamental Research Funds for the Central Universities.

### **Conflicts of Interest**

The authors declare no conflicts of interest.

### **Ethical Approval and Consent to Participate**

Not applicable.

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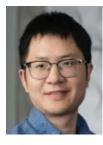
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### 5 Appendix

**Table A1.** Overlap and assignment of each reference.

Ref	Category 1	Category 2	Category 3	Category 4	Category 5
1	Category 1	\( \text{Category 2}	Category 5	✓ (Main)	✓
2	✓	√ (Main)		v (ividiti)	<b>~</b>
3	•	√ (1 <b>/1</b> aiii)		✓ (Main)	•
4		·		✓ (Main)	✓
5	✓ (Main)	·		√ (=:====)	·
6	√ (Main)	$\checkmark$		·	
7	(			✓ (Main)	
8	$\checkmark$		✓ (Main)	(	$\checkmark$
9	✓ (Main)		, ,		
10	√ (Main)				
11	√(Main)	$\checkmark$			$\checkmark$
12	√(Main)	$\checkmark$			
13	√(Main)	$\checkmark$			$\checkmark$
14	√(Main)	$\checkmark$			$\checkmark$
15	√(Main)	$\checkmark$		$\checkmark$	$\checkmark$
16		✓ (Main)	$\checkmark$	$\checkmark$	
17	$\checkmark$	$\checkmark$			✓ (Main)
18		√ (Main)			$\checkmark$
19		$\checkmark$	✓ (Main)	<b>√</b>	
20		$\checkmark$		✓ (Main)	
21	✓ (Main)				
22		√ (Main)		$\checkmark$	<b>√</b>
23	(35.)	√(Main)			<b>√</b>
24	✓ (Main)	(0.6.)			✓
25	$\checkmark$	✓ (Main)	( ( ) ( ) ( )	,	
26		(/Main)	√ (Main)	<b>√</b>	,
27	,	√(Main)	✓	✓	(Main)
28	<b>√</b>	,		( (Main)	✓ (Main)
29		✓		✓ (Main)	
30 31		(Main)		✓ (Main)	✓
32	√ (Main)	✓ (Main)			•
33	✓ (Main)	✓			
34	√ (ividiii) √	√ (Main)			
35	•	(ividiri)		✓ (Main)	
36	✓ (Main)		✓	(1/14111)	
37	√ (Main)	$\checkmark$	·		$\checkmark$
38	()	· ✓		✓ (Main)	·
39		√		√ (Main)	
40	$\checkmark$	✓ (Main)		` /	
41		, ,		$\checkmark$	✓ (Main)
42		√ (Main)	$\checkmark$		, ,
43		✓ (Main)		$\checkmark$	
44	$\checkmark$		$\checkmark$		√ (Main)
45			$\checkmark$	√ (main)	$\checkmark$
46	√(Main)	$\checkmark$			
47		$\checkmark$			✓ (Main)
48		✓ (Main)			$\checkmark$
49	✓ (Main)				$\checkmark$
50	✓ (Main)	$\checkmark$			
51	✓ (Main)				
52				√ (main)	<b>√</b>
53		✓			✓ (Main)
54	✓ (Main)	✓			
_55	√ (Main)				

**Table A2.** Mergence of category 5.

Ref	Category 1	Category 2	Category 3	Category 4	Category 5
1	0 7	<b>√</b>	0 7	√ (Main)	Merge into 4
2	$\checkmark$	√ (Main)			Merge into 2
4		✓ `		√ (Main)	Merge into 4
8	$\checkmark$		√ (Main)		Merge into 3
11	√(Main)	$\checkmark$			Merge into 1
13	√(Main)	$\checkmark$			Merge into 1
14	√(Main)	$\checkmark$			Merge into 1
15	√(Main)	$\checkmark$		$\checkmark$	Merge into 1
17	√ (Main)	$\checkmark$			Merge into 1
18		√ (Main)			Merge into 2
22		√(Main)		$\checkmark$	Merge into 2
23		√(Main)			Merge into 2
24	√ (Main)				Merge into 1
27		√(Main)	$\checkmark$	$\checkmark$	Merge into 2
28	√ (Main)				Merge into 1
31		✓ (Main)			Merge into 2
37	√ (Main)	$\checkmark$			Merge into 1
41				√(Main)	Merge into 4
44	√(Main)		$\checkmark$		Merge into 1
45			✓	√ (main)	Merge into 4
47		√(Main)			Merge into 2
48		√ (Main)			Merge into 2
49	√ (Main)				Merge into 1
52				√(main)	Merge into 4
53		✓ (Main)			Merge into 2



**Table A3.** Summary of evaluation metrics.

1 2		consumption	ntime	Throughput	Delivery Ratio	Coverage	Operational Cost	Completion Quality	Security & Others
7	<b>√</b>			✓	,	,			
3	$\checkmark$	$\checkmark$			$\checkmark$	$\checkmark$			$\checkmark$
4	✓				✓				V
5	•			✓	√	$\checkmark$			
6									$\checkmark$
7	$\checkmark$	,	,	$\checkmark$	$\checkmark$	,			
8 9		$\checkmark$	$\checkmark$			✓	,		
10							<b>√</b>	$\checkmark$	
11		$\checkmark$					·	· ✓	
12							$\checkmark$		
13								$\checkmark$	
14					,	$\checkmark$		$\checkmark$	
15 16	$\checkmark$	./		./	<b>√</b>			✓	
17	V	V		V	V		✓	$\checkmark$	
18							·	√	
19		$\checkmark$	$\checkmark$						
20			$\checkmark$	$\checkmark$	$\checkmark$				
21						/	$\checkmark$	/	
22 23						✓		✓	./
24							✓		•
25								$\checkmark$	
26		$\checkmark$			$\checkmark$				
27	$\checkmark$	$\checkmark$				,			$\checkmark$
28 29				<b>√</b>		✓	✓		
30	✓			V	$\checkmark$	$\checkmark$			
31			$\checkmark$		·	•			
32							$\checkmark$	$\checkmark$	
33	,						<b>√</b>		
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38									$\checkmark$
39	✓			$\checkmark$	$\checkmark$				
40	$\checkmark$						✓	/	
41 42			$\checkmark$			<b>√</b>	✓	<b>√</b>	
43	✓		•		$\checkmark$	$\checkmark$	•		
44		$\checkmark$				•	$\checkmark$		
45			$\checkmark$	$\checkmark$	$\checkmark$			$\checkmark$	
46	,							$\checkmark$	
47 48	$\checkmark$							(	
48 49							$\checkmark$	✓	
50							✓		
51							$\checkmark$		
52									$\checkmark$
53 E4			$\checkmark$				/	$\checkmark$	
54 55							<b>v</b>	./	



**Table A4.** Summary of algorithm adopted.

Ref	Greedy Algorithms	Divide and Conquer Algorithms	Dynamic Programming Algorithms	Backtracking Algorithms	Heuristic Algorithms	Machine Learning Algorithms
					<b>√</b>	
					$\checkmark$	
					$\checkmark$	
					$\checkmark$	
					$\checkmark$	
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)	$\checkmark$		$\checkmark$		$\checkmark$	
1			•			$\checkmark$
2					$\checkmark$	·
3			$\checkmark$		<b>↓</b>	
4			V		<b>√</b>	./
5					<b>√</b>	<b>√</b> ✓
	/					V
5	$\checkmark$				<b>√</b>	
7			$\checkmark$		<b>√</b>	,
8					$\checkmark$	$\checkmark$
9					$\checkmark$	$\checkmark$
0			$\checkmark$		<b>√</b>	
1					$\checkmark$	
2						$\checkmark$
3						$\checkmark$
4					$\checkmark$	
5					$\checkmark$	
6					$\checkmark$	
7					$\checkmark$	
8						$\checkmark$
9	$\checkmark$				$\checkmark$	
0					√	
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<i>)</i>					<b>√</b>	
6 7			/		V	
			$\checkmark$			/
8 9						<b>√</b>
					<b>√</b>	✓
0					<b>√</b>	
1					<b>√</b>	
2					<b>√</b>	,
3					✓	$\checkmark$
4					$\checkmark$	
5						
6						
7					$\checkmark$	
3					$\checkmark$	
9					$\checkmark$	
0					$\checkmark$	
1			$\checkmark$			
2						
3					$\checkmark$	
4					<b>√</b>	
-					•	