OPTIMIZATION APPROACH TO MULTI-DRONE PATH PLANNING

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Amit Das

Examination Roll Number:M4ETC24010

Registration Number: 160218 of 2021-22

Under the Guidance of

Dr. Pratyusha Rakshit

Department of Electronics and Telecommunication Engineering Faculty of Engineering and Technology
JADAVPUR UNIVERSITY KOLKATA–700032

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Faculty of Engineering and Technology

JADAVPUR UNIVERSITY

Kolkata-700032

Certificate of Recommendation

This is to certify that **Mr. Amit Das (002210702012)** has completed his dissertation entitled, "**OPTIMIZATION APPROACH TO MULTI-DRONE PATH PLANNIG**", under the direct supervision of **Dr. Pratyusha Rakshit**, Department of Electronics and Telecommunication Engineering, Jadavpur University. We are satisfied with her work, which is being presented for the partial fulfilment of the degree of **Master of Engineering** in **Electronics and Telecommunication Engineering** of Jadavpur University, Kolkata-700032.

.....

Dr. Pratyusha Rakshit

Assistant Professor,
Electronics and Telecommunication Engineering Department,
Jadavpur University, Kolkata-700032

....

Prof. Sudhabindu Ray

Head of the Department,
Electronics and Telecommunication Engineering Department, Jadavpur University, Kolkata-700032

Prof. Dipak Laha

Dean,
Faculty of Engineering & Technology
Jadavpur University, Kolkata-700032

Faculty of Engineering and Technology

JADAVPUR UNIVERSITY

Kolkata-700032

Certificate of Approval

The foregoing thesis entitled "**Optimization Approach to Multi-Drone Path Planning**" is hereby approved as a creditable study of an Engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as a pre-requisite to the degree of Master of Engineering in Electronics and Telecommunication Engineering for which it has been submitted. It is understood that, by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed, or conclusion therein but approve this thesis only for the purpose for which it is submitted.

Final Examination for Evaluation of the Thesis

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Declaration of Originality

I hereby declare that this thesis contains a literature survey and original research work by the undersigned candidate, as part of her Master of Engineering in Electronics and Telecommunication Engineering curriculum. All information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name: Amit Das

Examination Roll No.:M4ETC24010

Thesis Title: Optimization Approach to Multi-Drone Path Planning

Signature with Date:

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Amit Das

Jadavpur University,

Kolkata – 700032

ABSTRACT

This paper proposes a novel multi-objective optimization (MOO) approach to cooperative path-planning of multiple unmanned aerial vehicles (UAVs). The cooperative multi-UAV path-planning problem is formulated in a MOO framework to determine optimal trajectories from the given source to the destination, while avoiding collision with obstacles, teammates, and mountains. To address this challenge, a Firefly Algorithm with Non-dominated Sorting (FANS) is developed, offering a robust solution to the MOO problem by facilitating rapid convergence of solutions to the optimal Pareto Front.

This makes it particularly suitable for tackling real-world MOO problems. Comprehensive experiments undertaken with diverse workspaces reveal the superiority of the proposed algorithm over its state-of-the-art contenders in the present context. These experiments demonstrate not only the efficiency of the FANS algorithm in achieving optimal path-planning but also its adaptability to varying environmental complexities, highlighting its potential for practical applications in UAV navigation.

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	List of Abbreviation
DE	Differential Evolution
UAVs	Unmanned Aerial Vehicles
MOO	Multi Objective Optimization
FANS	Firefly Algorithm with Non-dominated Sorting
ACO	Ant Colony Optimization
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
GIS	Geographic Information Systems
TSP	traveling salesman problem
CR	crossover rate

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Chapter 1

Introduction

1.1 History and Background

Unmanned aerial vehicles (UAV) have become highly sought after for their roles in ecological surveillance, military maneuvers, search and recovery operation and border monitoring owing to their cost effectiveness and superior capabilities [1]-[3]. The cooperative multi-UAV path planning stands as a formidable challenge within the UAV domain for researchers. Researchers have carried out extensive practical research on UAV applications in various settings [4], [5]. Its primarily aims is to determine an optimal flight path from start to goal position, devoid of collision with fellow UAVs or environmental constraints, all while adhering to UAV kinematics constraints to ensure the viability of planned route. Researches on multi-UAV path-planning can be primarily categorized into three groups, including a) traditional/classical approach [6], b) heuristic approach [7] and soft computing approach [8]. Traditional path-planning algorithms mainly include the artificial potential field, simulate anneal arithmetic and visibility graph [9]-[11]. These algorithms employ deterministic mathematical models to navigate environments enhancing robustness at the cost of flexibility and target inaccessibility in dynamic scenarios. Heuristic path planning algorithms relying on segmented maps consist of well-established methods like Dijkstra algorithm, A* algorithm, RRT algorithm, and *artificial potential field* (APF) algorithm [12]-[14]. Such algorithms usually exhibit a strong path search capability with a good real time performance. But the disadvantages are that the size of the robot itself is ignored in actual motion process yielding high time complexity and unsuitable for big data calculations. On the other hand, intelligent/soft computing algorithms utilize environmental data and self-location to dynamically plan paths in real time. These include that *ant colony optimization* (ACO), *genetic algorithm* (GA), *differential evolutionary* (DE), *particle swarm*

optimization (PSO), *artificial bee colony* (ABC) to name a few [15]-[18]. Till date, these algorithms envisage as the most promising path-planners offering flexibility and adaptability to uncertain or changing condition.

1.2 Disaster Management

Unmanned Aerial Vehicles (UAVs) have become essential tools in disaster management due to their ability to collect data quickly and efficiently, deliver supplies, and assist rescue operations. Effective UAV path planning is critical to increasing the efficiency and effectiveness of these operations. Mission objectives, environmental factors, UAV capabilities, and operational constraints are all important considerations when planning UAV paths for disaster management. Mission objectives could include surveillance and assessment, delivery and support, or serving as communication relays. Terrain, weather conditions, and no-fly zones are all important environmental factors to consider. UAV capabilities such as range, endurance, payload capacity, and sensors are also required. Regulatory compliance, as well as safety and security, are examples of operational constraints.

To ensure effective UAV path planning, several strategies can be used. Pre-planning and simulation assist in determining feasibility and efficiency prior to deployment. Dynamic path planning enables real-time rerouting in response to changing conditions. Coordinating multiple UAVs allows for more efficient coverage of larger areas, while heuristic and optimization algorithms can handle complex scenarios. Integrating UAV operations with ground teams improves communication and decision-making.

Geographic Information Systems (GIS), remote sensing, autonomous systems, and robust communication networks all help to improve UAV capabilities. UAVs, for example, can assess earthquake damage, monitor floods, and provide real-time data to aid in firefighting efforts. By taking these factors into account and implementing effective strategies, UAV path planning can significantly improve disaster management operations, resulting in more efficient and effective responses to natural and man-made disasters.

1.3 Role of UAV's in Disaster Management

Unmanned Aerial Vehicles (UAVs) have become indispensable in disaster management due to their versatility, speed, and efficiency. These drones can quickly reach disaster-affected areas, providing real-time aerial imagery and data to aid in assessing the extent of damage and identifying critical zones requiring immediate attention. UAVs are instrumental in search and rescue operations, as they can cover large areas more rapidly

than ground teams and access hard-to-reach locations, thus enhancing the chances of locating

and saving victims. They also play a crucial role in delivering essential supplies such as food, water, and medical aid to stranded individuals, particularly in areas where traditional transportation methods are hindered. Moreover, UAVs are equipped with sensors and advanced imaging technologies that can monitor environmental conditions, helping to predict secondary hazards like landslides or flooding. This capability allows for better planning and resource allocation, ultimately improving the overall response and recovery efforts during disasters. Additionally, UAVs can facilitate communication by setting up temporary networks in areas where infrastructure has been damaged, ensuring that coordination between different emergency response teams remains uninterrupted. The integration of artificial intelligence with UAVs also enables automated analysis of collected data, speeding up decision-making processes and increasing the efficiency of disaster management operations.

1. 4 Unmanned Aerial Vehicle (UAV) Path Planning

An unmanned aerial vehicle (UAV) is a pilotless aircraft that combines programming devices with radio remote control equipment. UAVs are classified into fixed-wing UAVs, rotary-wing UAVs, and fixed/rotary-wing hybrid UAVs based on their flight mechanisms. These aerial platforms can be remotely controlled by humans or pre-programmed to fly predetermined flight plans autonomously. UAVs vary significantly in size, configuration, and functional capabilities, representing a wide range of applications across multiple domains. This aircraft category includes fixed-wing, rotary-wing, and hybrid UAVs, each with unique flight mechanisms. Advancements in Internet and UAV-related technologies have contributed to the proliferation of UAVs, making them indispensable in modern society due to their flexibility, high mobility, simplicity, concealment, cost-effectiveness, and security attributes. Projections indicate that the UAV market will grow significantly, with a value of USD 38.3 billion by 2027 [19]. UAVs play critical roles in a variety of civil applications, including express transportation [20], traffic control [21], data acquisition [22], disaster rescue [23], and intelligent agriculture generation [24,25].

Furthermore, their implementation in the military domain for surveillance, reconnaissance, and tracking tasks demonstrates their versatility [26,27]. Some applications, such as rescue operations, disaster management, and data collection, rely heavily on UAV communication networks (UAVCNs) [28]. The dynamic nature of UAVs, enabled by their high mobility, allows for real-time trajectory adjustment to adapt to changing environmental conditions.

As a result, a systematic classification and summarization of UAV path-planning algorithms

is necessary. Path planning is critical for UAV operations because it takes into account physical flight capabilities, path security, tactical feasibility, real-time planning, and mission reliability. It entails determining a viable flight path from the origin to the destination that is tailored to the specific mission**.** Despite advances in AI, cloud computing, and big data technologies, UAV path planning remains a difficult cross-disciplinary challenge [29]. Existing research has attempted to divide UAV path-planning techniques into representative, collaborative, and non-collaborative approaches [30-31].

UAV path-planning algorithms are analyzed in detail. We innovatively study the generic path-planning algorithm at the algorithmic and functional levels. Path-planning algorithms are classified into three categories at the algorithmic level: traditional, intelligent, and hybrid. Path-planning algorithms are classified at the functional level into space-based, time-based, and task-based planning. The shortest path problem, traveling salesman problem (TSP), and area coverage problem are introduced. The specific classification is shown in **Figure 1**.

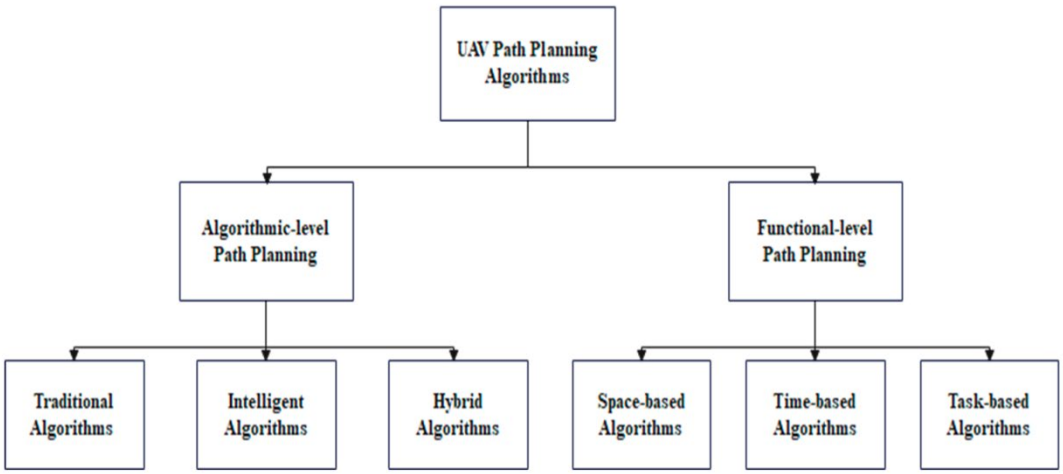


Figure 1. The Classification of UAV Path-Planning Algorithm.

1.4.1 Path-Planning Objectives

The study of UAV path planning is a dynamic and heavily scrutinized research area in academia. Exploiting UAV mobility provides opportunities for dynamic state optimization and alignment with the communication environment via strategic trajectory planning. The imperative of ensuring feasibility, safety, and optimality highlights the importance of thoroughly integrating environmental information. Simultaneously, attention to constraints such as navigation accuracy, fuel power

platform maneuverability, and arrival time becomes critical for mitigating potential threats and obstacles.

Within the UAV path-planning research context, the primary focus is on developing mathematical models that effectively articulate specific tasks, outline relevant constraints, and prescribe optimization methodologies. This procedural approach requires a comprehensive definition of the planning space, which includes factors such as the starting point, environmental terrain conditions, mission area, and potential airborne threats. The formulation of constraint conditions and the corresponding mathematical path-planning model are inextricably linked to task specifications and performance constraints. The sequential stages involve the careful selection or development of an appropriate search algorithm to systematically identify the best feasible path within the planning space while ensuring compliance with all prescribed conditions. The identified path is then refined and assessed rigorously, resulting in a definitive output.

1.4.2 Optimization Objective Function

The path planning of UAVs usually needs to build corresponding objective functions according to different task requirements or decision-maker preferences. Generally, flight time, flight distance, and threat cost are used as objective functions. The planning model can be a single target or multiple targets. References [32,33] used the minimum path length satisfying the reconnaissance coverage as the optimization objective function. A two-objective optimization model was constructed based on the maximum number of reconnaissance targets and the minimum sum of all UAV flight distances [34]. Reference [35] took the shortest residence time exposed to enemy radar monitoring range as the objective optimization function. The authors used minimizing path length and threat cost as objective optimization functions [36].

The specific optimization objective function can be expressed as follows:

$$min\ F=\sum_i \omega_i J_i \quad , \qquad (1)$$

where F is the optimization objective function; J_i is the ith cost; and ω_i is the according weight, $\sum_i \omega_i = 1$. When every cost is constructed into the individual target

and not weighted, the problem can be converted into a multi-target optimization problem.

By considering the path length cost, threat cost, and height cost, the total cost function can be expressed as follows:

$$J=\omega_1 L+\omega_2 T+\omega_3 H,\ \omega_1+\omega_2+\omega_3=1 \qquad (2)$$

where J is the total cost; L is the distance cost, which is also called the fuel cost in the literature [37]; T is the threat cost; H is the height cost; ω_1, ω_2, and ω_3 are the weights corresponding to different objective functions. Of course, other cost functions can also be

introduced as needed. For example, the literature [38] also presents the yaw angle in the cost function. It takes the comprehensive weighting of the yaw angle, path length, and threat cost as the objective function.

1.4.3 Function-Level UAV Path-Planning Classification

A comprehensive overview of generic algorithms for the subproblem of UAV path planning focusing on path and trajectory planning is provided. The subsequent discussion aims to classify existing path-planning algorithms at the functional level to build upon this foundation. This classification is based on three distinct perspectives: time-based planning, space-based planning, and mission-based planning. By examining UAV path planning from these alternative viewpoints, researchers can gain a nuanced understanding and make informed choices when selecting path-planning algorithms. **Figure2**. shows the classification of function-level path planning.

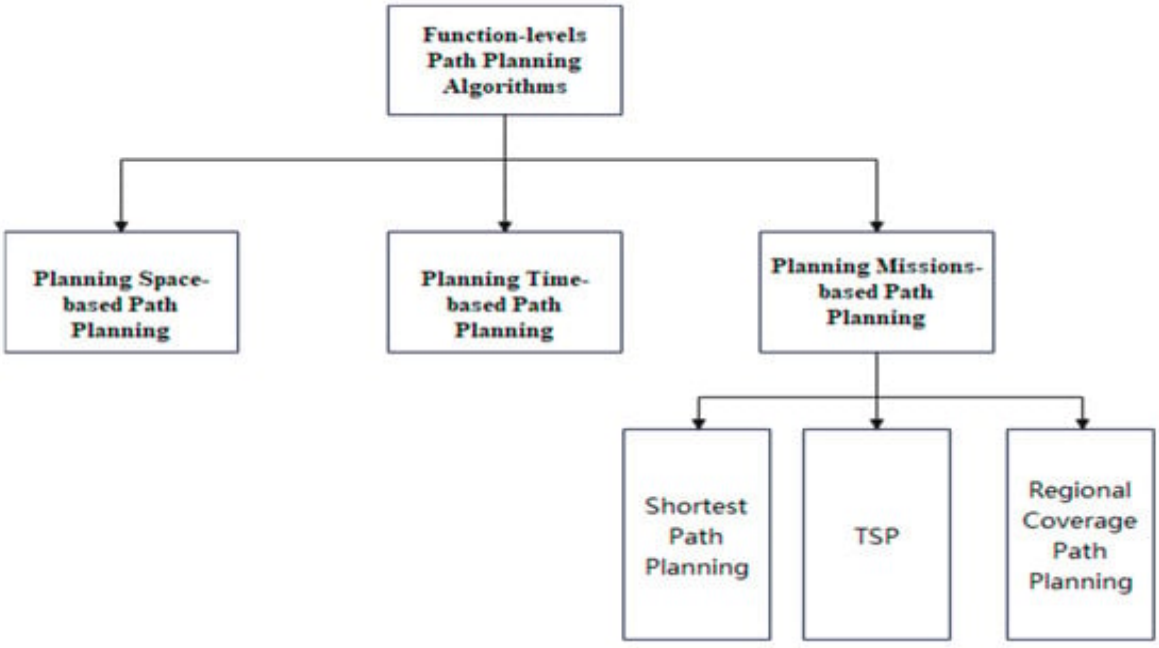


Figure 2. The Classification of Function-Level UAV Path-Planning Algorithms.

Planning time-based algorithms are analyzed and classified based on their temporal characteristics. This perspective considers how algorithms perform in terms of planning time, responsiveness, and adaptability to dynamic and time-sensitive environments. The goal is to understand how well algorithms address the temporal constraints inherent in UAV missions.

Space-based algorithms focus on the spatial aspects of path-planning algorithms. They delve into how algorithms handle the spatial intricacies of the environment, considering factors such as obstacles, terrain, and 3D space. Researchers can evaluate their efficacy in diverse operational backgrounds by categorizing algorithms based on spatial characteristics.

Missions-based algorithms are classified here based on their alignment with specific mission requirements. Different UAV missions may necessitate distinct path-planning approaches. This perspective evaluates how well algorithms cater to mission-specific objectives, whether they be area coverage, target visitation order, or optimization of mission parameters.

By adopting these functional classifications, researchers can gain insights into the strengths and limitations of path-planning algorithms from various angles. This multifaceted analysis enables a more nuanced understanding of how algorithms perform in different contexts and aids in selecting or developing algorithms that align with specific mission requirements.

1.5 Scope of Optimization in Unmanned Aerial Vehicle (UAV) Path Planning

Optimization in Unmanned Aerial Vehicle (UAV) path planning is a critical area of research and application, focusing on enhancing the efficiency, safety, and effectiveness of UAV operations. The primary goals include minimizing flight time, reducing energy consumption, and ensuring collision-free navigation. Techniques such as genetic algorithms, particle swarm optimization, and artificial neural networks are frequently employed to solve these complex problems. Additionally, path planning must consider dynamic environments, requiring real-time adaptability to obstacles and changes. Factors such as wind speed, terrain, and no-fly zones further complicate the optimization process. As UAVs are increasingly used in diverse fields like agriculture, surveillance, and delivery services, optimizing their flight paths becomes essential to maximize performance and reliability while minimizing operational costs and risks. The integration of advanced sensors and communication technologies also plays a vital role in achieving optimal path planning in UAVs.

1.6 Thesis Outline

In this thesis, **Chapter 1** includes the introduction to the Optimization Approach to Multi-Drone Path Planning. It discusses the multi-objective optimization (MOO) approach to cooperative path-planning of multiple unmanned aerial vehicles (UAVs).. It also contains the motivation for the thesis.

Chapter 2 provides the literature review about the different efforts and strategies developed optimization problem as well as reaching towards the Multi UAV Path Planning. It also briefs about different literary works done towards the advancement in the field of differential algorithms. In the last section, summary in brief is provided.

Chapter 3 discusses about the formulation of Multi UAV Path Planning in details. In this regard, the chapter presents the various factors which are important related to Differential Algorithms.

Chapter 4 contains the experimental results for Multi UAV Path Planning.

Chapter 5 concludes the contributions of the thesis and points out the scope of future work.

Chapter 2

LITERATURE SURVEY:

In the paper 'Autonomous UAV Path-Planning Optimization Using Metaheuristic Approach for Predisaster Assessment' proposed by Zakria Qadir [39], an in-depth exploration of metaheuristic algorithms for optimizing UAV path planning in disaster scenarios is presented. The study found that the DGBCO algorithm consistently outperformed other metaheuristic approaches such as PSO, GWO, WOA, and BMO. With a focus on collision-free path planning, DGBCO achieves remarkable efficiency, lowering transportation costs by 24.5% and computational times by 13.3%. These findings highlight the importance of DGBCO in improving UAV path planning across diverse environments, opening up new avenues for effective disaster management.

In the study "A Novel Hybrid Particle Swarm Optimization for Multi-UAV Cooperative Path Planning" proposed by Wenjian He, the HIPSO-MSOS algorithm is introduced for path planning in a 3D environment. This hybrid algorithm combines Improved Particle Swarm Optimization (IPSO) and Modified Social Spider Optimization (MSOS) to enhance exploration and exploitation. The HIPSO-MSOS algorithm outperforms traditional algorithms such as PSO, Firefly, DE, MSOS, and HSGWO-MSOS in terms of accuracy, convergence speed, stability, and robustness. By using a Time Stamp Segmentation (TSS) model, the HIPSO-MSOS algorithm generates feasible and effective paths for each UAV, ensuring superior performance in multi-UAV path planning tasks. [40]

Xiande Wu has proposed a novel hybrid PSO algorithm called SDPSO for UAV path planning, which significantly enhances the global optimal solution update strategy for more efficient path planning. The SDPSO algorithm incorporates the Metropolis Criterion as an acceptance policy, merging the simulated annealing algorithm to improve the update strategy of the global optimal solution in the PSO algorithm [41]. Each particle utilizes the beneficial information of the optimal solution through a dimensional learning strategy. As a result, SDPSO can quickly plan higher quality paths for UAVs and demonstrates better robustness in complex 3-D environments compared to other algorithms.

In a paper presented by Chao Zhang, Ziyang Zhen, Daobo Wang, Meng Li [42], The Ant Colony Optimization (ACO) algorithm is an effective approach to UAV path planning that optimizes routes based on threat intensity, distance, and yaw angle constraints. This method improves flight path planning within enemy threat regions. The ACO algorithm efficiently determines optimal paths between grid points, demonstrating its effectiveness while remaining simple to implement. Simulation results demonstrate the algorithm's ability to provide reliable optimization guidance for UAVs in grid-based regions. The ACO-based

UAV path planning method is not only efficient, but also easy to code, making it a viable solution for complex navigation scenarios. Furthermore, ACO's flexibility enables it to adapt to changing environments, reinforcing its role in UAV path planning.

Similarly, the improved Ant Colony Optimization (ACO) algorithm for UAV path planning significantly reduces the occurrence of local optima while improving overall performance [43]. The algorithm optimizes path length and adaptability by incorporating upper and lower pheromone limits, as well as multi-heuristic factors. While existing methods for UAV path planning have benefits and drawbacks, the improved ACO algorithm shows significant improvements. It eliminates local optima and achieves a path length that is 93.6% of the original algorithm's, with an optimal path length variance of only 14.22%. This demonstrates the improved algorithm's ability to reduce path length while increasing performance, making it a reliable solution for UAV path planning in complex environments.

One-by-one, a Multi-Colony Ant Colony Optimization (ACO) algorithm is presented in the paper by Ugur Cekmez and Mustafa Ozsiginan [44] for UAV path planning with obstacle avoidance. It is demonstrated that this approach yields more workable solutions when compared to the traditional single-colony ACO. Experiments show that the Multi-Colony ACO algorithm performs better when it comes to UAV path planning. The suggested model provides more efficient UAV navigational solutions than the traditional Ant Colony Optimization algorithm. To improve the algorithm's performance even more, future work will investigate parallel processing modes and run experiments with more colonies.

A paper presented by YongBo Chen and JianQiao Yu introduces an efficient path planning algorithm for multi-UAV formation in known environments. To optimize path planning, this method uses the artificial potential field method, which has been enhanced with an additional control force. The algorithm efficiently plans paths for multi-UAV formations, using the artificial potential field method in conjunction with an optimal control approach to calculate the additional control force. This enhancement greatly improves path planning, allowing UAVs to track formations with quadrotor helicopter PID controllers. The results show that the artificial potential field method with additional control force improves path planning while also ensuring effective formation tracking for UAVs.

In paper [45], LIU Xiao-feng, GUAN Zhi-wei , SONG Yu-qing, CHEN Da-shan ,The UAV route planning model for road segment surveillance leverages a multi-objective optimization approach, utilizing an evolutionary algorithm based on Pareto optimality to derive optimal solutions. This model specifically addresses the limitations posed by the maximum flight distance of UAVs. By considering the impact of varying road segment lengths on UAV route planning, the model effectively optimizes the cruise distance, achieving a reduction of 38.43%. Additionally, the number of UAVs required for surveillance operations is decreased by 33.33%, demonstrating the model's efficiency and effectiveness in resource utilization.

In 2013, Vincent Roberge, Mohammed Tarbouchi, and Gilles Labonté, talked about a new method to use the genetic algorithm (GA) and the particle swarm optimization algorithm (PSO). The comparison between Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for real-time UAV path planning demonstrates notable differences in performance. Both algorithms achieved real-time performance on standard multicore CPUs, with a quasi-linear speedup of 7.3 on 8 cores for both methods, indicating effective parallel implementation. However, GA consistently produced superior trajectories compared to PSO, with this superiority being statistically significant. These findings highlight that real-time UAV path planning is feasible using parallelized GA, which outperforms PSO in trajectory optimization [46].

In the year of 2005, Athina N. Brintaki and Ioannis K. Nikolos, In static maritime environments, differential evolution (DE) is used to plan UAV paths. It generates 2-D trajectories that take coordination [47], collision avoidance, and velocity distribution into account. Operating within constraints, this off-line path planner gives priority to coordinated navigation, avoiding collisions, and completing the mission. The DE framework is used to plan off-line paths by applying the principles of Evolutionary Algorithms (EA). The DE algorithm iterates until 10,000 cost function evaluations are reached with the following settings: a population of 50, a F parameter of 1.05, and a Cr parameter of 0.85. The DE algorithm works well at determining viable routes within given limitations, guaranteeing mission execution success and resolving navigational issues.

In the paper by Xing Zhang and Jie Chen [48], In paper presents a 3D online path planning algorithm for unmanned aerial vehicles (UAVs), designed to provide smooth flight routes using B-Spline curves to describe the UAV's path. The control points of these curves are optimized by an improved differential evolution (DE) algorithm, which is particularly effective in hostile environments. The algorithm enhances diversity, prevents local optima, and speeds up convergence through an improved von Neumann topology and an enhanced mutation operator. These improvements allow the DE algorithm to outperform its unimproved counterpart in UAV path planning. Additionally, a coding method combining coordinates is used to enhance searching efficiency in simulations. The improved DE algorithm ensures a more reliable and efficient path planning process, crucial for UAV operations in challenging conditions. The approach not only facilitates real-time adjustments but also maintains optimal performance, making it a robust solution for dynamic and unpredictable environments. For dynamic UAV path planning, an improved differential evolution (DE) algorithm is adopted to achieve optimal control. In this algorithm, a larger scaling factor (F) increases the search range but slows down the convergence rate. To address this, an adaptive scheme for setting the crossover rate (Cr) is utilized, balancing exploration and convergence efficiency.

In a paper presented by Xiaoning Zhu and Rui Yan [49], A new algorithm has been developed to optimize the route and sensing tasks of UAVs, aiming to minimize energy consumption, maximize sensing rewards, and ensure the delivery of goods. This innovative

algorithm combines routing and sensing tasks, converting the problem into a weighted routing challenge using the Bellman-Ford algorithm. It has been shown to outperform alternatives by over 18% in task reward. The approach has been validated through a real-world case study. To enhance dynamic path planning for UAVs, an improved Differential Evolution (DE) algorithm is utilized. This improved DE algorithm incorporates a larger scaling factor (F), which allows for a wider search range but results in a slower convergence rate. Additionally, an adaptive scheme for setting the crossover rate (Cr) is implemented to optimize the control of the UAV.

In the year of 2021, Xuzhao Chai, Zhishuai Zheng, Junming Xiao and Li Yan. The paper proposes a novel approach to UAV path planning in complex obstacle environments that combines Nash equilibrium methods with genetic algorithms [50]. This approach seeks to strike a balance between the algorithm's searchability and convergence, resulting in efficient path planning. Specifically, the Nash equilibrium method is used to strike a balance between these two critical aspects, improving the algorithm's performance in terms of convergence time, flight distance, and flight duration. The method is intended to facilitate effective path planning for multiple UAVs navigating complex environments. Furthermore, a multi-strategy fusion differential evolution algorithm (MSFDE) is presented, which incorporates multiple swarm strategies, novel adaptive strategies, and interactive variation strategies. This integration balances the algorithm's development and exploration capabilities, ensuring robust performance in diverse situations and challenging scenarios.

In the paper by Yanxiang Yang, Xiangyin Zhang, Bo Li, Kaiyu Qin, the paper presents a method for UAV swarm topology shaping that leverages the Grey Wolf optimizer to enhance energy efficiency. This approach involves the joint optimization of the mapping relationship and the shaping position for the UAV swarm, using a specialized model designed for topology shaping. The Grey Wolf optimizer algorithm is employed to solve this model, demonstrating superior convergence performance in shaping the UAV swarm's topology. By effectively balancing exploration and exploitation, the Grey Wolf optimizer ensures that the UAVs are positioned optimally. Simulation results indicate that the proposed method successfully maintains minimal global energy consumption, highlighting its effectiveness in optimizing energy efficiency within the swarm while ensuring robust and reliable performance [51].

In order to find collision-free and optimal paths, Abdurrahim Sonmez, Emre Kocyigit, and Emin Kugu presented a path planning algorithm for UAVs that uses a genetic algorithm [52]. Using OpenMP to maximize efficiency, this real-time path planner makes use of parallel processing on multi-core processors. The execution time is greatly shortened by the parallel implementation. The effectiveness of the genetic algorithm in path planning optimization is demonstrated by the proposed real-time path planner for UAVs, and its parallel processing capability ensures timely and effective operation. Moreover, the algorithm is a promising

solution for dynamic environments encountered in UAV missions due to its adaptability to real-time scenarios.

In the year of 2023[53], Hazha Saeed Yahia · Amin Salih Mohammed showed that Meta-heuristic algorithms are well known for their ability to solve complicated problems quickly, especially when it comes to unmanned aerial vehicle (UAV) path planning. This review looks at the use of heuristics in UAV path planning, concentrating on how well meta-heuristic algorithms address these issues. Through the use of meta-heuristic algorithms, UAV path planning can effectively tackle complex issues. The application of meta-heuristic algorithms to UAV path planning is examined in this review, which emphasizes the effectiveness of these algorithms in navigating challenging environments. It also explores the benefits and drawbacks of using meta-heuristic techniques for UAV path planning, offering suggestions for future development and practical implementation.

Further, SHENG-KAI HUANG and WEN-JUNE WANG presented A New Priority Order Based on the Generalized Voronoi Diagram For multi-robot navigation, a novel path planning technique called the Priority Order Navigation Algorithm (PONA) is proposed [54]. PONA uses the Generalized Voronoi Diagram (GVD) to facilitate effective and collision-free space travel. This method uses the GVD for effective collision-free navigation and introduces the Priority Order Navigation Algorithm to prioritize multi-robot path planning. Comparing the PONA algorithm to other techniques like SDA and ROA, the former shortens the trajectory by more than 10%. PONA ensures effective and collision-free multi-robot navigation by utilizing the GVD for both navigation point links and initial map establishment. This novel approach offers a workable solution for intricate navigation scenarios involving multiple robots, marking a substantial advancement in the field.

In 2018, Chao Yan and Xiaojia Xiang presented a novel learning algorithm for UAV path planning in hostile environments. This novel approach is based on an improved Q-learning algorithm, which includes an optimized reward function and an improved action selection strategy. The new learning algorithm uses these enhancements, as well as Q-function initialization strategies, to effectively guide UAVs through difficult scenarios. The methods used are an improved Q-learning algorithm with a new reward function, action selection, and Q-function initialization strategies. The improved method was shown to be more effective than the original, indicating that the proposed algorithm is both feasible and effective for UAV path planning. This advancement marks a significant improvement in UAV navigation capabilities, especially in hostile or complex environments [55].

In 2010[56], YongBao, Xiaowei Fu, and Xiaoguang Gao presented a method for fixed-point reconnaissance path planning for UAVs that employs Particle Swarm Optimization (PSO). This method optimizes target values to generate efficient paths for UAV reconnaissance missions. The method introduces PSO for optimal reconnaissance path planning and modifies the algorithm to improve its suitability for fixed-point reconnaissance. In addition to PSO,

other algorithms mentioned for context include dynamic programming, the A* algorithm, the ant colony algorithm, and the genetic algorithm. The PSO-based method produces satisfactory results in simulations of reconnaissance UAV path planning, demonstrating its effectiveness. The factors influencing UAV path planning are thoroughly examined, ensuring a complete understanding of the planning process.

In 2021, Yu Wu, Kin Huat Low, Bizhao Pang, and Qingyu Tan presented a paper on 4D path planning for drone operations in urban environments, proposing a swarm-based method to solve the optimization problem[57]. Drones have a variety of applications in urban areas, where flight safety and efficiency are critical. The method uses a swarm-based approach for 4D path planning, which includes a Clustering Improved Ant Colony Optimization (CIACO) algorithm and a Genetic Algorithm (GA)-based task scheduling algorithm. The CIACO algorithm outperforms traditional ACO and IACO algorithms by efficiently evaluating the quality of flight paths using a fitness function. This coordinated path planning approach is tailored for drones operating in urban environments. utilized the 'AirMatrix' concept to describe urban areas and flight rules. This novel approach ensures the safety and efficiency of drone operations in complex urban environments.

In the paper by JOO-SEOK LEE and KEE-HO YU, Optimized path planning used gravitational potential energy significantly increased the endurance of solar-powered UAVs [58]. Solar-powered UAVs' flight endurance is improved by leveraging gravitational potential energy, which reduces battery dependence and overall aircraft weight. This method uses real-time optimization to improve flight efficiency and endurance. The approach uses attitude control to manage energy efficiently, allowing the UAV to perform optimally throughout its flight. The UAV's flight endurance is significantly increased through the use of gravitational potential energy and real-time optimization. This novel approach reduces battery dependence, increasing the operational duration and efficiency of solar-powered UAVs.

Chapter 3

3.1 Formulation of Multi UAV Path Planning

Multi-UAV co-operative path planning refer to identify *N* near optimal paths for a network of *N* UAV's from a given starting position $\vec{C}_0(x_0,y_0,z_0)$ to a predefined goal position $\vec{C}_g(x_g,y_g,z_g)$by satisfying environmental and physical constraints. Let, the position of the *i*-th UAV at time *t* be denoted by$\overrightarrow{D_{i,t}}$compressing $(x_{i,t},y_{i,t},z_{i,t})$for *i*=1,2, ..., *N*. The respective centroid is then given by

$$\vec{C}_t = \sum_{i=1}^{N} \frac{\overrightarrow{D_{i,t}}}{N} \quad (1)$$

The UAV's first attempt to align themselves with the predefined goal position $\vec{C}_g(x_g,y_g,z_g)$. In case, the alignment results in possible collision with obstacles and/or teammates and/or mountain, the UAV's have to turn left or right by a prescribed angel to marginally avoid the collision and/or detection by threat sources.
The multi-UAV path planning problems addressed here is called the local path planning problems , where we aim at determining the optimal next positions of the individual UAVs ($\overrightarrow{D_{i,t+1}}$ for *i*=1,2, …, *N*) from their current position ($\overrightarrow{D_{i,t}}$ for *i* = 1, 2,…., *N*) by minimizing path lengths, however avoiding collision and satisfying constraints related to UAV flight environment and the flight characteristics.
Eventually, the next centroid $\vec{C}_{t+1}$ is computed using (1) with $t \leftarrow t+1$. In each local planning step, the *multi-objective optimization* (MOO) algorithm (to be proposed) is executed to move the UAVs from $\overrightarrow{D_{i,t}}$ to $\overrightarrow{D_{i,t+1}}$ for *i* = 1, 2,…., *N*. A sequence of such local planning steps ultimately moves the UAVs to the destination. An exemplar figure of the local path-planning of UAVs is given in Fig. 3, for disaster management.

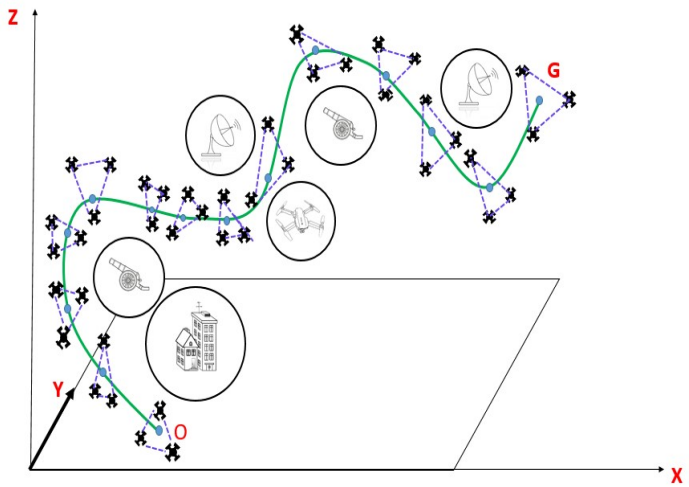


Fig.3. Illustration of multi-UAV local path planning for disaster management

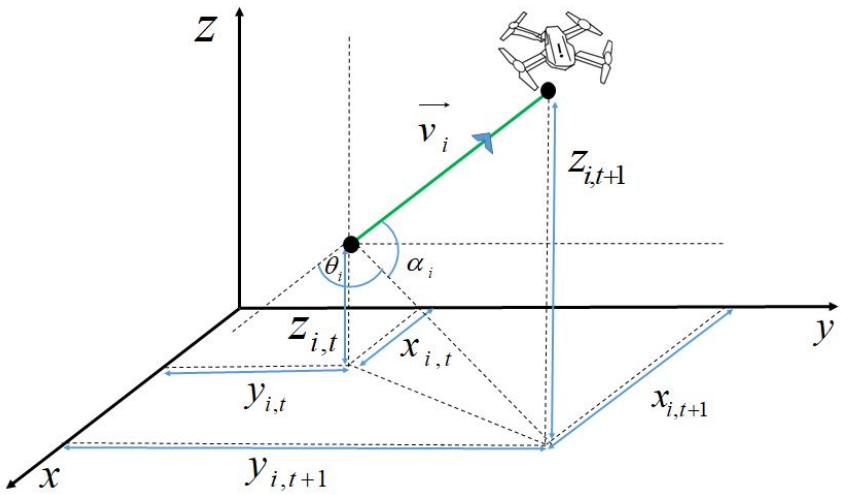


Fig.4. Graphical representation of UAVs' positions in three-dimensional workspace

Let us assume that each UAV is moving with a constant velocity $\vec{v_i}$ for i=1,2, ..., N. It is evident from Fig. 4 that

$$x_{i,t+1} = x_{i,t} + |\vec{v_i}| \cos \alpha_i \cos \theta_i \quad (2.a)$$

$$y_{i,t+1} = y_{i,t} + |\vec{v_i}| \cos \alpha_i \sin \theta_i \quad (2.a)$$

$$z_{i,t+1} = z_{i,t} + |\vec{v_i}| \sin \alpha_i \quad (2.c)$$

Hence, in the present context, the local path-planning for a network of N UAVs boils down to find the optimal settings of θ_i and α_i for i = 1, 2,…., N for each local step of movements of N UAVs.

While determining the optimal next centroid$\vec{C}_{t+1}$ from the current centroid $\vec{C}_t$the following objectives are considered.

- The UAV-network should follow the shortest path to minimize the fuel consumption and hence the energy. This is captured by the objective function f_1, given by

$$f_1 = \text{length of the path predicted from } \vec{C}_t \text{ to } \vec{C}_{t+1} + \text{length of the path to be covered from } \vec{C}_{t+1} \text{ to } \vec{C}_g$$

$$= \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2 + (z_{t+1} - z_t)^2} + \sqrt{(x_g - x_{t+1})^2 + (y_g - y_{t+1})^2 + (z_g - z_{t+1})^2} \quad (3)$$

- The UAVs should avoid collisions with obstacles by minimizing the objective function f_2 ,given by

$$f_2 = \frac{1}{dist(\vec{C}_{t+1}, nearest_obstacle)} \quad (4)$$

Here, $dist(\vec{C}_{t+1}, nearest_obstacle)$ represents the distance measure between $\vec{C}_{t+1}$ and the nearest obstacle.

- While planning for the shortest path, in addition to the obstacles, the UAVs need to avoid collision with the teammates in the network. This is captured by the objective function f_3, given by

$$f_3 = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} \left[min\left(0, dist\left(\overrightarrow{D_{i,t+1}}, \overrightarrow{D_{j,t+1}}\right) - \varepsilon\right)\right]^2 \quad (5)$$

Here $dist\left(\overrightarrow{D_{i,t+1}}, \overrightarrow{D_{j,t+1}}\right)$ symbolizes the distance between the i-th and the j-th UAV of the network at t+1 for $i, j = 1, 2, \ldots, N$ but $i \neq j$. If $dist\left(\overrightarrow{D_{i,t+1}}, \overrightarrow{D_{j,t+1}}\right)$ is greater than the safety distance ε, zero penalty is given. Otherwise, high penalty $\left[dist\left(\overrightarrow{D_{i,t+1}}, \overrightarrow{D_{j,t+1}}\right)\right]^2$ is added to the objective function indicating high risk of collision among the i-th and the j-th teammates.

- The UAV network has to also ensure that altitude/ height of the UAV network is not too height to ensure safety and reduces fuel consumption as well. However, maintaining a low altitude may result in a collision with mountain. In other words,

the height $z_{i,t+1}$ of the i-th UAV at t+1 should be above the height H_{mount} of the nearest mountain but below the maximum permissible altitude H_{max}. This is ensured by minimizing the cost function

$$f_4 = \sum_{i=1}^{N\Sigma} \left\{\left[min(0, Hi, t + 1_{max}()) \square^2 \left[min\left(0, z_{i,t+1} - H_{mount}\right)\right]^2\right] \{\}\right\} \quad (6)$$

In addition reduces the height cost, the UAV network has to ensure minimal change in the altitude at the consecutive location of N UAVs. To capture this, f_4 *in* (6) is modified to

$$f_4 = \sum_{i=1}^{N\Sigma} \left\{\left[min(0, Hi, t + 1_{max}()) \square^2 \left[min\left(0, z_{i,t+1} - H_{mount}\right)\right]^2 \left(z_{i,t} - z_{i,t+1}\right)^2\right] \{\}\right\} \quad (7)$$

3.2 FANS Based Optimization Technique for Multi UAV

In *firefly algorithm with non-dominated sorting* (FANS), a possible solution to the given MOO problem is encoded by the position of a firefly [30] and the light intensity at that position represents the objective function value of the respective solution. Here we present an overview of the main steps of the FANS concerned with joint minimization of M objectives.

(a) **Initialization:** FANS commences from unoform random initialization of a population **P**(g) of *S* trial solutions (firefly positions) $\vec{\rho}_i(g) = \{\rho_{i,1}(g), \rho_{i,2}(g), ..., \rho_{i,D}(g)\}$, each of *D*-dimension at the initial generation $g = 0$ in the pre-defined search space $[\vec{\rho}^{\min}, \vec{\rho}^{\max}]$ where $\vec{\rho}^{\min} = \{\rho_1^{\min}, \rho_2^{\min}, ..., \rho_D^{\min}\}$ and $\vec{\rho}^{\max} = \{\rho_1^{\max}, \rho_2^{\max}, ..., \rho_D^{\max}\}$ by setting

$$\rho_{i,j}(0) = \rho_j^{\min} + \text{rand}(0,1) \times (\rho_j^{\max} - \rho_j^{\min}) \tag{8}$$

for *j*=1, 2, …, *D*. Here rand(0,1) is a positive value randomly selected from the uniform distribution in (0, 1). The *k*-th objective function is evaluated for *i*= 1, 2, …, *S* and *k* = 1, 2, …, *M*.

(b) **Identification of Dominating Sets:** Two sets of population members, denoted by ${}^1\mathbf{\Omega}_i(g)$ and ${}^2\mathbf{\Omega}_i(g)$, are selected for each trial solution $\vec{\rho}_i(g)$ from the current population **P**(*g*). ${}^1\mathbf{\Omega}_i(g)$ is formed by selecting those members of **P**(*g*) that dominate $\vec{\rho}_i(g)$. Mathematically, a member $\vec{\rho}_j(g) \in {}^1\mathbf{\Omega}_i(g)$ should satisfy the following conditions.

(i) $f_k(\vec{\rho}_j(g)) \le f_k(\vec{\rho}_i(g))$ for $k = 1, 2, ..., M$.

(ii) $f_l(\vec{\rho}_j(g)) < f_l(\vec{\rho}_i(g))$ for at least one $l \sqsubset \{1, 2, ..., M\}$.

Similarly, ${}^2\mathbf{\Omega}_i(g)$ comprises the members of **P**(*g*) dominated by $\vec{\rho}_i(g)$. We repeat this step for all population members with *i*=1, 2, …, *S*.

(c) **Attraction to Brighter Fireflies:** In this phase, the trial solution (or the firefly at the position) $\vec{\rho}_i(g)$ improves its quality by getting attracted towards the dominating members $\vec{\rho}_j(g) \in {}^1\mathbf{\Omega}_i(g)$. The attractiveness $\beta_{i,j}$ of $\vec{\rho}_i(g)$ towards $\vec{\rho}_j(g)$ diminishes exponentially as the distance $d_{i,j}$ between them as specified in (9).

$$\beta_{i,j} = \beta_o \, exp(-\gamma \times d_{i,j}^m), \quad m \ge 1 \tag{9}$$

Here β_0 denotes the maximum permissible attractiveness and γ denotes the light absorption coefficient. It is worth mentioning that γ=0 results in constant attractiveness for all population members, inhibiting their movements in the search space. Contrarily, γ approaching infinity leads to complete random movement. In (9), m>0 denotes a non-linear modulation index. The distance $d_{i,j}$ between $\vec{\rho}_i(g)$ and $\vec{\rho}_j(g)$ is calculated using Euclidean norm in the following manner.

$$d_{i,j} = \| \vec{\rho}_i(g) - \vec{\rho}_j(g) \| \tag{10}$$

This procedure is carried out again for. *i*= 1, 2, …, *S*.

(d) **Movement of Fireflies:** The dynamic given in (11) is used for controlled movement of a trial solution (or the firefly at position) $\vec{\rho}_i(g)$ towards a better

dominating solution (or firefly at the position) $\vec{\rho}_j(g) \in {}^1\mathbf{\Omega}_i(g)$.

$$\vec{\rho}_i^{next}(g) = \vec{\rho}_i(g) + \sum_{\forall \vec{\rho}_j(g) \in {}^1\mathbf{\Omega}_i(g)} \beta_{i,j} \times (\vec{\rho}_j(g) - \vec{\rho}_i(g)) + \delta \times (\vec{r} - 0.5) \tag{11}$$

The first term on the right hand side of (11) represents the current i-th trial solution (or position of the i-th firefly). The second term denotes the motion of $\vec{\rho}_i(g)$ induced by the better domination members of ${}^1\mathbf{\Omega}_i(g)$.Apparently, the best member (or the brightest firefly) of the current population $\mathbf{P}(g)$ will be devoid of any motion and may get stuck at the local optima in the multi-modal fitness terrain. This is overcome by adding a random movement, given by the third term of (11), with a maximum step size of $\delta \in (0, 1)$. Here $\vec{r}$ symbolizes a D-dimensional random vector with its components uniformly distributed in (0, 1). This step is iterated for $i = 1, 2, \ldots, S$. In short, the motion of the trial solutions controlled by their dominating members help in the exploitation in the search space. Contrarily, the random movement helps the population members to avoid deceptive local optima by their explorative ability. Intuitively, the convergence of the algorithm depends on the judicious setting of the step size β. However, in the traditional firefly algorithm, δ is set as a positive constant for all population members ignoring their quality. Consequently, a large setting of δ may deviate away the good quality trial solutions from the neighborhood of the true global optima. Contrarily, the poor performing population members with a small value of δ are deprived of any opportunity to move towards the global optima. The issue is resolved here by varying δ with the relative merit of a trial solution $\vec{\rho}_i(g)$ over other inferior members of the population $\mathbf{P}(g)$, captured by ${}^2\mathbf{\Omega}_i(g)$. It is achieved here by setting

for $i = 1, 2, \ldots, S$. (12)

It is evident from (12) that the quality solutions with a large size of ${}^2\mathbf{\Omega}_i(g)$ (dominating large portion of the current population) is assigned with a small step size to concentrate on local exploitation in the vicinity of the global optima. The poor performing members with a small size of ${}^2\mathbf{\Omega}_i(g)$ participates the exploration with δ approaching 1. The k-th objective function is determined for $i = 1, 2, \ldots, S$ and $k = 1, 2, \ldots, M$.

(e) **Selection:** If $\vec{\rho}_i(g)$ is dominated by $\vec{\rho}_i^{next}(g)$, $\vec{\rho}_i^{next}(g)$ substitues $\vec{\rho}_i(g)$. However if $\vec{\rho}_i(g)$ and $\vec{\rho}_i^{next}(g)$ are non-dominated, both members are kept in the population $\mathbf{P}(g)$. This step is reiterated for $i = 1, 2, \ldots, S$ resulting in a population with size $|\mathbf{P}(g)| \in \{S, S+1, \ldots, 2S\}$.

(f) **Non-dominated Sorting:** This step is concerned with sorting the population $\mathbf{P}(g)$ into a number of Pareto fronts using the principle of non-domination. All the non-dominated members of $\mathbf{P}(g)$ are identified and are placed in the approximate Pareto front, $\mathbf{F}^1(g)$. The second Pareto front $\mathbf{F}^2(g)$ is formed by selecting the non-dominated members from $\{\mathbf{P}(g) - \mathbf{F}^1(g)\}$. Continuation of this process eventually divides $\mathbf{P}(g)$ into a set of Pareto fronts, denoted by $\mathbf{F}^1(g)$, $\mathbf{F}^2(g)$, $\mathbf{F}^3(g)$, and so on.

(g) **Truncation of Extended Population:** This step involves promotion of the Pareto

fronts of $\mathbf{P}(g)$ (of size $S< |\mathbf{P}(g)|< 2S$), thus formed to the next generation population $\mathbf{P}(g+1)$ (of size S) staring from $\mathbf{F}^1(g)$ (the best ranked Pareto front). Let $\mathbf{F}^l(g)$ be the Pareto front such that by promoting all the members of $\mathbf{F}^l(g)$ to the next generation, the resulting population size $|\mathbf{P}(g+1)|$ exceeds S. To judiciously select members from $\mathbf{F}^l(g)$ to $|\mathbf{P}(g+1)|$, *crowding distance CD* [31] measure is used to sort the trial solutions of $\mathbf{F}^l(g)$ in descending order.$CD(\vec{\rho}(g))$ describes the perimeter of a hypercube formed by the nearest neighbors of $\vec{\rho}(g) \in \mathbf{F}^l(g)$ at the vertices in the fitness landscapes. To preserve diversity in population, the trial solutions of $\mathbf{F}^l(g)$ with the highest *CD* measures are prioritized for entering $\mathbf{P}(g+1)$ until $|\mathbf{P}(g+1)|$ becomes S.

After each evolution, we reiterate from step (b) until the convergence termination condition is met. The proposed FANS algorithm's pseudo-code with M objectives is listed below.

Procedure FANS

Input: Population size S, maximum attractiveness β_0, random movement control parameter γ, modulation index m, optimizing objective function $f_k(.)$ for $k = 1, 2, \ldots, M$ and related parameters.

Output: Set of solutions approximate Pareto front.

Begin

1. Initialize a population $\mathbf{P}(g)$ of S, D-dimensional trial solutions $\vec{\rho}_i(g)$ at generation g=0 using (8) for $i= 1, 2, \ldots, S$.
2. Evaluate for $i= 1, 2, \ldots, S$ and $k= 1, 2, \ldots, M$.
3. **While** termination condition is not achieved **do**

Begin

3.1. Construct the sets ${}^1\mathbf{\Omega}_i(g)$ and ${}^2\mathbf{\Omega}_i(g)$ associated with $\vec{\rho}_i(g)$ for $i= 1, 2, \ldots, S$ using the guideline given in section III.(b).

3.2. Update $\vec{\rho}_i(g)$ to $\vec{\rho}_i^{next}(g)$ using the dynamics in (11) and (12) for $i= 1, 2, \ldots, S$.

3.3. Determine for $i= 1, 2, \ldots, S$ and $k= 1, 2, \ldots, M$.

3.4. **If** $\vec{\rho}_i^{next}(g)$ dominates $\vec{\rho}_i(g)$ **Then** replace $\vec{\rho}_i(g)$ with $\vec{\rho}_i^{next}(g)$;

Else If $\vec{\rho}_i^{next}(g)$ are $\vec{\rho}_i(g)$ non-dominated **Then** ;

End If

Reiterate the step for $i= 1, 2, \ldots, S$.

3.5. Sort $\mathbf{P}(g)$ into Pareto fronts $\mathbf{F}^1(g)$, $\mathbf{F}^2(g)$, $\mathbf{F}^3(g)$,… using non-dominated sorting principle.

3.6. Promote the members from $\mathbf{P}(g)$ into $\mathbf{P}(g+1)$ starting from $\mathbf{F}^1(g)$ until the front $\mathbf{F}^l(g)$is identified in order that $|\mathbf{P}(g+1)| + |\mathbf{F}^l(g)| > S$. Sort the members of $\mathbf{F}^l(g)$ in descending order of *CD* measures.

3.7. Promote top $(S - |\mathbf{P}(g+1)|)$ members of the sorted Pareto front $\mathbf{F}^l(g)$ to $\mathbf{P}(g+1)$.

3.8. $g \leftarrow g+1$.

End While.

4. Return $\mathbf{F}^1(g)$.

End.

3.3 Solution to Multi-UAV Path-Planning Problem by FANS

Fig. 2 reveals that the optimal path of the i-th UAV from the current position to the next position for each local planning step relies on the accurate estimation of θ_i and α_i for $i = 1, 2, \ldots, N$. This is encoded by a trial solution of FANS, as given in Fig. 5. Evidently, in the present context, the dimension of the trial solution $\vec{\rho}$ of FANS is given by $D = 2N$.

$\vec{\rho}$	θ_1	θ_2	…	θ_N	α_1	α_2	…	α_N

Fig.5. FAN Encoded Solution to Multi-UAV Path Planning

Moreover, after convergence of FANS algorithm for each local-planning step of N UAVs, a set of equally good non-dominated solutions is obtained from the optimal Pareto front $\mathbf{F}^1$. To judiciously select the appropriate solution to the multi-UAV path-planning problem from $\mathbf{F}^1$, the following steps are executed.

- For all members $\vec{\rho}_j$ of $\mathbf{F}^1$ compute normalized objective function value, given by

$$f_k^*(\vec{\rho}_j) = \frac{f_k(\vec{\rho}_j)}{\sum_{\forall \vec{\rho}_l \in \mathbf{F}^1} f_k(\vec{\rho}_l)} \quad \text{for } k = 1, 2, \ldots, 4. \tag{13}$$

- Compute the composite objective function value

$$f^*(\vec{\rho}_j) = \prod_{k=1}^{4} f_k^*(\vec{\rho}_j) \quad \forall \vec{\rho}_j \in \mathbf{F}^1. \tag{14}$$

- Sort the members of $\mathbf{F}^1$ in ascending order of $f^*(.)$.
- Declare the solution at the top-most position of the sorted list as the winner.

The pseudo-code to solve the cooperative multi-UAV path-planning problem using FANS is given below.

Procedure multi UAV path planning

Input: Initial positions of N UAVs $\overrightarrow{D_{i,0}}$ for $i = 1, 2, ..., N$, final destination $\vec{C}_g$, position of set of obstacles **obstacle positions**, maximum permissible height $H_{\max}$, height of mountain H_{mount}.

Output: Predicted paths of N UAVs from the starting to the goal position.

Begin

1. Set $t \leftarrow 0$.
2. Determine $\vec{C}_t$ using (1).
3. **Repeat** until $|\vec{C}_t - \vec{C}_g| \leq \varepsilon$

3.1. Set $\mathbf{F}^1 \leftarrow$ FANS (S, β_0, γ, m, $f_k(.)$ for k = 1, 2, …, 4, **obstacle positions**, $H_{\max}$, H_{mount}).

3.2. For all members of $\mathbf{F}^1$ compute normalized objective function value using (13).

3.3. Compute the composite objective function value for all members of $\mathbf{F}^1$ using (14).

3.4. Decode the member of $\mathbf{F}^1$ with minimum $f^*(.)$ measure to identify θ_i and α_i for i = 1, 2, …, N.

3.5. Determine $\overrightarrow{D_{i,t+1}}$ for i = 1, 2, …, N using (2).

3.6. Move the UAVs from $\overrightarrow{D_{i,t}}$ to $\overrightarrow{D_{i,t+1}}$ for i = 1, 2, …, N.

3.7. Set $t \leftarrow t+1$.

3.8. Determine $\vec{C}_t$ using (1).

End

End.

Chapter 4

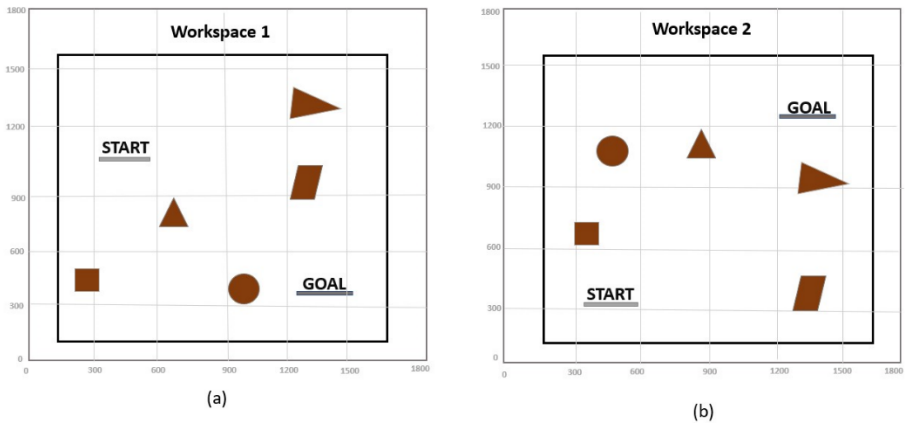
4 Experiments and Results

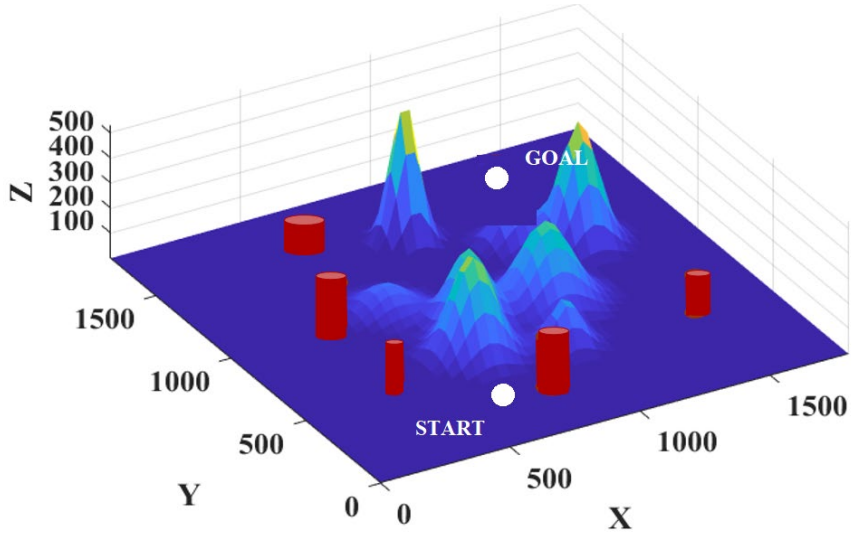
4.1. Experimental Set-Up

The experiment is conducted in a simulated environment using an Intel Core i5-6200U CPU with a maximum clock speed of 2.8 GHz. A MATLAB 2019a-compatible script is created to solve the simultaneous optimization of the objectives concerned with multi-UAV path-planning problem. Experiments are undertaken for diverse settings of workspaces. Three exemplar cases are given in Fig. 4 (a)-(c). Fig. 4 (a) and (b) portray two different configurations of two-dimensional workspaces containing only obstacles. Fig. 4 (c) shows a three-dimensional workspace comprising both obstacles and mountains to examine the proficiency of the path-planners in the complex terrain.

4.2. Comparative Framework and Parameter Settings

The effectiveness of FANS to solve the cooperative multi-UAV path-planning problem is validated by comparing its performance with its two competitors, including *differential evolution for multi-objective optimization* (DEMO) [31] and *non-dominated sorting genetic algorithm*-II (NSGA-II) [32]. The control parameters of DEMO and NSGA-II are taken from their respective sources [31], [32].
The control parameters for the proposed FANS algorithm include maximum attractiveness β_0, random movement control parameter γ and modulation index m. Exhaustive experiments are undertaken to determine the values of these control parameters with an aim to balance the trade-off between the computational run-time and the optimization proficiency. This results in $\beta_0 = 5$, $\gamma = 0.83$ and $m = 2$.





(c)

Fig. 5. Two- and three-dimensional workspaces for multiple UAVs

4.3. Experimental Results

Fig. 5 and 6 show the paths of a network of three UAVs from the given starting position to the pre-defined goal location in the first and second workspaces as determined by FANS, DEMO and NSGA-II. It reveals that FANS-based path-planning algorithm results in the near-ideal paths for all UAVs avoiding collision with teammates and/or obstacles irrespective of the workspaces. The capability of the path-planners to help a network of five UAVs to avoid collision with mountains in a complex terrain has been examined with respect to the third workspace and the resulting paths are shown by Fig. 7.

Let s_k be the number of steps used by the UAV network to reach the destination as governed by the k-th algorithm in the comparative frame work. Let, ${}^k f_i^j$ be the normalized value of the objective function $f_i(.)$ corresponding to the j-th local step of planning for the k-th path-planning algorithm for $i = 1, 2, \ldots, 5$ and $j = 1, 2, \ldots, s_k$. To compare the performance of the contender algorithms we take the average of the objective function values of the entire paths, as given by

$$ {}^k f_i = \sum_{j=1}^{s_k} {}^k f_i^j \Big/ s_k \quad . \tag{15}$$

The mean and standard deviation (within parenthesis) of ${}^k f_i$ after 50 runs of the k-th algorithm are tabulated in Table-1 for $i = 1, 2, \ldots, 4$. Table-1 also reveals the similar trend of superiority of the FANS-based path-planner over its competitors to achieve the minimum values of the normalized objectives in most of the cases. DEMO provides best results for $f_2(.)$ and $f_1(.)$ for workspaces 1 and 2 respectively. In case of $f_3(.)$, FANS is outperformed by NSGA-II for workspace-2. It is worth mentioning that for a complex terrain like workspace-3, FANS has achieved the best values for all objectives.

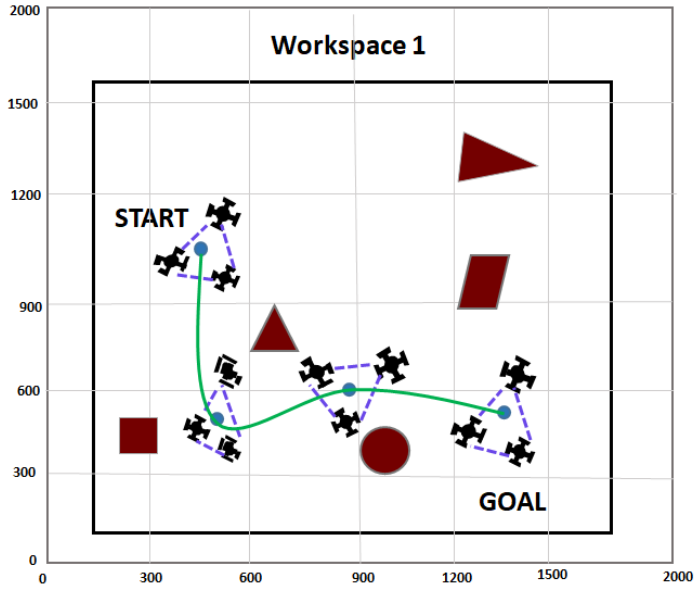


Fig. 5. (a) Paths obtained for a network of three UAVs using FANS for workspace 1 (4 steps)

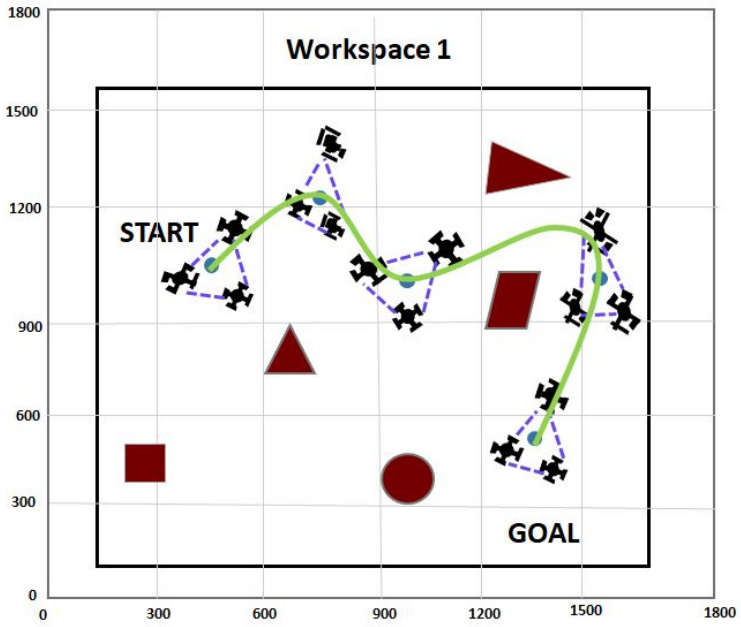


Fig. 5. (b) Paths obtained for a network of three UAVs using DEMO for workspace 1 (4 steps)

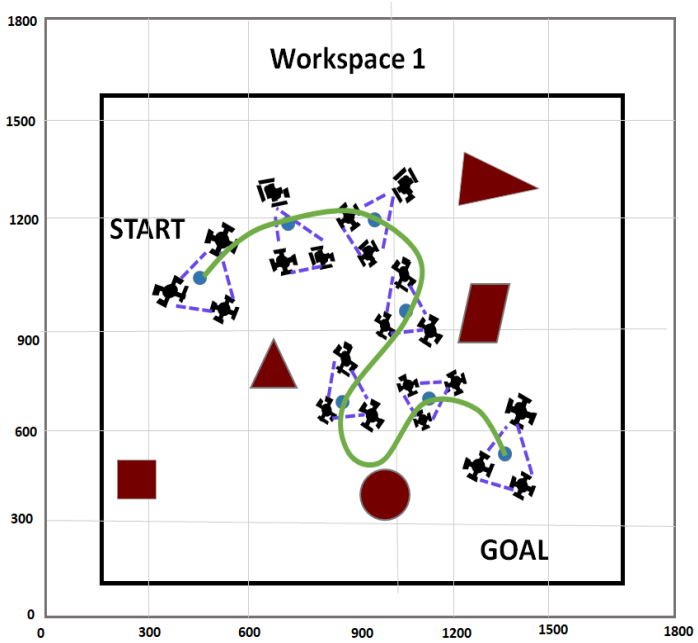


Fig. 5. (c) Paths obtained for a network of three UAVs using NSGA-II for workspace 1 (6 steps)



Fig. 6. (a) Paths obtained for a network of three UAVs using FANS for workspace 2 (5 steps)

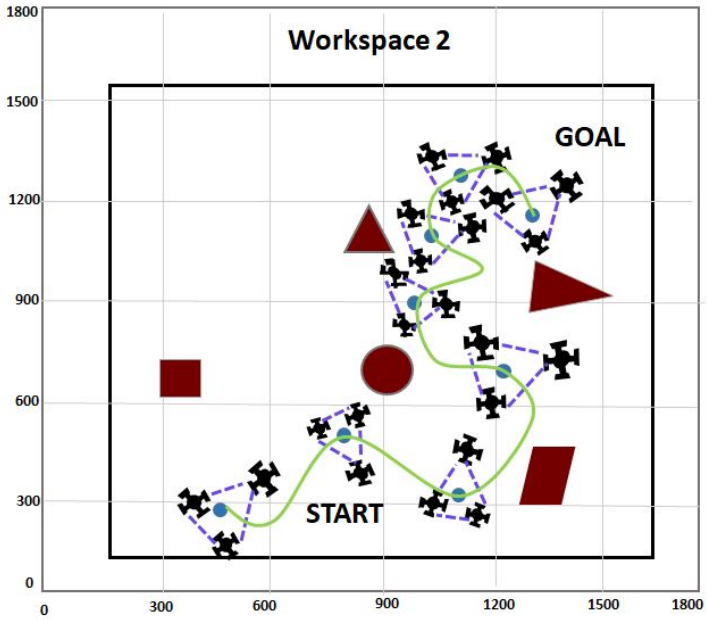


Fig. 6. (b) Paths obtained for a network of three UAVs using DEMO for workspace 2 (7 steps)



Fig. 6. (c) Paths obtained for a network of three UAVs using NSGA-II for workspace 2 (6 steps)

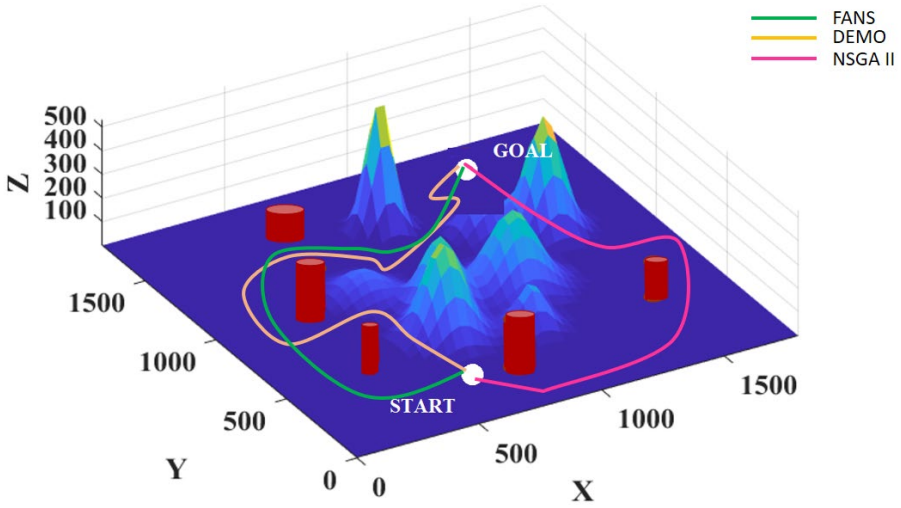


Fig. 7.(a) Paths obtained for a network of three UAVs using different path-planning algorithms for workspace 3

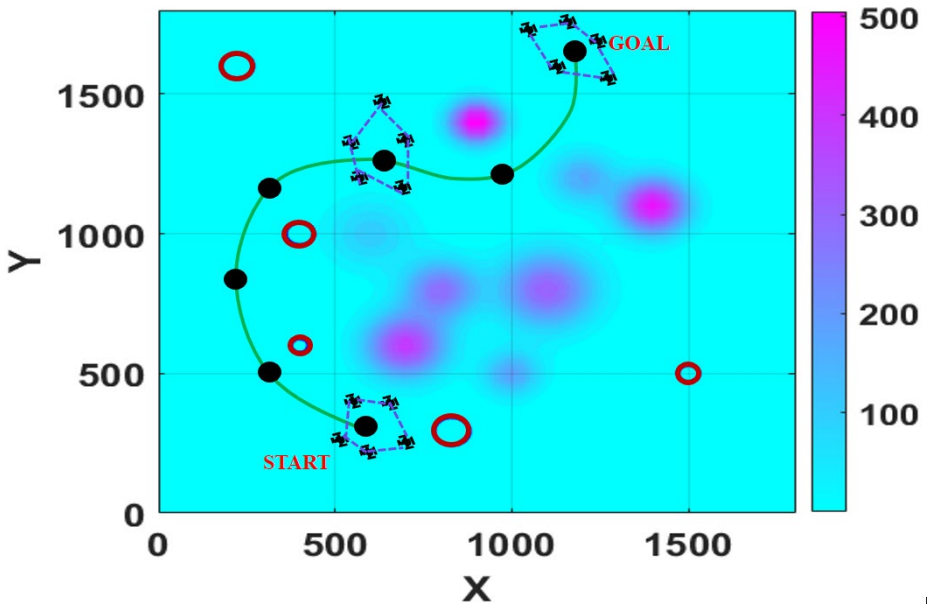


Fig. 7.(b) Paths obtained for a network of five UAVs using FANS for contour map of workspace 3 (6 steps)

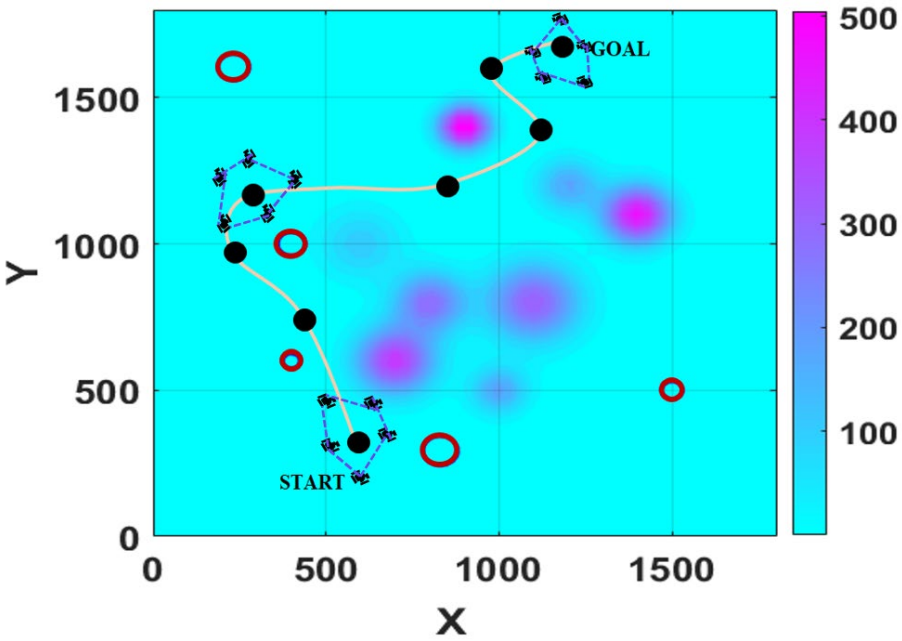


Fig. 7.(c) Paths obtained for a network of five UAVs using DEMO for contour map of workspace 3 (7 steps)

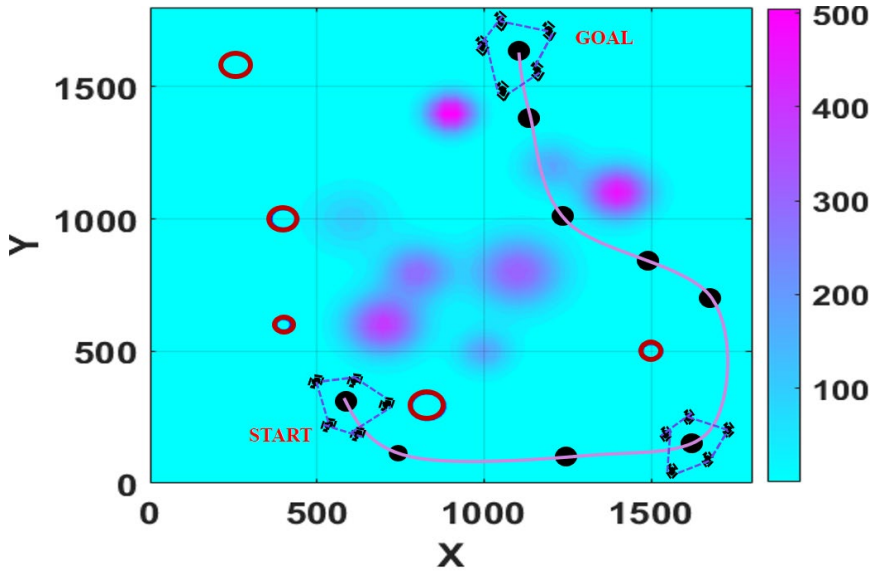


Fig. 7.(d) Paths obtained for a network of five UAVs using NSGA-II for contour map of workspace 3 (8 steps)

Table 1. Comparative analysis of contender algorithms for multi-UAV path-planning

Normalized objectives	Algorithms	Workspace 1	Workspace 2	Workspace 3
f_1	FANS	**0.52 (0.026)**	0.43 (0.015)	**0.56 (0.028)**
	DEMO	0.61 (0.120)	**0.37 (0.100)**	0.67 (0.130)
	NSGA-II	0.89	0.76	0.87

		(0.230)	(0.210)	(0.225)
f_2	FANS	0.60 (0.035)	**0.45** **(0.016)**	**0.53** **(0.046)**
	DEMO	**0.56** **(0.100)**	0.75 (0.400)	0.78 (0.405)
	NSGA-II	0.94 (0.340)	0.93 (0.330)	0.94 (0.340)
f_3	FANS	**0.46** **(0.016)**	0.61 (0.036)	**0.68** **(0.039**
	DEMO	0.68 (0.130)	0.67 (0.120)	0.69 (0.122)
	NSGA-II	0.83 (0.293	**0.59** **(0.050)**	0.74 (0.450)
f_4	FANS	**0.37** **(0.030)**	**0.63** **(0.046)**	**0.63** **(0.046)**
	DEMO	0.48 (0.120	0.64 (0.122)	0.64 (0.122)
	NSGA-II	0.76 (0.420)	0.85 (0.330)	0.95 (0.330)

Chapter 5

Conclusions

5.1 Contribution of the thesis

The paper proposes a novel MOO strategy to solve multi-UAV path-planning problem. The MOO framework considers four objectives to determine optimal trajectories of a network of *N* UAVs from the given source to the pre-defined destination, however avoiding collision with obstacles and teammates and mountains. The MOO path-planning problem has been solved by the proposed FANS algorithm. The algorithm is developed with an aim to balance the runtime and the optimization capability. Experiments undertaken in diverse settings of workspaces reveal that the proposed FANS-based path-planner outperforms the state-of-the-art-techniques used for the same application.

5.2 Scope of Future Work

The results of this study suggest a number of significant directions for future research in the area of Optimization Approach to Multi-Drone Path Planning. The following areas present promising prospects for more investigation and improvement:

UAV Path Planning in 3D Environment: Due to structural constraints and uncertainties, path planning is deemed more feasible than its 2D counterpart in 3D environments. Path planning algorithms aim to determine conflict-free trajectories while minimizing travel distance or energy consumption. Despite the advancements, existing algorithms are underexplored for intricate environments, such as those with U-shaped obstacles or densely populated dynamic scenarios. It highlights the need for more integrated representations of spatial context in 3D path planning in complex settings.

Given the widespread integration of UAVs in military and civil applications, the limitations of a single UAV in payload and flight capabilities become apparent. Collaborative efforts involving multiple UAVs are crucial for executing complex tasks, showcasing enhanced viability and expanded task execution capabilities. Adherence to spatially defined target points and strict temporal constraints in scenarios with multiple UAVs necessitates four-dimensional path planning technology. The ascendancy of four-dimensional path planning, offering superior real-time performance, is inevitable in the evolution of UAV path planning. Therefore, future research should focus on developing and enhancing four-dimensional path-planning algorithms tailored to the challenges of cooperative task execution by multiple UAVs.

The path-planning algorithm holds paramount importance at the core of this technological landscape. Future research must prioritize selecting and refining algorithms to address intricacies in four-dimensional multi-UAV cooperative path planning. This urgency is emphasized by the growing prevalence of cooperative UAV missions, demanding precision in spatial and temporal coordination, thus requiring advancements in path-planning algorithms tailored to these complex operational requirements.

Dynamic UAV Path Planning: The increasing use of UAVs in both military and civilian applications is driven by the necessity imposed by the uncertain and adversarial nature of operational environments and the potential for encountering unforeseen circumstances during flight. In future research, real-time planning will become a focal point, requiring attention to two critical concerns: the computational speed prerequisites and the fidelity of environmental information. Pioneering works, exemplified by the papers [64,65,68], have used reinforcement learning and deep learning in dynamic path planning, resulting in commendable outcomes. Therefore, an essential trajectory for future investigations involves pursuing UAV dynamic path planning based on deep learning or reinforcement learning principles. Simultaneously, challenges associated with applying existing AI methodologies in path planning need proactive resolution, addressing issues such as relatively low convergence and the scarcity of suitable datasets.

5.3. Game Theory Applied to UAV Decentralized and Cooperative Control: Game theory has emerged as a potent tool for optimizing energy consumption, augmentation of network coverage, resource management, coordinated control of multiple, and enhanced connectivity in UAVCNs [32]. Notably, decentralized cooperative control for UAVs involving multiple UAVs is deemed more consequential than centralized control. Delineating an individual aircraft's action scope and cooperative path planning is pivotal in designing a decentralized cooperative control structure. Game theory is a foundational framework for facilitating distributed decision-making and cooperative behavior within UAVs. Simultaneously, the intrinsic coupling of UAV target functions and multiple game scenarios, influenced by factors such as interference or collision, markedly advance the applicability of the game theory in the realm of UAVCNs.

5.4. UAV Cluster Path Planning: In extant research about the coordinated planning of multiple paths, a notable lacuna exists in formulating inter-cluster collaboration. A conspicuous divergence is observed, wherein certain studies neglect to consider collaborative aspects and focus solely on the individual planning of multiple paths. Conversely, others incorporate collaboration constraints limited to temporal and spatial considerations. In the broader context, a lack of investigations into the intricacies of deep-level synergy exists. It is imperative to recognize that future agent clusters are envisioned to resemble living systems characterized by integration, hierarchy, and interrelatedness. Consequently, further scholarly inquiry is warranted to delineate the interrelationship between the entire cluster and its constituent components,

emphasizing enhancing synergy to optimize the collective benefits accrued by the clusters.

Hybrid Path-Planning Algorithm: Significant strides have been achieved in UAV path-planning algorithms; nonetheless, each algorithm exhibits inherent limitations. Consequently, the current focal point within the field of path planning is the exploration of novel, efficient path-planning algorithms and fusion algorithms. The synergistic integration of diverse algorithms, leveraging their respective strengths and mitigating weaknesses, has catalyzed the evolution of a spectrum of improved algorithms.

One illustrative instance involves amalgamating machine learning, swarm intelligence, and traditional algorithms in UAV path planning. This integrated approach effectively addresses challenges associated with swarm intelligence algorithms, such as susceptibility to locally optimal solutions, leading to convergence speed and robustness enhancements. Future research endeavors are advised to develop hybrid path-planning algorithms, particularly emphasizing the amalgamation of AI with other algorithmic paradigms. This pursuit aims to refine the UAV path-planning algorithm system, rendering it more comprehensive and creating a more promising landscape for UAV applications.

5.6. UAV Path Planning in 4D Environment: 4D path planning is usually referred to as incorporating time as the 4th dimension, including multi-UAV cooperation path planning as the 4th dimension. Effective collaboration and information exchange among UAVs and between UAVs and users relies on a pivotal communication network during task execution. The complexities of path planning surpass those in single UAV networks. These challenges span various factors, including the quantity of UAVs, inter-vehicle distances, functional structures, flight durations, path configurations, device-to-device channel parameters, coordination methodologies, kinematic characteristics, safety considerations, and connectivity requirements.

Within UAV clusters, communication dynamics among UAVs and between UAVs and ground stations impose stringent latency demands, particularly critical in scenarios requiring frequent data interactions for large-scale crowd area detection. Communication channel instability may introduce delays or packet losses, jeopardizing real-time environmental data perception within the cluster system and posing potential security risks. Multi-UAV path planning constitutes a complex, large-scale, and constrained multi-objective optimization problem. The intricate interplay of numerous variables and considerations necessitates sophisticated algorithms and methodologies to navigate the challenges posed by cooperative communication, control, and safety. Optimizing collective performance in UAV clusters demands an integrated approach that addresses the diverse and interconnected aspects of multi-UAV path planning within the context of communication network constraints. This comprehensive perspective is vital for effectively deploying UAV clusters in real-world scenarios, ensuring the optimization problem's multifaceted nature is appropriately addressed.

Technology Level: Modeling multi-UAV cooperative path planning introduces complexities surpassing those associated with single-UAV path planning, leading to a greater diversity of available solution algorithms. Prevailing research typically divides the process into path-generation and collaborative planning, with initial studies concentrating on constructing path-generation models. Enhancing path planning accuracy necessitates comprehensively considering cluster tasks, temporal coordination constraints, and track smoothing, presenting a multifaceted challenge warranting further investigation.

The prevalent reliance on swarm intelligence algorithms or hybrid methodologies, such as ACO, PSO, and GA, in existing research, signals a need for a more nuanced approach. Recent advancements in AI, particularly in deep learning and reinforcement learning, have demonstrated remarkable efficacy in addressing sequential decision optimization problems. Thus, employing deep learning and reinforcement learning for UAV cluster path planning emerges as a crucial future research direction, promising accelerated and dynamic path planning capabilities. Existing studies exhibit limitations in elucidating collaboration dynamics between clusters, with some overlooking collaboration considerations and others confining synergy within temporal and spatial bounds. A noticeable gap in research on deep-level synergy is apparent. Envisioning intelligent clusters akin to living systems requires renewed attention to global and local relationship planning. Therefore, future research should strive for a more holistic understanding of intelligent clusters and their collaborative dynamics, focusing on optimizing synergy for enhanced collective performance.

Representative Result: A thorough evaluation of multi-UAV dynamics, encompassing radar threat, missile threat, terrain threat, connectivity, fuel consumption, and mission time considerations, was conducted [**133**]. The authors improved the individual fitness within the GWO framework by initializing the population within predefined constraints. A coefficient was introduced to balance global and local search capabilities, and the PSO concept was incorporated for optimal particle solutions, enhancing the GWO algorithm's convergence and solution quality.

A distribution method addressed a multi-UAV task assignment problem [**134**]. Path planning used neighbor search and PSO, ensuring a secure approach applicable in dynamic environments. This methodology provides a robust solution for coordination challenges in multi-UAV scenarios. In another study [**135**], the focus was on determining the number of UAVs and their task assignments based on priority. Path planning followed the assigned tasks, enhancing the fruit fly optimization algorithm with optimal reference points, a reference point mechanism, and a judgment matrix for improved stability and precision. The established cost function derived an optimal path, highlighting the method's efficacy in optimizing path-planning processes for UAVs in dynamic environment.

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