AN EFFICIENT PATH PLANNING TECHNIQUE FOR UNMANNED AERIAL VEHICLES TO IMPROVE THE QUALITY OF SERVICE

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DOCTOR OF PHILOSOPHY

in

Computer Science & Engineering

By

Anshu Vashisth

Registration Number: 41800393

Supervised By

Dr. Balraj Singh (13075)

Department of Computer Science & Engineering (Associate Professor)

Lovely Professional University, Punjab, India

Co-Supervised by

Dr. Ranbir Singh Batth (64540)

School of Computer, Data and Mathematical Sciences (Academic Course Coordinator)

Western Sydney University-Melbourne (ATMC) Campus, Australia

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2024

DECLARATION

I, hereby, declare that the presented work in the thesis entitled **"An Efficient Path Planning Technique for Unmanned Aerial Vehicles to Improve the Quality of Service."** in fulfilment of the degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of Dr. Balraj Singh, working as Associate Professor, in the Department of Computer Science and Engineering, Lovely Professional University, Punjab, India and Co-supervision of Dr. Ranbir Singh Batth, working as Academic Course Coordinator, in the Western Sydney University-Melbourne (ATMC) Campus, Australia. In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of another investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

Anshu Vashisth

(Signature of Scholar)

Anshu Vashisth
41800393
Department of Computer Science and Engineering
Lovely Professional University,
Punjab, India

CERTIFICATE

This is to certify that the work reported in the PhD. thesis entitled **An Efficient Path Planning Technique for Unmanned Aerial Vehicles to Improve the Quality of Service** submitted in fulfillment of the requirement for the award of the degree of **Doctor of Philosophy (Ph.D.)** in the Department of Computer Science and Engineering, is a research work carried out by Anshu Vashisth, 41800393, is bonafede record of his original work carried out under my supervision and that no part of the thesis has been submitted for any other degree, diploma or equivalent course.

Signature of Supervisor
Name of Supervisor: Dr. Balraj Singh

Designation: Associate Professor
Department/school: School of Computer Science & Engineering
University: Lovely Professional University, Punjab, India

Signature of Co-Supervisor
Name of Co-Supervisor: Dr. Ranbir Singh Batth
Designation: Academic Course Coordinator
Department/school: School of Computer, Data and Mathematical Sciences
University: Western Sydney University-Melbourne (ATMC) Campus, Australia

Abstract

The advancement of Unmanned Aerial Vehicle (UAV) networks has opened up unprecedented possibilities across diverse industries. These networks, vital for surveillance, disaster management, agriculture, and telecommunications, offer rapid deployment, manoeuvrability, and access to remote regions. However, their full potential hinges on efficient and adaptive routing. UAV routing is challenging due to the dynamic and unpredictable operational environment. Conventional routing protocols prove inadequate for the dynamic nature of UAV operations, necessitating innovative strategies. This thesis introduces a comprehensive exploration of UAV routing optimization by integrating Q-Learning, a reinforcement learning technique, to enhance adaptability and intelligence in routing decisions. Furthermore, the bioinspired Mayfly Optimization (MO) Model is integrated to select optimal paths, emphasizing Quality of Service (QoS) even under high routing requests and congestion. The integration of Q-Learning and MO Model significantly enhances temporal routing performance, demonstrating reduced routing delay, improved energy efficiency, and enhanced routing throughput. The rapid proliferation of Unmanned Aerial Vehicle (UAV) networks across diverse industries necessitates efficient and adaptive routing for their optimal utilization. Traditional routing protocols prove inadequate in addressing the dynamic and unpredictable nature of UAV operations. This approach empowers UAV nodes to make informed routing choices based on past experiences and rewards. The Extensive empirical testing of our model demonstrates remarkable reductions in routing delay, improved energy efficiency, and enhanced routing throughput compared to conventional techniques. This research offers a comprehensive understanding of the innovative routing model's potential for more efficient and adaptive UAV networks, heralding a new era of possibilities for this transformative technology. Empirical evaluations validate the superiority of the proposed model over traditional routing techniques, making it a compelling choice for real-time UAV routing applications.

Acknowledgement

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Anshu Vashisth

Anshu Vashisth

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Glossary

UAV ....Unmanned Aerial Vehicle

QoS ....Quality of Service

OA..Obstacle Avoidance

MO ....Mayfly Optimization

GWO ....Grey Wolf Optimization

CLF ....Continuous Learning Framework

FFO ....Firefly Based Optimization

AOMDV ....Adhoc On-Demand Multipath Distance Vector

AODV ....Adhoc On-Demand Distance Vector

MANET ....Mobile Adhoc Network

QL ....Quality Learning

GA..Genetic Algorithm

ACO ....Ant Colony Optimization

NLP ....Vehicular Adhoc Network

QTAR...Q-Learning based quality aware routing

CMOP ....Constrained multiobjective optimization problem

CNN ....Convolution Neural Network

GDRL...Geometric Distance Reinforcement Learning

DSR..Dynamic Source Routing

RRT…………………………………...Rapidly Exploring Random Trees

VO………………………………….... Velocity Obstacle

CHAPTER 1

INTRODUCTION

Unmanned Aerial Vehicle (UAV) networks were established to bring up new possibilities in the fields of communications, farming to, surveillance and emergency management. These networks have advantages which are rare, like being able to set up rapidly, move around easily, and connect to places that are far away or otherwise impossible to reach. For the UAV network, the most important thing is to work well with rapid and adjustable transportation. There are a lot of problems with UAV tracks since the places they work are always changing and are always unpredictable. Unlike regular wireless networks, UAV networks have to deal with nodes that are not all in the same place, changes in the network's structure that happen rapidly, and weather that changes all the time [1]. Figure 1.1 represents the simple architecture of an unmanned aerial vehicle to understand the functionality of its components to achieve better efficiency. Therefore, there is of need for routing systems that help to change and speed things up in real time because things are so complicated.

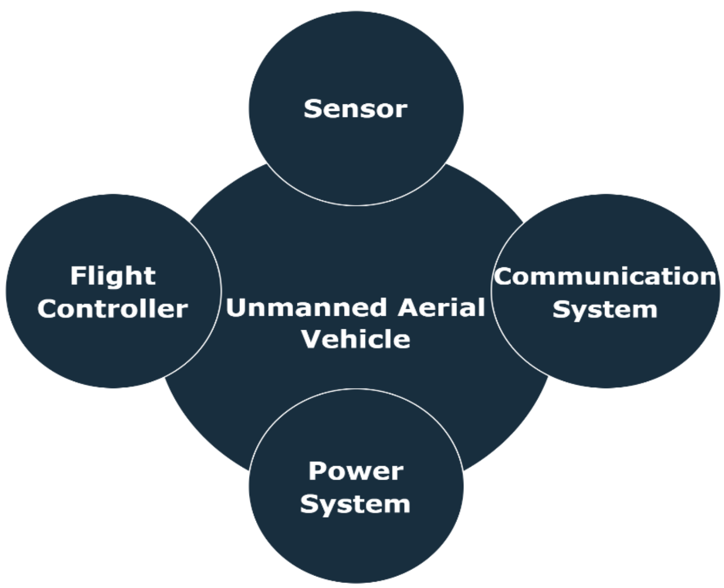

Figure1.1- Simple Architecture of Unmanned Aerial Vehicle

Traditional routing methods work well for static networks, but they are often unable to handle the unique problems that UAV networks have. The flexible nature of UAV activities makes it hard for traditional methods to handle them. This results in bad routing decisions, more delays, and wasteful use of resources. Because of this, there is an increasing need for novel routing algorithms that make UAV networks efficient while also making them easier to use. To deal with these problems, this research work represents a way to improve UAV routes by using methods that are based on nature [2]. The aim of the research work is to improve and use a useful routing model that uses Q-Learning, a reinforcement learning technique, to improve the routing adaptability and sensitivity to the dynamic UAV environment [3]. The basis of this model lies in Q-Learning, a reinforcement learning model that avoids standard state transition models. By incorporating Q-Learning, our method brings adaptability and intelligence into UAV routing, thus allowing nodes to make informed routing decisions based on past experiences and benefits. To address the challenges to UAV networks, our model goes further by integrating bioinspired optimization techniques, specifically the Mayfly Optimization (MO) Model. This augmentation enables the selection of optimal routing paths that prioritize Quality of Service (QoS), even in scenarios characterized by high routing requests and congestion [4].

The MO Model's ability to find alternate paths through the evaluation of a high-density routing fitness function ensures that the routing system stays agile and responsive, even when standard routing methods would fail. This innovation significantly enhances temporal routing performance, a critical factor in keeping the effectiveness and usefulness of UAV networks in real-world applications. Research work discussed the routing model under a variety of network scenarios by giving a result comparison of its superiority compared to conventional routing methods. Our model shows a reduction in routing delay, better energy efficiency, and enhanced routing speed, making it a better choice for an extensive variety of real-time UAV routing applications. UAVs were first developed in the early twentieth century as pilotless military aircraft. However, substantial developments happened during and after World War II, resulting in the contemporary UAVs we know today. Advances in technology, especially in electronics, sensors, and materials, have catapulted UAVs from simple designs to advanced structures capable of complicated tasks. Modern UAVs range from small enthusiast drones to big, high-altitude, long-endurance reconnaissance aircraft. Path planning is an important part of UAV operations, that involves determining the best route from a preliminary point to a target [5]. This approach must consider a variety of limitations, including barriers, no-fly zones, and environmental variables. Effective route planning ensures that UAVs carry out their missions effectively and safely. Path planning algorithms include A* (A-star), Dijkstra's algorithm, as well as advanced methods such as Rapidly Exploring Random Trees (RRT) and Genetic Algorithms. These approaches differ in complexity and processing needs, with some better suited to dynamic situations and real-time applications. A* and Dijkstra's algorithms are fundamental approaches in path planning. Dijkstra's approach identifies the shortest path between nodes in a network, which is beneficial in static situations when all information about the space is known in advance [6]. A*, a modification of Dijkstra's algorithm, uses heuristics to select pathways that are likely to get to the target faster, making it more efficient in many cases. Both algorithms, while strong, may struggle to make real-time adaptations in extremely dynamic situations, necessitating the development of more adaptable approaches. More complex path planning systems, such as Rapidly Exploring Random Trees (RRT) and Genetic Algorithms (GA), overcome the limitations of previous methods. RRT is very beneficial in high-dimensional areas and complicated situations since it gradually builds a tree that investigates possible pathways. Genetic algorithms use natural selection processes to iteratively refine route solutions, making them ideal for optimization problems with many constraints. These innovative technologies improve the capacity of UAVs to navigate uncertain and congested surroundings [7]. Collision avoidance is another critical component of UAV operations that ensures the UAV's safety and helps to prevent accidents. This includes recognizing possible obstructions and making real-time changes to the UAV's course. Collision avoidance techniques may be divided into two categories: reactive and deliberate. Reactive approaches employ real-time sensor data to make fast modifications, whereas deliberative methods use pre-planned procedures and prediction models to prevent accidents. Collision avoidance gets more difficult when many UAVs operate at the same time. To coordinate the movements of several UAVs, complex algorithms that take into account all vehicles' locations and trajectories are required. The Velocity Obstacle (VO) technique, Potential Fields, and decentralized methodologies allow UAVs to dynamically change their routes to avoid collisions while still achieving their mission objectives [8].

1.1 Background and Motivation

The purpose of this research work is to provide significant context for understanding the significance of routing efficiency in UAV networks.

i) Background

Unmanned aerial vehicle (UAV) networks have rapidly become a game-changing technology with applications in a wide range of fields, including emergency response, environmental monitoring, surveillance, and agriculture. These unmanned aerial vehicles provide unparalleled capabilities for data collecting, remote sensing, and on-demand airborne services because of their sophisticated sensors and communication systems. However, robust routing algorithms that can adjust to the dynamic and sometimes unpredictable nature of these surroundings are necessary for UAV networks to operate well. When used with UAV networks, traditional routing protocols—which were mostly created for stationary terrestrial networks—have built-in drawbacks [9]. The main obstacles that UAV operations face are unequal node distribution, the frequent topological changes brought on by mobility, and the climatic variables. Due to these complications, routing techniques need to be flexible enough to continuously improve network performance [10]. Real-world applications of UAV path planning and collision avoidance are vast and varied. In agriculture, UAVs autonomously navigate fields to monitor crops and apply treatments precisely. In logistics, they plan routes to deliver packages efficiently while avoiding obstacles. In search and rescue operations, UAVs can rapidly map out paths to locate and assist individuals in distress.

The ability to plan paths and avoid collisions enhances the utility and reliability of UAVs across these diverse applications.

ii) Motivation

The necessity to solve the inherent difficulties in UAV routing and realize the full potential of UAV networks is what drives this research work. The motivation for creating and deploying Unmanned Aerial Vehicles (UAVs) originates from their potential to transform a wide range of sectors by delivering new capabilities, efficiency, and solutions to complicated problems. One of the key reasons for UAV acceptance is the capacity to carry out risky activities without risking human life. In military applications, UAVs may perform reconnaissance, surveillance, and even combat missions in difficult settings, lowering the risk to human soldiers. Similarly, in disaster response and search and rescue operations, UAVs may enter dangerous regions, evaluate damage, and identify survivors without endangering first responders. The desire to explore novel routing strategies is driven by many important factors [11]:

a. **Dynamic Nature of UAV Operations:** UAVs are by nature dynamic, frequently functioning in ever-changing surroundings with changing goals for their missions. Inadequate performance results from conventional routing protocols' inability to keep up with the rapid changes in topology and routing requirements.

b. **Resource Efficiency:** In UAV networks, where resources such as battery power and bandwidth are limited, resource-efficient routing is paramount. Conventional routing approaches often lead to inefficient resource utilization, impacting the operational lifespan of UAVs.

c. **Real-time Responsiveness:** Many UAV applications demand real-time data collection and delivery, such as disaster response and surveillance. Ensuring low-latency routing in dynamic scenarios is essential for meeting these requirements.

d. **Quality of Service (QoS):** UAV networks often serve applications with stringent QoS requirements, including high data throughput, low latency, and reliable communication. Existing routing solutions may struggle to prioritize QoS, leading to service degradation.

e. **Scalability:** As UAV networks expand to accommodate a growing number of nodes and increasing demands for connectivity, scalability becomes a paramount concern. Traditional routing models may not scale effectively to address the requirements of larger networks.

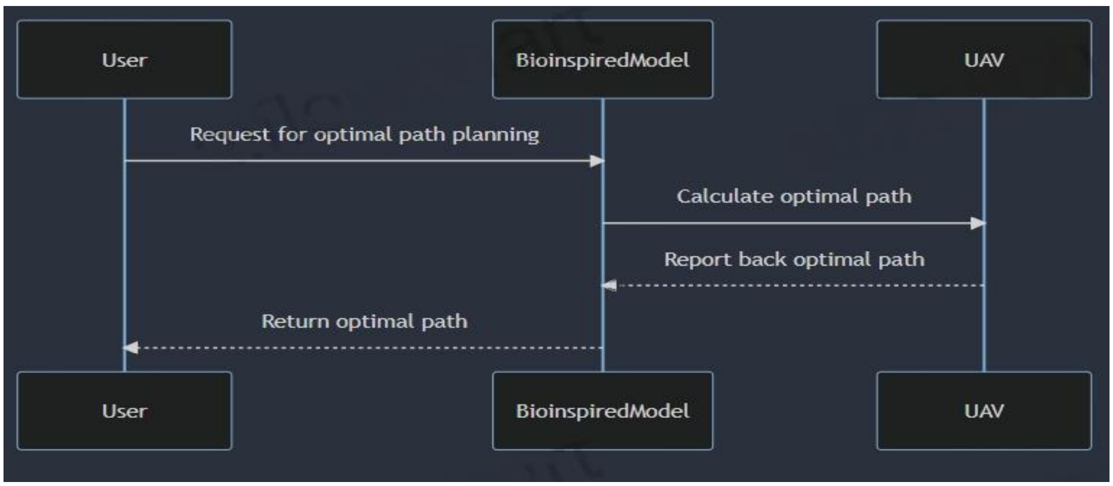

Figure1.2- Bioinspired Model Layer in path planning in Unmanned Aerial Vehicle

Figure 1.2 represents the use and role of the bioinspired model in the UAV path planning process for the calculation of optimal and collision less paths to increase the overall performance of the network. The model used in this research work offers a feasible way to improve routing efficiency, responsiveness, and flexibility in UAV networks by combining bioinspired optimization with the reinforcement learning approach Q-Learning. This research work aims to offer useful insights and solutions that can enable UAV networks to function more successfully across a range of applications and scenarios through comparative analysis [12].

1.2 Problem Statement

It represents the specific challenges and issues within the area of Unmanned Aerial Vehicle (UAV) networks that require the development of an innovative routing solution. In UAV networks, several complex challenges and limitations have been identified, prompting the need for a sophisticated routing model. Following are the challenges collectively constitute the problem statement that this research work endeavours to address [13].

a. **Dynamic and Unpredictable Environments**: UAVs operate in dynamic and often unpredictable environments, where factors such as weather conditions, obstacles, and mission objectives can change rapidly. Conventional routing protocols designed for stable terrestrial networks struggle to adapt to these dynamic circumstances. This dynamic nature poses a fundamental challenge to efficient routing in UAV networks.

b. **Resource Constraints**: UAVs are equipped with limited onboard resources, including battery power and processing capacity. Effective routing in UAV networks must consider these constraints to maximize mission duration and data transmission capabilities. Traditional routing approaches often fail to optimize resource utilization, leading to premature exhaustion of critical resources.

c. **Real-time Responsiveness**: Many UAV applications, such as disaster response and surveillance, necessitate real-time data collection and delivery. Delays in routing decisions can result in missed opportunities or mission failure. Existing routing protocols may not meet the inflexible latency requirements of these applications.

d. **Quality of Service (QoS) Demands**: UAV networks serve a various array of applications, each with unique QoS requirements. These requirements may encompass high data throughput, low latency, and dependable communication. Conventional routing strategies often lack the adaptability to prioritize and guarantee QoS, leading to a compromise in service quality.

e. **Scalability Challenges**: As UAV networks expand to accommodate a larger number of nodes and handle increasing communication requests, scalability becomes a critical concern. Conventional routing models face challenges in scaling efficiently to support the growing demands of larger network scenarios.

f. **Inefficiency in Path Optimization**: Existing path optimization models show either excessive complexity or limited scalability. Moreover, as more demands for communication are made, the efficiency of these models reduces, thus constraining their applicability in scenarios with high routing demands.

g. **Network Heterogeneity**: UAV networks are characterized by network heterogeneity, where nodes may vary in terms of their capabilities and communication range. Designing routing protocols that can effectively operate in such heterogeneous environments is a complex undertaking.

The research work addresses the questions by proposing a novel routing model that integrates Q-Learning, a reinforcement learning technique, with bioinspired optimization. By doing so, it aims to provide a comprehensive solution that enhances routing adaptability, resource efficiency, real-time responsiveness, and scalability while meeting the various QoS demands of UAV applications. Through comparative analysis, research work aims to contribute valuable insights and solutions to overcome the details challenges in the UAV network routing process [14].

1.3 Purpose of the Research work

The purpose of research work is to set the direction towards novelty and vision in UAV path planning by improving the knowledge of various aspects of the dynamic environment. The study in UAV route planning is driven by many major aims, all of which are to be used to improve the efficiency, safety, and dependability of unmanned aerial vehicles (UAVs) in a variety of applications [15]. One of the primary goals of UAV route planning research work is to provide algorithms and approaches for optimizing the routes followed by UAVs to perform their missions. This involves decreasing trip distance, time, and energy consumption while guaranteeing that the UAV reaches its goal. Efficient route planning lowers operational costs and increases the operational range of

UAVs, making them more economical for commercial and industrial use [16]. UAVs frequently operate in complicated, dynamic situations where circumstances might change rapidly. Path planning research work aims to create algorithms capable of handling this complexity, allowing UAVs to navigate urban areas, woods, and other difficult terrains. Research work aims to increase the use of UAV applications in a wide variety. Effective route planning increases the versatility of UAVs and their ability to answer particular demands across sectors [17]. Various factors which influence the purpose of research work are as follows:

a. **Development of an Efficient Routing Model**: The primary purpose of research work is the design of a new and efficient routing model for the unique characteristics of Unmanned Aerial Vehicle (UAV) networks. This model will integrate Q-Learning, a reinforcement learning technique, with bioinspired optimizations to enhance routing adaptability, resource utilization, and real-time responsiveness.

b. **Adaptation to Dynamic Environments**: The research work endeavours to design a routing model capable of adapting to the dynamic and often unpredictable environments in which UAVs operate. It pursues to develop mechanisms that enable the routing protocol to respond intelligently to changing conditions, ensuring reliability and efficient data communication.

c. **Optimization of Resource Utilization**: Resource constraints are a critical concern in UAV networks. The research work objective is to optimize the utilization of onboard resources, including battery power and processing capacity, to extend mission durations and improve the overall efficiency of UAV operations.

d. **Real-time Responsiveness**: The research work aims to achieve real-time responsiveness in routing decisions, particularly critical for applications such as disaster response and surveillance. The routing model will be designed to meet rigorous latency requirements, ensuring timely data collection and delivery.

e. **Quality of Service (QoS) Guarantees**: Meeting various QoS demands is of utmost priority. The research work aims to develop mechanisms within the routing model to prioritize and guarantee QoS requirements, including high data throughput, low latency, and dependable communication, for various UAV applications.

f. **Scalability Enhancement**: Addressing scalability challenges is a pivotal research work objective. The routing model should efficiently scale to accommodate a growing number of nodes and increase communication requests, ensuring its applicability in larger network scenarios.

g. **Efficient Path Optimization**: The research work aims to resolve inefficiencies in path optimization. The routing model will be designed to handle a higher number of communication requests without sacrificing efficiency. It will prioritize optimal path selection to reduce routing delays [18].

h. **Heterogeneous Network Support**: Considering the heterogeneity of UAV networks, the research work objectives include the development of routing strategies that can effectively operate in environments where nodes exhibit varying capabilities and communication ranges.

These research work objectives collectively form the framework for the research work. By achieving these objectives, the research work aims to contribute valuable insights and solutions to enhance the efficiency, adaptability, and performance of routing protocols in UAV networks.

1.4 Node-Level and Network-Level Parameters in UAV Routing

In Unmanned Aerial Vehicle (UAV) routing, the efficiency and effectiveness of the routing strategies heavily depend on a refined understanding of node-level and network-level parameters. These parameters play a vital role in shaping the behaviour and performance of UAV networks. This explains the significance of node-level and network-level parameters, shedding light on their role in the optimization of UAV routing [19].

i) Node-Level Parameters

Node-level parameters pertain to the characteristics and attributes of individual UAV nodes within the network. These parameters include a range of variables that impact the routing process:

a. **Location and Mobility**: The spatial coordinates of UAV nodes (latitude, longitude, altitude) are fundamental node-level parameters. The mobility patterns of UAVs, including speed and trajectory, influence their ability to establish and maintain connections. Nodes in motion require routing protocols that adapt to dynamic topologies.

b. **Energy Resources**: Node-level energy parameters, such as initial energy levels and power consumption rates during various operations (e.g., transmission, reception, sensing), are critical. Energy-efficient routing strategies are essential to extend the operational lifespan of UAVs, especially in scenarios with limited recharging opportunities [20].

c. **Communication Range**: The range within which a UAV can communicate effectively with neighbouring nodes is a crucial node-level parameter. It determines the local neighbourhood of a node and influences its routing decisions. Nodes must consider the signal strength and interference levels when selecting next-hop neighbours.

d. **Sensor and Payload Data**: Depending on the application, UAVs may carry different types of sensors and payloads (e.g., cameras, environmental sensors, cargo). Node-level parameters include the data generated, data rates, and the need for real-time or periodic data transmission. Routing should optimize data collection and delivery.

e. **Quality of Service (QoS) Requirements**: Each UAV may have specific QoS requirements based on its mission. Node-level parameters related to QoS include latency tolerance, data reliability, throughput expectations, and priority levels. Routing decisions should align with these requirements.

ii) Network-Level Parameters

Network-level parameters include characteristics that define the overall UAV network's structure, behaviour, and capacity [21]. These parameters are integral to designing scalable and efficient routing strategies:

a. **Network Topology**: The arrangement of UAV nodes and their interconnections forms the network topology. Dynamic topologies in UAV networks require adaptive routing algorithms capable of accommodating changes caused by node mobility and connectivity fluctuations.

b. **Network Density**: The density of UAV nodes in an assumed range impacts routing decisions. High-density networks require routing protocols that can efficiently manage congestion and select optimal paths. Node distribution and deployment strategies play a role in network density.

c. **Communication Protocols**: The choice of communication protocols, including wireless standards (e.g., IEEE 802.11, 802.16) and medium access control (MAC) protocols, affects network-level parameters like data transfer rates, interference levels, and collision avoidance mechanisms. Routing strategies should align with the selected protocols.

d. **Scalability**: The ability of the UAV network to scale to accommodate a growing number of nodes and increasing communication demands is a critical network-level parameter. Scalable routing algorithms should be able to handle larger networks without sacrificing performance.

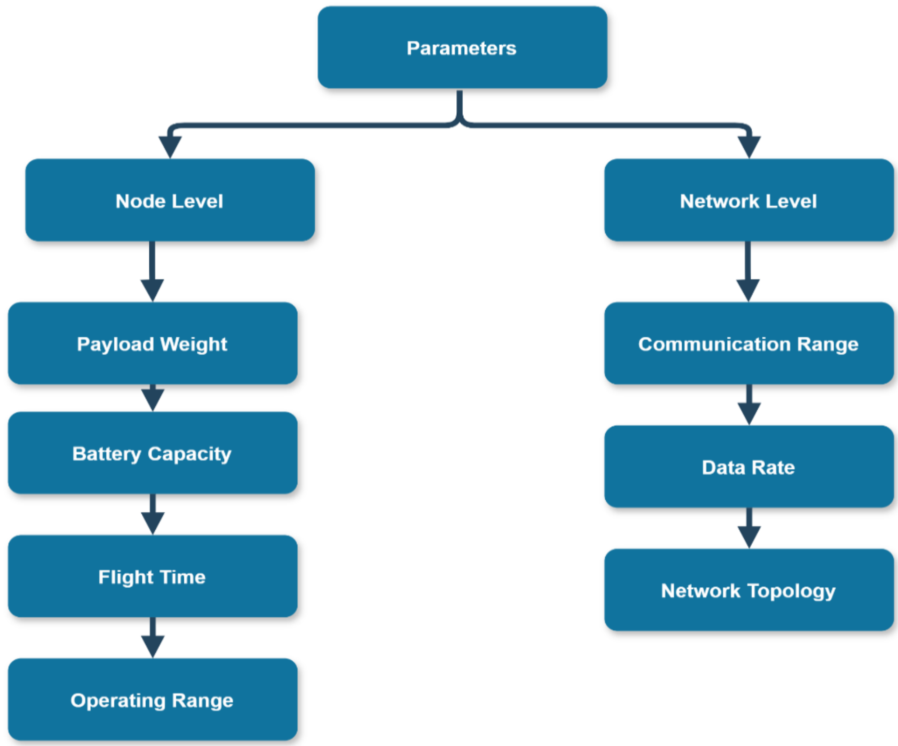

Figure 1.3- Various Node and Network Level Parameters

Figure 1.3 depicts a few critical node and network level parameters that need to be taken care of while performing path planning calculations. Node-level and network-level parameters serve as the initial level elements upon which UAV routing strategies are built [22]. Effectively binding these parameters through intelligent routing algorithms is key to achieving the desired objectives of UAV missions, whether they involve surveillance, data collection, communication, or any other application [23]. As UAV knowledge carries on to improvement, routing strategies must evolve to adapt to the dynamic interplay of these parameters, ensuring the efficient and reliable operation of UAV networks.

1.4.1 Importance of Node-Level and Network-Level Parameters

i) Node-Level

In Unmanned Aerial Vehicle (UAV) routing, the significance of node-level parameters cannot be exaggerated. These parameters, which encapsulate the characteristics and attributes of individual UAV nodes, are essential in shaping the efficiency, adaptability, and overall performance of routing strategies within UAV networks. This research work investigates the importance of node-level parameters in the context of UAV routing [24].

a. **Spatial Awareness and Mobility**: Node-level parameters include critical spatial information, including the precise coordinates (latitude, longitude, altitude) of each UAV within the network. This spatial awareness is fundamental to routing decisions, as it enables nodes to calculate distances, identify neighbouring UAVs, and determine their relative positions. Mobility-related parameters, such as speed and trajectory, further refine routing strategies, allowing UAVs to adapt to dynamic network topologies resulting from node movement [25].

b. **Energy Management**: Node-level parameters associated with energy resources are of vital importance, particularly in UAV networks where energy constraints are common. These parameters cover initial energy levels and power consumption rates during various operations, including data transmission, reception, and sensing. Effective routing strategies must consider these energy constraints to optimize the utilization of available power resources, thereby extending the operational lifespan of UAVs.

c. **Communication Capabilities**: A fundamental node-level parameter is the communication range, which dictates the distance over which a UAV can establish and maintain reliable connections with neighbouring nodes. Communication range, often influenced by factors like signal strength and interference, directly impacts routing decisions. UAVs must select next-hop neighbours within their communication range to ensure efficient data exchange.

d. **Payload and Sensor Data**: Node-level parameters incorporate the payload and sensor data carried by UAVs. These parameters incorporate data types, data rates, and the specific requirements for data transmission. Routing strategies must align with the data generation and collection needs of individual UAVs, optimizing data delivery while considering payload constraints.

e. **Quality of Service (QoS) Requirements**: Each UAV may have unique QoS requirements based on its mission objectives. Node-level QoS parameters encompass factors such as latency tolerance, data reliability, required throughput, and priority levels for different data streams. Routing decisions must prioritize meeting these QoS requirements, ensuring that mission-critical data receives the necessary treatment.

f. **Adaptation to Node Variability**: UAV networks often consist of heterogeneous nodes with varying capabilities and attributes. Node-level parameters allow routing protocols to adapt to this variability. For example, a routing algorithm can dynamically adjust its routing decisions established on the energy stages of individual nodes or the capabilities of specific UAVs.

g. **Efficient Resource Utilization**: By considering node-level parameters, routing strategies can efficiently allocate network resources. For instance, routing decisions can aim to balance energy consumption among nodes, prevent overloading specific UAVs, or distribute data traffic evenly across the network. This resource management optimizes the overall network performance.

h. **Dynamic Decision Making**: Node-level parameters enable dynamic decision making in response to changing network conditions. When node parameters change due to factors such as energy depletion or mobility, routing protocols can adapt by selecting alternative routes or adjusting transmission power levels.

ii) Network-Level

In the complex field of Unmanned Aerial Vehicle (UAV) routing, network-level parameters have considerable influence over the design, efficiency, and adaptability of routing strategies within UAV networks. These parameters, which encapsulate the collective attributes and conditions of the entire network, play a vital role in shaping the performance and functionality of UAV routing. This research work explores the insightful influence of network-level parameters in the context of UAV routing [26].

a. **Network Topology and Density**: Network-level parameters include the spatial arrangement and density of UAV nodes within the network. The network's topology dictates how UAVs are interconnected and influences the paths available for data transmission. In sparse networks, UAVs may need to cover larger distances, while in dense networks, they have more potential neighbours to choose from. The network's density intensely affects routing decisions, especially in terms of path selection and interference management.

b. **Communication Protocols**: The selection of communication protocols at the network level significantly impacts UAV routing. Parameters related to communication protocols, such as data transmission rates, error handling mechanisms, and frequency bands, dictate the efficiency and reliability of data exchange. Routing strategies must align with the chosen communication protocols to optimize data delivery.

c. **Traffic Patterns and Load Balancing**: Network-level parameters cover the traffic patterns and data load within the UAV network. Understanding the distribution of data traffic, including the volume and frequency of communication, is crucial for effective routing. Routing protocols can utilize this information to balance the load among UAVs, preventing network congestion and ensuring efficient resource utilization.

d. **Network Connectivity and Reliability**: The connectivity status of the network and its reliability in maintaining communication links are fundamental network-level parameters. In dynamic UAV environments, connectivity can be disrupted due to node mobility or interference. Routing protocols must continuously assess connectivity and adapt to changing conditions to ensure uninterrupted data transmission.

e. **Quality of Service (QoS) Constraints**: Network-level parameters often define overarching QoS constraints and objectives for the entire UAV network. These constraints may include maximum latency tolerances, minimum data reliability thresholds, and overall network capacity. Routing decisions must struggle to meet these global QoS requirements, guaranteeing that the network as a whole satisfies mission-critical demands.

f. **Security and Privacy Considerations**: Security parameters at the network level incorporate encryption mechanisms, authentication protocols, and intrusion detection systems. These parameters are vital in safeguarding data integrity and network privacy. Routing strategies must incorporate security measures to protect sensitive information from threats and attacks.

g. **Scalability and Network Size**: The size of the UAV network is a network-level parameter that intensely influences routing strategies. Large-scale networks introduce scalability challenges, as routing protocols must efficiently handle a growing number of nodes and communication requests. Scalable routing algorithms are essential for networks that may expand or contract in size.

h. **Resource Availability and Constraints**: Network-level parameters include information about the availability and constraints of network resources, such as energy, bandwidth, and processing power. These parameters guide routing decisions to improve the application of offered resources while adhering to resource limitations.

i. **Dynamic Environmental Conditions**: Environmental factors, such as weather conditions and interference from external sources, are network-level parameters that affect UAV routing. Routing strategies must be adaptive and capable of responding to environmental changes to maintain reliable communication and routing performance.

Node-level parameters are the building blocks of effective UAV routing strategies. They empower routing protocols to make informed decisions that optimize data transmission, energy efficiency, and overall network performance. The ability to consider and influence these parameters is central to the success of UAV missions, as it ensures that routing strategies align with the distinctive features and requirements of individual UAVs within the network [27]. As UAV knowledge continues to change, binding node-level parameters will remain crucial for achieving effective and consistent routing in dynamic and resource-constrained environments. Whereas network-level parameters serve as the contextual framework within which UAV routing strategies operate. They provide critical information about the network's characteristics, conditions, and objectives, enabling routing protocols to make informed decisions. Effective UAV routing demands a deep understanding and consideration of these network-level parameters to optimize data transmission, adapt to changing conditions, and achieve the overarching mission goals of the UAV network [28]. As UAV technology continues to advance, the influence of network-level parameters on routing strategies will remain fundamental to ensuring efficient and reliable performance in diverse and challenging environments [29].

1.5 Dynamic Routing and Collision Avoidance

Dynamic routing and collision avoidance are fundamental aspects of Unmanned Aerial Vehicle (UAV) networks that play a critical role in ensuring safe, efficient, and reliable operations. In this chapter, the significance of dynamic routing and collision avoidance, their challenges, and the innovative approaches used to address these critical aspects in UAV networks have been addressed [30].

1.5.1 Significance in UAV Networks:

a. **Real-Time Adaptation**: Dynamic routing allows UAVs to adapt their flight paths in real-time based on network conditions, mission requirements, and environmental factors.

b. **Optimized Resource Usage**: Dynamic routing optimizes the utilization of available network resources, such as bandwidth and power, leading to efficient data transmission.

c. **Collision Avoidance**: Collision avoidance mechanisms prevent in-air collisions between UAVs, ensuring safe and uninterrupted operations, particularly in congested airspace.

1.5.2 Challenges in Dynamic Routing and Collision Avoidance:

a. **Scalability**: In large UAV networks, routing decisions become increasingly complex. Balancing scalability with real-time responsiveness is a challenge.

b. **Dynamic Environments**: UAVs operate in unpredictable environments with varying obstacles and interference sources. Adapting to these dynamic conditions is essential.

c. **Collision Prediction**: Predicting potential collisions accurately is an essential task in a dynamic environment by using collision avoidance algorithms.

d. **Communication Latency**: Real-time routing decisions require low-latency communication, which can be challenging in UAV networks, especially in remote or congested areas.

1.5.3 Integration with Communication Protocols:

Dynamic routing and collision avoidance should flawlessly integrate with UAV communication protocols. For instance, protocols like Dynamic Source Routing (DSR) and Ad hoc On-Demand Distance Vector (AODV) can incorporate real-time routing updates to adapt to changing network topologies. Table 1.1 emphasizes the link between dynamic routing and collision avoidance in UAVs. The table describes the many features of dynamic routing and how they connect to or affect collision avoidance strategies. Advanced technologies like AI and machine learning are used in dynamic routing and collision avoidance to improve their capabilities and efficacy. Table 1.1 shows how dynamic routing and collision avoidance are connected and how advances in one area might assist the other [31].

Table1.1- Relationship of dynamic routing and collision avoidance in UAVs with a common aspect

Feature	Dynamic Routing	Collision Avoidance
Objective	Optimize UAV path efficiency in real-time considering dynamic factors.	Ensure safe operation by avoiding collisions and maintaining safe distances.
Key Algorithms	A*, RRT (Rapidly-exploring Random Trees), Genetic Algorithms, Dijkstra's Algorithm	Velocity Obstacle (VO), Potential Fields, Sense-and-Avoid, Reactive Methods
Environment	Operates in dynamic, unpredictable environments.	Requires awareness of static and dynamic obstacles in the environment.
Adaptability	High adaptability to changes such as new obstacles, weather conditions, and moving targets.	High adaptability to the sudden appearance of obstacles or changes in the trajectory of other UAVs.
Use Cases	Search and rescue, dynamic surveillance, and delivery in urban environments	Close-formation flying, urban navigation, operations in crowded airspaces

1.5.4 Future Directions:

a. **5G and Beyond**: The integration of 5G and future communication technologies will enable low-latency, high-throughput communication, enhancing dynamic routing and collision avoidance capabilities.

b. **Swarm Intelligence**: Implementing swarm intelligence principles can improve collaboration among UAVs, enabling them to coordinate routing and collision avoidance methods more effectively.

By seamlessly integrating dynamic routing and collision avoidance mechanisms with robust communication protocols, UAV networks can achieve new levels of performance and reliability, opening up opportunities for varied kinds of applications, from surveillance and delivery to disaster response and beyond [32].

1.5.6 Challenges in Dynamic Routing

Dynamic routing, a foundation of modern network management, faces many of the challenges in today's complex and ever-evolving technological landscape. In this chapter, we investigate the challenges, their implications, and the innovative strategies being employed to navigate through them effectively.

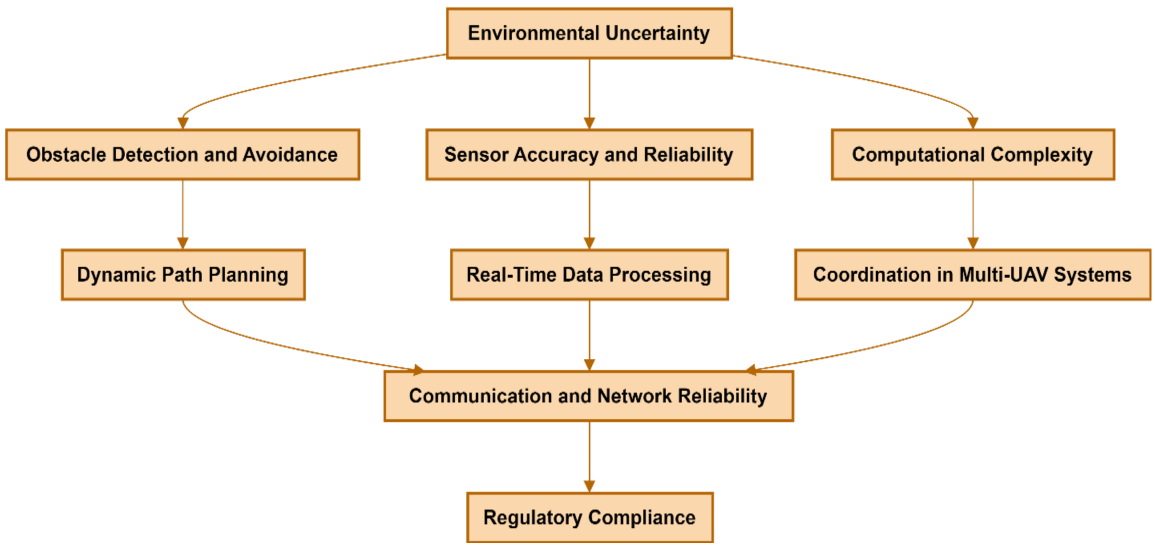

Figure 1.4- Some Common Challenges in Dynamic Routing

Figure 1.4 displays the primary issues in dynamic UAV routing, with explanations for each. Each of these issues represents an important factor that must be addressed in order to achieve effective and dependable dynamic routing for UAVs. To overcome these obstacles, a multidisciplinary strategy is required, which includes advanced algorithms, robust sensor technologies, and efficient computing approaches. Figure 1.4 shows the interrelated issues in the dynamic routing of UAVs and their influence on one another [33].

i) Scalability and Network Size:

One of the primary challenges in dynamic routing is scalability, especially in large-scale networks. As networks grow to accommodate a multitude of devices, nodes, and routes, the routing infrastructure must efficiently handle the increasing complexity. The management and computation overhead required for routing decisions in massive networks can lead to delays and inefficiencies.

ii) Real-Time Responsiveness:

The demand for real-time data transmission and low-latency communication presents a significant challenge. Dynamic routing protocols must make instant decisions to adapt to changing network circumstances and improve traffic flow. Achieving real-time responsiveness without compromising on the accuracy of routing decisions is a delicate balance.

iii) Network Dynamics:

Networks are inherently dynamic, with nodes joining, leaving, or failing regularly. Dynamic routing protocols must seamlessly adapt to these changes without causing network disruptions. The challenge lies in developing algorithms that can detect and react to network dynamics while maintaining stability.

iv) Security Concerns:

Security flaws are also introduced by the dynamic nature of routing. The adaptability of dynamic routing protocols may be used by hackers to conduct different kinds of attacks, update routing tables, or redirect traffic. The integrity, confidentiality, and dependability of network communications may all be severely impacted by these assaults. Typical risks include route deletion, which eliminates valid routes to interfere with network connection, and route injection, in which attackers introduce false routing information to reroute traffic through compromised nodes. Man-in-the-middle attacks can be made possible via traffic diversion, giving hackers the ability to intercept, change, or eavesdrop on private information.

v) Quality of Service (QoS):

Dynamic routing must prioritize and maintain the quality of service, especially in networks where different types of traffic require varying levels of bandwidth and reliability. Ensuring that critical applications receive the necessary resources while efficiently utilizing available bandwidth is a balancing act.

vi) Interoperability:

In heterogeneous environments with diverse hardware and software components, achieving interoperability among different routing protocols and devices can be complex. Routing systems must effectively communicate and exchange routing information across these varied platforms.

vii) Resource Utilization:

Dynamic routing decisions should optimize resource utilization, including bandwidth and processing power. Inefficient routing can lead to resource bottlenecks, wastage, and reduced overall network performance.

viii). Complex Routing Policies:

Organizations often have specific routing policies and constraints that need to be incorporated into dynamic routing algorithms. Adhering to these policies while ensuring efficient routing can be a challenge, especially when policies conflict.

ix) Convergence Time:

When network changes occur, routing protocols must converge to a stable state rapidly. Lengthy convergence times can result in temporary disruptions, affecting the overall user experience.

x) Fault Tolerance:

Ensuring network robustness and fault tolerance is a vital task. Dynamic routing should be robust to failures and capable of rerouting traffic in the event of link or node failures.

1.5.7 Collision Avoidance Strategies

Collision avoidance strategies are at the heart of ensuring the smooth and safe operation of autonomous systems, particularly in the context of Unmanned Aerial Vehicle (UAV) networks and beyond. In this section, the significance of collision avoidance, the challenges it poses, and the strategies have been explored [34].

i) Importance of Collision Avoidance:

Collision avoidance is a fundamental concern in autonomous systems, including UAVs. The avoidance of collisions is not only critical for preserving the integrity of the vehicles themselves but also for the safety of individuals, property, and the environment. UAVs, which operate in diverse and often dynamic environments, rely on collision avoidance to prevent accidents, maintain operational efficiency, and adhere to regulations.

ii) Challenges in Collision Avoidance:

Several challenges complicate the task of collision avoidance in UAV networks:

a. **Dynamic Environments**: UAVs often operate in environments characterized by rapidly changing conditions, including the presence of other UAVs, manned aircraft, and unexpected obstacles. Adapting to these dynamics in real-time is a substantial challenge.

b. **Sensor Limitations**: Collision avoidance heavily depends on sensor data, including GPS, LIDAR, radar, and cameras. Ensuring the accuracy and reliability of this data, especially in adverse weather conditions or urban canyons, poses a challenge.

c. **Communication Latency**: UAVs within a network must communicate and share their positions and intentions to avoid collisions. Minimizing communication latency while maintaining network integrity is vital.

d. **Regulatory Compliance**: Compliance with flight regulations is non-negotiable. Collision avoidance strategies must align with these regulations and adapt to changes in legal frameworks.

e. **Scalability**: As UAV networks expand to accommodate more vehicles, scaling collision avoidance mechanisms becomes complex. Ensuring that the system remains efficient and effective with a growing number of participants is challenging.

iii) Collision Avoidance Strategies:

To address these challenges, a range of collision avoidance strategies and technologies are used as follows:

a. **Sense and Avoid Systems**: UAVs are equipped with innovative sensor suites that enable them to detect obstacles and other vehicles. These systems include LIDAR, radar, and computer vision, which provide data for collision prediction and avoidance.

b. **Machine Learning and AI**: Machine learning algorithms are used to scrutinize sensor data and predict potential collision scenarios. AI-driven decision-making processes allow UAVs to take evasive action autonomously.

c. **Communication Protocols**: UAVs communicate with each other through standardized protocols to exchange position and intent data. These protocols ensure that vehicles are aware of each other's presence and can plan routes accordingly.

d. **Dynamic Path Planning**: UAVs utilize dynamic path planning algorithms to adapt their flight paths in real-time. These algorithms consider not only static obstacles but also dynamic elements such as other UAVs and manned aircraft.

e. **Testing and Simulation**: Rigorous testing and simulation environments allow collision avoidance systems to be evaluated comprehensively before deployment. This reduces the risk of accidents during real-world operations.

In summary, collision avoidance strategies play a significant role in the safe and efficient operation of UAV networks and autonomous systems. While challenges such as dynamic environments and sensor limitations continue, ongoing advancements in technology, including sensors, machine learning, and communication protocols, are continuously improving collision avoidance capabilities. As UAV networks expand and become more integrated into daily life, the development and refinement of these strategies will remain a top priority to ensure safe and reliable autonomous operations [35].

1.5.8 Integration of Dynamic Routing and Collision Avoidance

The integration of dynamic routing and collision avoidance is an essential aspect of ensuring the safe and efficient operation of Unmanned Aerial Vehicle (UAV) networks. In this discussion, we examine the significance of combining these two critical elements, the challenges it presents, and the advantages it offers in the framework of UAV networks [36].

i) Significance of Integration:

The integration of dynamic routing and collision avoidance is essential for achieving seamless and effective UAV operations. It includes the coordination of UAVs' flight paths in real-time while simultaneously avoiding collisions with other UAVs, manned aircraft, and obstacles. This integration serves several crucial purposes [37]:

a. **Safety**: Safety is on top in UAV networks. The integration ensures that UAVs can dynamically adapt their routes to prevent collisions, thereby minimizing the risk of accidents, damage, and potential harm to people on the ground.

b. **Efficiency**: Dynamic routing allows UAVs to optimize their flight paths for factors like fuel efficiency and mission objectives. Integrating collision avoidance ensures that these optimized paths do not compromise safety.

c. **Network Scalability**: As UAV networks expand to accommodate a growing number of vehicles, the integration of dynamic routing and collision avoidance ensures that the system can scale effectively without compromising safety or efficiency.

Although UAV has so many advantages in context to their application areas, as shown in figure 1.5, at the same time, it is very difficult to integrate dynamic routing with collision avoidance strategies with various types of challenges explained in the next section of part of this chapter.

ii) Challenges in Integration:

The integration of dynamic routing and collision avoidance poses several complex challenges:

a. **Real-Time Decision-Making**: UAVs must make instant decisions to adjust their routes and avoid collisions. Ensuring that these results are both safe and effective requires advanced algorithms and reliable data.

b. **Sensor Data Fusion**: Collision avoidance relies on data from various sensors, including LIDAR, radar, GPS, and cameras. Integrating and processing this diverse sensor data in real-time is challenging but crucial for accurate decision-making.

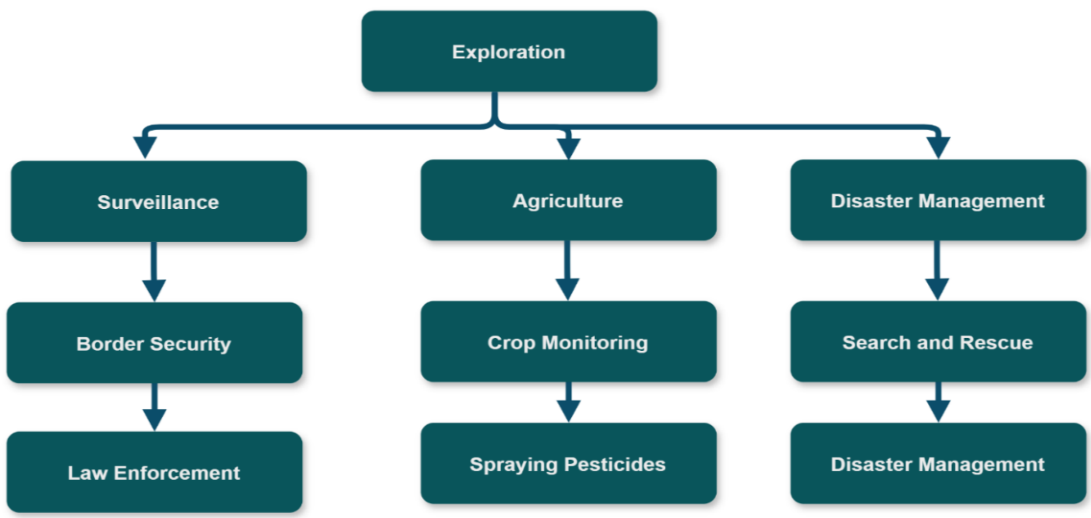

Figure 1.5- Applications Areas where UAV can be used with optimal path planning

a. **Communication Latency**: Coordination among UAVs is dependent on data sharing. Minimizing communication latency while ensuring data integrity is a delicate balance that must be maintained.

b. **Dynamic Environments**: Dynamic routing accounts for factors like weather, mission objectives, and traffic. Integrating these dynamic elements with collision avoidance adds complexity, especially when conditions change rapidly.

iii) Advantages of Integration:

Despite these challenges, the integration of dynamic routing and collision avoidance offers several advantages:

a. **Enhanced Safety**: Integration minimizes the risk of collisions, safeguarding UAVs and the surrounding environment.

b. **Efficient Operations**: UAVs can optimize routes for efficiency while avoiding obstacles and other vehicles, resulting in cost savings and improved mission success rates.

c. **Adaptability**: The integrated system can adapt to changing conditions, including unexpected obstacles or airspace restrictions, without manual intervention.

d. **Compliance**: UAV operators can maintain compliance with flight regulations seamlessly, avoiding legal complications.

In summary, the integration of dynamic routing and collision avoidance represents a critical innovation in the development of UAV networks. While challenges related to real-time decision-making and sensor data fusion persist, ongoing advancements in technology, including machine learning, AI, and communication protocols, are progressively improving the capabilities of integrated systems. As UAV networks become more prevalent in various industries, the successful integration of these two elements will be crucial in ensuring their continued safe and efficient operation [38].

1.5.9 Real-time Considerations

The Unmanned Aerial Vehicle (UAV) routing and collision avoidance is inherently dynamic and demands real-time considerations to ensure safe and efficient operations. In this section, we explore the critical importance of real-time factors, the challenges they present, and the strategies employed in addressing them within the context of UAV networks [39].

i) Challenges in Real-time Considerations:

Several challenges arise when integrating real-time considerations into UAV routing and collision avoidance:

a. **Data Processing**: Processing vast amounts of real-time data from various sensors and sources requires robust computational capabilities and algorithms to ensure accurate decision-making.

b. **Latency**: Minimizing latency in data transmission and decision execution is critical.

c. **Dynamic Decision-Making**: UAVs must make rapid decisions in complex and evolving scenarios. Developing algorithms capable of handling real-time decision-making under uncertainty is a significant challenge.

1.6 Significant Contribution

A review and research work on existing route planning methodologies in UAVs can provide a solid foundation for identifying gaps and opportunities in the current state of knowledge. It may determine the merits and drawbacks of various tactics, such as heuristic, probabilistic, and machine learning-based approaches. This analysis will not only improve our understanding of how these techniques work in different situations but will also improve the way of development of more refined and successful path planning strategies. Furthermore, putting this data into a well-structured framework might provide the groundwork for future UAV path planning research work and development [40].

Second, developing and implementing a new target identification technique based on optimal path selection is a significant advancement in UAV technology. Novel algorithms for route planning and target recognition can be utilized to increase UAV operations' precision and efficiency. This innovation might include utilizing AI and machine learning to estimate and react to changing conditions, ultimately increasing mission outcomes. Finally, presenting a collision minimization technique and comparing it to existing tactics in terms of Quality of Service (QoS) measurements will demonstrate the research work's practical importance [41]. Addressing collision dangers with innovative techniques, including real-time course change, cooperative collision avoidance algorithms, and improved sensor integration, may significantly enhance the safety and reliability of UAV operations. Implementing these tactics and comparing them to current standards will provide actual evidence of their success, including improvements in key QoS metrics like as latency, reliability, and throughput. This comparative study will not only analyze your proposed approaches but will also give helpful insights into their scalability and real-world application, thereby contributing considerably to the field of UAV technology [42].

1.7 Research work Objectives

Following four objectives have been finalized in line with the research work:

I. **To review and investigate the existing path planning techniques in UAVs.**
   This objective aims to conduct a review of current path planning methodologies used in Unmanned Aerial Vehicles (UAVs), evaluating their effectiveness, limitations, and potential areas for improvement.

II. **To design and implement a target detection technique based on an optimal path selection.**
   This objective focuses on developing a novel target detection method that leverages optimal path planning to enhance the accuracy and efficiency of UAV missions.

III. **To propose a scheme for minimizing the collision in UAVs.**
   This objective is centred on creating a robust scheme to reduce collision risks among UAVs, thereby improving the security and consistency of UAV operations.

IV. **To implement and compare the proposed work for QoS with existing techniques.**

This objective involves the implementation of the proposed techniques and their comparison with current methods, focusing on Quality of Service (QoS) metrics to demonstrate the improvements and benefits of the new approach.

1.8 Research work Organization

This research work is being structured to provide a clear and complete study of the research work conducted on Unmanned Aerial Vehicle (UAV) routing, bioinspired optimization, and collision-aware routing. The organization of this research work follows a logical progression, allowing readers to investigate the subject matter with clarity and depth. Each chapter contributes to the overall understanding of the research work and builds upon the preceding chapters, ultimately concluding a combination of findings, implications, and future directions.

Chapter 1: Introduction

The research work begins with Chapter 1, the "Introduction." In this opening chapter, the introductory aspects of the research work are established. It begins with "1.1 Background and Motivation," which provides a context for the study by exploring the significance of UAV networks and the motivations behind this research work. "1.2 Problem Statement" follows, articulating the challenges and limitations faced in the dominion of UAV routing, setting the stage for the subsequent chapters. "1.3 Purpose of research work" outlines the specific goals and objectives of the research work, offering a roadmap for what the reader can expect to discover. "1.4 Node-Level and Network-Level Parameters in UAV Routing " provides outlines of various parameters used in UAV routing. "1.5 Dynamic Routing and Collision Avoidance" explained challenges while performing dynamic routing in real time consideration and also strategies to be used to avoid Collison in UAV routing. "1.6 Significant Contribution" outlines the research work's contribution to society. "1.7 Research work Objectives" provides a detailed description of research work objectives and their need of addressed in UAV routing. Finally, "1.8 Research work Organization" provides an overview of the structure and content of the entire research work, guiding the reader through the upcoming chapters.

Chapter 2: Bioinspired Optimization Algorithms

Chapter 2 provides basic knowledge of existing bioinspired models which are further to be used in research work explained in other chapters of this research work. This chapter begins with "2.1 Q-Learning", which provides the advantage and principle fundamentals of the Q-Learning model. "2.2 Mayfly Optimization (MO)" outlines the basic process to be used by Mayfly for optimization. "2.3 Grey Wolf Optimization (GWO)" provides an idea about the use of GWO in UAV routing for optimization. "2.4 Firefly Optimization" explained about benefits and challenges of FFO while used in UAV routing. Finally, "2.5 Continuous Learning Process (CLF)" provides an overview of CLF in a dynamic environment for a continuous learning framework.

Chapter 3: Literature Review

Chapter 3, the "Literature Review," serves as the intellectual foundation of the research work. It comprises three sections, each with a distinct focus. "3.1 Historical Evolution of UAV Routing Protocols" provides a complete understanding of UAV networks and their various applications with some latest and existing authors' and scholar's research work. "3.2 Related work" provides a complete understanding of UAV networks and their various applications with some latest and existing authors' and scholars' research work. "3.3 Research work Question" provides deep knowledge of why research work is important in this field and what result we can expect after implementation. Finally, "3.4 Literature Summary" synthesizes the overall crux of existing and latest research work to prepare the reader for the innovative solutions presented in the subsequent chapters.

Chapter 4: QMRNB: Q-Learning Model for UAV Network Routing

Chapter 4 introduces the first routing model, "QMRNB." This chapter is divided into four sections, each contributing to a comprehensive understanding of the model. "4.1 Introduction to QMRNB" sets the foundation by introducing the model's core concepts. "4.2 Design of the model" explains the steps which are to be followed for the integration of Q-learning within the routing framework. "4.3 Result Analysis" showcases the performance of the model used in research work by comparing it with the existing model. "4.4 Conclusion and Future Scope" provides a summary of research work and their future scope of improvement in detail.

Chapter 5: BPACAR: Hybrid Bioinspired Model for Collision-Aware Routing

Chapter 5 continues the exploration of novel routing models with "BPACAR." Like the previous chapter, this one is organized into four sections, each contributing to a complete understanding of the model. "5.1 Introduction to BPACAR" introduces the model's core concepts and objectives. "5.2 Design of the model" explains the steps which are to be followed for the integration of Q-learning within the routing framework. "5.3 Result Analysis" showcases the performance of the model used in research work by comparing it with the existing model. "5.4 Conclusion and Future Scope" provides a summary of research work and their future scope of improvement in detail.

Chapter 6: Conclusion and Future Work

The final chapter, Chapter 6, provides a conclusion to the research work. It is organized into six sections. "6.1 Performance of QMRNB" summarizes the performance of the QMRNB model used in research work. "6.2 Performance of BPACAR" summarizes the performance of the BPACAR model used in research work. "6.3 Inferences of the Research work" discusses the practical implications of the findings. "6.4 Future Scope" outlines potential possibilities for future exploration. "6.5 Summary of BPACAR & QMRNB" summarizes both the model’s advantage and further improvements."6.6 Summary of Findings" offers closing reflections on the research work journey undertaken.

CHAPTER 2

BIOINSPIRED OPTIMIZATION ALGORITHMS

Bioinspired optimization algorithms, also known as nature-inspired or metaheuristic algorithms, are computational approaches that utilize natural processes, occurrences, and behaviours as inspiration to tackle complex optimization problems. These algorithms compete with the efficiency and adaptability observed in biological and ecological systems, offering innovative solutions to an extensive variety of optimization challenges. The research work explores the fundamental concepts, key algorithms, and applications of bioinspired optimization in various domains. Bioinspired optimization, also known as nature-inspired or metaheuristic optimization, is a computational approach that draws inspiration from natural processes, biological systems, and ecological phenomena to solve complex problems. It influences the efficiency, adaptability, and robustness observed in the natural world to develop innovative algorithms for optimization tasks. The research work provides an introduction to the interesting field of bioinspired optimization, outlining its fundamental principles, key methodologies, and diverse applications. It explores the ways in which bioinspired algorithms replicate swarm intelligence, evolutionary methods, and other natural characteristics to maximize solutions in artificial intelligence, engineering, and other domains. For example, the effectiveness of algorithms like Ant Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) for rapidly navigating huge search areas and locating optimum or nearly optimal solutions is investigated.

2.1 Fundamental Principles:

Bioinspired optimization is grounded in several fundamental principles:

a. **Mimicking Nature**: It involves emulating the behaviours, mechanisms, and strategies observed in living organisms, physical phenomena, and ecological systems. Nature serves as a source of inspiration for problem-solving.

b. **Population-Based Search**: Most bioinspired algorithms keep a pool of possible answers. The idea of "survival of the fittest" in biological evolution is similar to how these methods change and shift over time.

c. **Exploration and Exploitation**: To quickly move through solution spaces, these algorithms find a good mix between exploration (looking for new, good solutions) and exploitation (improving current solutions).

2.1.1 Key Methodologies:

A number of bioinspired optimization methods have become popular because they can solve a wide range of optimization problems:

a. **Genetic Algorithms (GAs)**: GAs draw inspiration from the principles of natural selection and genetics. They involve developing a population of candidate solutions through processes like selection, crossover (recombination), and mutation.

b. **Particle Swarm Optimization (PSO)**: PSO is inspired by the common behaviour of birds flocking or fish schooling. Particles (representing solutions) adjust their positions based on their own experiences and the experiences of their peers.

c. **Ant Colony Optimization (ACO)**: ACO mimics the searching behaviour of ants. Virtual ants deposit pheromones on paths as they explore, and future ants use pheromone concentrations to make routing decisions.

d. **Simulated Annealing (SA)**: SA follows the forging process in metallurgy. It explores the solution space by allowing probabilistic transitions to less optimal solutions, gradually reducing the probability over time.

e. **Firefly Algorithm (FA)**: FA is motivated by the flashing patterns of fireflies. Fireflies are attracted to others with higher brightness, promoting the convergence of solutions toward optimal ones.

f. **Bat Algorithm (BA)**: BA replicates the echolocation behaviour of bats. Bats adjust their positions in the search space while emitting loud calls to locate prey. The algorithm balances exploration and exploitation.

UAVs have so many existing models to be used for optimal path planning, but still, the bioinspired model has shown better results in terms of speed and accuracy. Figure 2.1 represents some existing bioinspired models, which can be further used with another bioinspired model to make the approach hybrid for better efficiency [43]. A bioinspired model in UAV path planning uses algorithms inspired by natural processes and behaviours, such as swarm intelligence, evolutionary techniques, and neural networks, to optimize unmanned aerial vehicle (UAV) paths. These models mimic effective problem-solving processes seen in nature, such as ant foraging patterns, bird flocking behaviour, and biological organisms' adaptive mechanisms. UAVs that use these bioinspired algorithms may automatically find the most efficient and safe pathways in dynamic and complicated situations. This strategy improves UAVs' capacity to negotiate obstacles, conserve energy, and perform mission objectives more successfully [44].

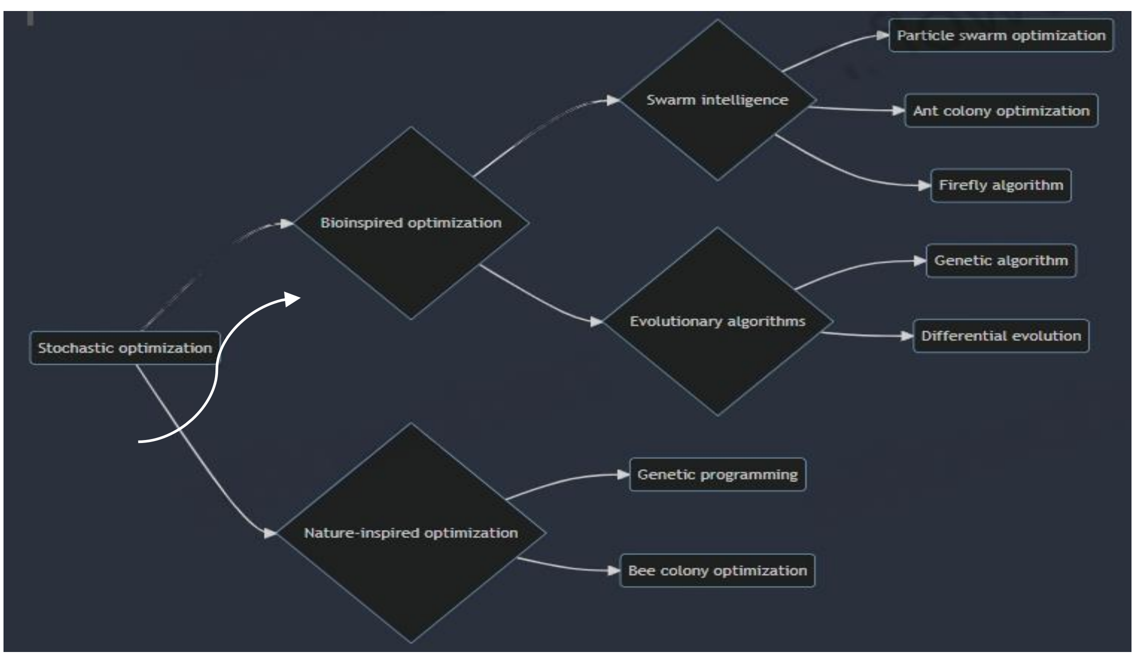

Figure 2.1- Existing Bioinspired Algorithm used in UAV path planning

2.1.2 Applications:

Bioinspired optimization finds applications across diverse domains:

a. **Engineering**: It optimizes complex engineering designs, including aircraft shapes, vehicle routing, and structural configurations.

b. **Finance**: Bioinspired algorithms are used for portfolio optimization, risk assessment, and stock market prediction.

c. **Data Mining**: They assist in clustering, feature selection, and pattern recognition tasks.

d. **Robotics**: These algorithms optimize robot motion planning, swarm robotics, and control strategies.

e. **Telecommunications**: Bioinspired algorithms enhance wireless sensor networks, signal processing, and network design.

f. **Healthcare**: They aid in optimizing treatment plans, drug discovery, and medical image analysis.

2.1.3 Challenges and Future Scopes:

Despite their successes, bioinspired optimization algorithms present several challenges and areas for future exploration:

a. **Parameter Tuning**: Selecting appropriate algorithm parameters can be a non-trivial task and may significantly impact performance.

b. **Hybridization**: Combining bioinspired algorithms with other techniques, such as deep learning or quantum computing, is an evolving research work area [45].

c. **Dynamic Environments**: Adapting these algorithms to dynamic and uncertain environments remains a challenge.

d. **Scalability**: Ensuring efficient performance on large-scale problems is crucial for practical applications.

e. **Interdisciplinary Collaboration**: Collaboration among experts in biology, computer science, and related fields can lead to innovative algorithm development.

In summary, bioinspired optimization represents an attractive field that continues to revolutionize problem-solving in various domains. By coupling the wisdom of nature's optimization processes, bioinspired algorithms offer promising solutions to complex real-world challenges. As research work in this field advances, bioinspired optimization is expected to play an increasingly essential role in optimizing and enhancing a wide array of systems and processes [46].

2.2 Q-Learning

Q-Learning, a reinforcement learning technique, has gathered significant attention in the context of Unmanned Aerial Vehicle (UAV) routing. This chapter focuses on exploring the application of Q-Learning to UAV routing, its underlying principles, and the potential benefits it offers to improve routing efficiency [47].

$$Q(S\_t, a\_t) \leftarrow Q(S\_t, a\_t) + \alpha[r\_t + \gamma max\_a' Q(S\_\{t+1\}, a') - Q(S\_t, a\_t \ldots \text{(1)}$$

Where Q (S_t, a_t) is the Q-value for the current state S_t and action a_t, α is the learning rate ($0 < \alpha \leq 1$), r_t is the immediate reward received after taking action a_t, γ is the discount factor ($0 \leq \gamma < 1$), max_a' Q(S_{t+1}, a') is the maximum Q-value for the next state S_{t+1} over all possible actions a'. Equation (1) is fundamental in updating the Q-values based on the agent's experiences, guiding the learning process toward optimal policy. Figure 2.2 depicts the process of the Q-learning model, which begins with zeros and progresses to parameter setting. The procedure iterates over several episodes, initializing the state at the start of each. Within each episode, the algorithm selects actions using the epsilon-greedy policy, executes them, monitors rewards and future states, and changes Q-values using the Q-learning formula. This cycle continues until a terminal condition is achieved, which signals the end of the episode. The procedure is repeated for each episode till the end condition is satisfied, at which time the Q-learning process is complete. This graphic clearly depicts the iterative and adaptive nature of Q-learning, showing the procedures required to update the Q-values and improve the agent's policy over time [48].

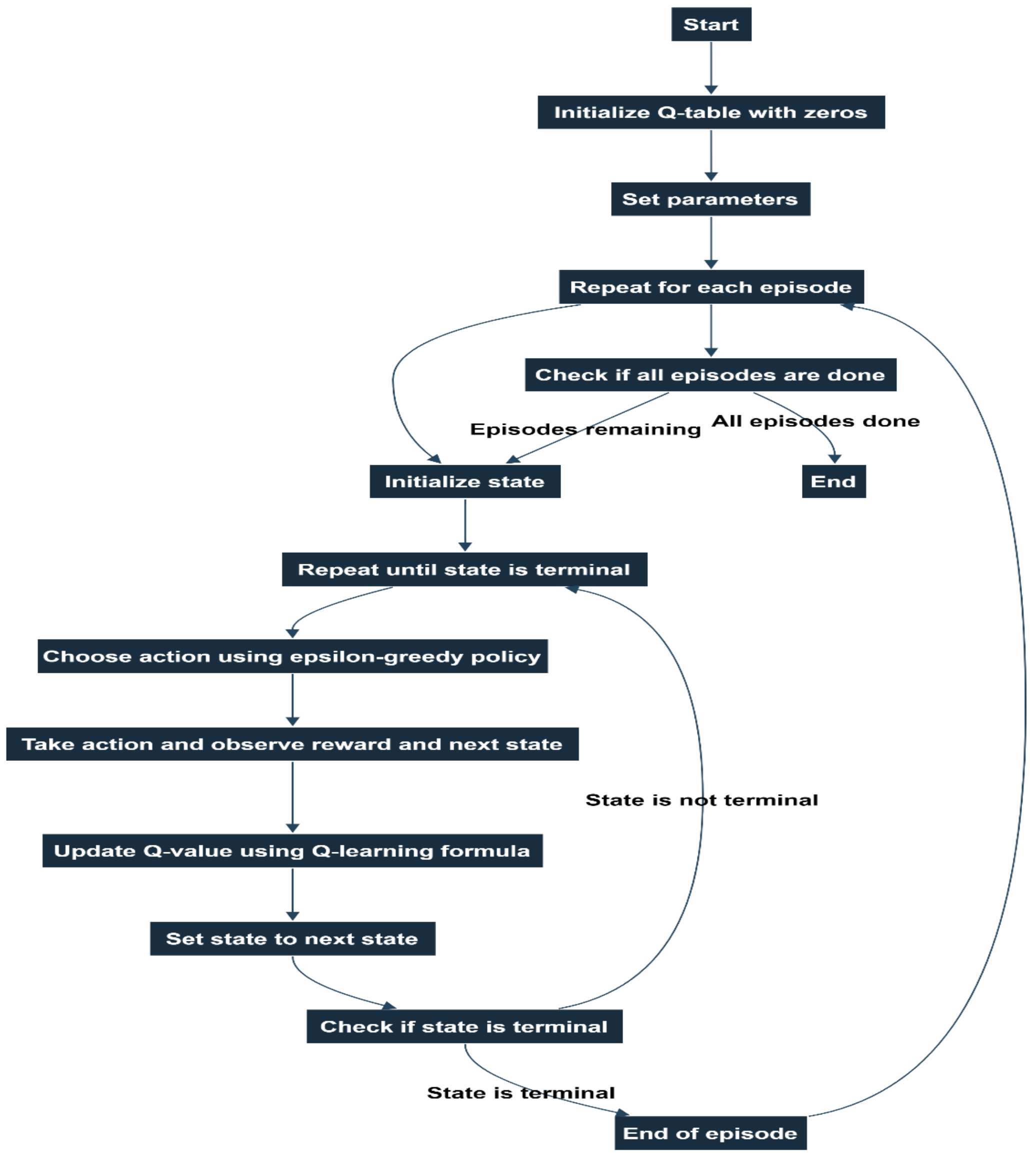

Figure 2.2- Q-learning model's workflow

2.2.1 Principles of Q-Learning:

Q-Learning model is a reinforcement learning algorithm used for optimizing decision-making in dynamic environments. It operates on the belief of learning an optimal action-selection policy through interaction with the environment. In Q-Learning, an agent explores an environment, takes actions, receives feedback (rewards), and updates its Q-values based on this feedback [49].

a. **State-Action Pairs**: Q-Learning maintains a Q-table, where each entry represents the expected cumulative reward (Q-value) for taking a specific action in a particular state.

b. **Exploration vs. Exploitation**: The algorithm balances exploration (trying new actions) and exploitation (choosing actions with known high rewards) to gradually converge toward an optimal policy.

c. **Q-Value Update Rule**: The Bellman equation is used to update Q-values over and over again. It takes into account both current rewards and the expected maximum future rewards.

2.2.2 Application to UAV Routing:

In the context of UAV routing, Q-Learning can be applied as follows:

1. **State Representation**: States represent the current status of the UAV network, including node positions, available paths, network congestion, and communication requests.

2. **Actions**: Actions correspond to routing decisions made by UAVs, such as selecting the next hop or choosing an alternate path.

3. **Rewards**: Routing goals, like reducing delays, increasing traffic, or saving energy, can be used to set rewards. UAVs earn awards based on their routing choices.

4. **Q-Table**: The Q-table stores Q-values for state-action pairs, helping UAVs learn which routing decisions lead to the best outcomes over time.

2.2.3 Benefits and Challenges:

a. **Adaptability**: Q-Learning enables UAVs to adjust to varying network circumstances, making it suitable for dynamic environments where node positions, communication requests, and interference levels may fluctuate.

b. **Efficiency**: By learning optimal routing strategies, Q-Learning can significantly improve routing efficiency, reducing delays and energy consumption.

c. **Scalability**: Q-Learning can handle large-scale UAV networks, making it applicable to scenarios with numerous UAVs and nodes.

However, several challenges need to be addressed:

a. **Complexity**: Building and updating Q-tables for large-scale networks can be computationally intensive.

b. **Exploration Strategies**: Designing effective exploration strategies is crucial to balance exploration and exploitation for optimal learning.

c. **Real-Time Implementation**: Implementing Q-Learning in real-time UAV systems requires efficient algorithms and hardware capabilities.

2.3 Mayfly Optimization (MO)

Mayfly Optimization (MO) is a bioinspired optimization algorithm that has gained recognition for its application in solving complex optimization problems. In this part of the chapter, the focus is on introducing MO, its principles, and its potential applications, including its role in improving routing efficiency in Unmanned Aerial Vehicle (UAV) networks. Mayfly Optimization is a nature-inspired metaheuristic algorithm that uses the mating behaviour of mayflies to solve optimization issues. Mayfly Optimization, named after the mating behaviour of mayflies, is a nature-inspired metaheuristic method for solving optimization issues [50]. In this approach, potential solutions, represented as mayflies, iteratively increase their locations in the search space until they locate the ideal solution. Mayflies' movements are driven by the mate selection principle, which states that individuals are attracted to the best-performing solutions. Mayfly Optimization achieves an appropriate combination of exploration and exploitation to navigate complicated search environments. This program, which simulates mayfly mating behaviour, provides a fresh approach to tackling a variety of optimization issues [51]. Its simplicity, efficiency, and capacity to tackle multi-modal and non-linear issues make it a viable tool for a variety of fields, including engineering, finance, and logistics. Mayfly Optimization, via continual refining and adaptation, has emerged as a promising approach for handling complicated optimization problems. Figure 2.3 illustrates the general workflow of the Mayfly Optimization algorithm.

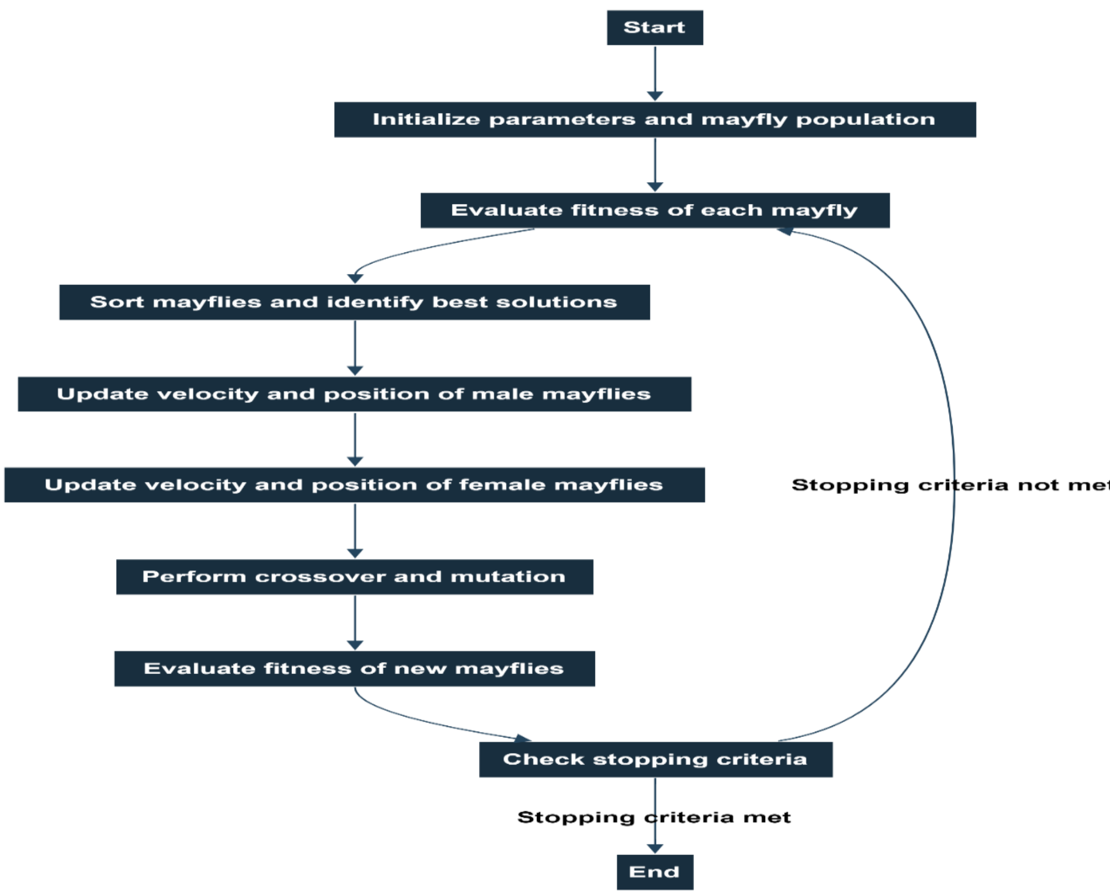

Figure 2.3- General workflow of the Mayfly Optimization algorithm

This diagram outlines the basic steps of the Mayfly Optimization algorithm. This process, shown in figure 2.3, iterates until the termination criteria are satisfied, leading to the discovery of an optimal solution to the optimization problem.

$$v\_i(t+1) = wv\_i(t) + c\_1r\_1(p\_i - x\_i(t)) + c\_2r\_2(g - x\_i(t)) \ldots \text{(1)}$$

Where v_i(t) is the velocity of the mayfly at time t, w is the inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers uniformly distributed in the range [0, 1], p_i is the personal best position of the mayfly, x_i(t) is the current position of the mayfly, g is the global best position. Equation (1) is used in the Mayfly Optimization algorithm for updating the velocity of a mayfly.

2.3.1 Principles of Mayfly Optimization:

MO is inspired by the short but purposeful life of mayflies, insects known for their brief existence as adults. The algorithm mimics the decision-making process of mayflies during their short lifespan, focusing on optimizing solutions within a limited timeframe [52]. Key principles of MO include:

a. **Limited Lifespan**: In MO, solutions, or "Mayflies," have a finite lifespan, representing a restricted time frame for optimizing a problem. This concept encourages rapid and effective decision-making.

b. **Exploration and Exploitation**: Mayflies strike a balance between exploring different solutions and exploiting the best ones. They aim to make the most of their limited time by adapting to their environment.

c. **Reproduction and Evolution**: Successful Mayflies have the opportunity to reproduce, passing on their characteristics to the next generation. Over time, this leads to the evolution of solutions toward optimal or near-optimal states.

d. **Dynamic Fitness Landscape**: MO adapts to the dynamic fitness landscape of the problem, responding to changes in the environment and problem constraints.

2.3.2 Application in UAV Routing:

MO can be applied to optimize routing decisions in UAV networks in the following manner:

a. **Route Optimization**: MO is used to evolve and optimize routing paths for UAVs within a limited time frame. This is especially valuable in scenarios with rapidly changing network conditions.

b. **Alternative Paths**: Mayflies in MO consider alternative routing paths, ensuring that optimal routes are available even if the initially selected paths become congested or unavailable.

c. **Fitness Evaluation**: MO employs a fitness function to evaluate the quality of routing solutions. This function accounts for factors like routing delay, energy efficiency, packet delivery rates, and other relevant metrics.

d. **Continuous Adaptation**: MO continuously adapts to the evolving UAV network conditions, enabling real-time adjustments to routing paths as needed.

2.3.3 Benefits and Challenges:

a. **Efficiency**: MO's focus on rapid optimization aligns well with the need for efficient routing in UAV networks, particularly in situations requiring fast response times.

b. **Adaptability**: The algorithm's ability to identify alternative paths and adjust to variations in the network environment makes it suitable for dynamic and unpredictable scenarios.

c. **Complexity**: Implementing MO effectively requires careful consideration of the fitness function and other algorithm parameters. Designing an appropriate fitness function can be challenging.

d. **Computational Overhead**: Like many bioinspired algorithms, MO can be computationally exhaustive, mainly for large-scale UAV networks.

2.4 Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is a nature-inspired optimization algorithm that draws motivation from the social hierarchy and hunting behaviours of grey wolves. In this part of the chapter, we explore the principles, applications, benefits, and challenges associated with GWO, particularly its relevance in addressing optimization problems within the context of Unmanned Aerial Vehicle (UAV) networks. Figure 2.4 represents the key steps of the Grey Wolf Optimization (GWO) algorithm in a structured flowchart format. The process starts with the initialization of the algorithm's parameters and the population of grey wolves. Each wolf's fitness is then evaluated to identify the top three wolves, termed alpha, beta, and delta, which lead the search process [53].

$$X(t+1) = (X\_alpha + X\_beta + X\_delta)/3 \ldots \text{(1)}$$

Where X(t+1) is the updated position of the grey wolf, X_alpha, X_beta, and X_delta are the positions of the alpha, beta, and delta wolves, respectively. Equation (1) is used to update the position of a grey wolf based on the average positions of the three best solutions (alpha, beta, and delta wolves) found so far. The primary purpose of this equation is to guide the search agents (grey wolves) towards the best solutions, balancing exploration and exploitation in the optimization process.

The positions of the wolves are updated based on these leading wolves' positions. This process iterates, continually updating positions and re-evaluating fitness until a set stopping measure is met, such as hitting a maximum number of iterations or getting an acceptable fitness level. The algorithm then terminates. The diagram effectively outlines the iterative nature and the hierarchical structure of the GWO algorithm, highlighting how the positions of wolves are influenced by the leading members of the pack.

Figure 2.4- Key steps of the Grey Wolf Optimization (GWO) algorithm

2.4.1 Principles of Grey Wolf Optimization:

GWO matches the cooperative hunting behaviours of grey wolves, with a particular focus on the roles and interactions within a pack [54]. Key principles of GWO include:

a. **Pack Hierarchy**: In GWO, optimization solutions are depicted as a pack of grey wolves. The pack comprises alpha, beta, and delta wolves, signifying the top-performing people in the population.

b. **Leader-Follower Dynamics**: Alpha wolves are dominant leaders who guide the pack, while beta and delta wolves are followers. These roles influence the exploration and exploitation of potential solutions.

c. **Hunting Strategy**: Grey wolves employ a collaborative hunting strategy, with the alpha wolf leading the pack to locate and capture prey. GWO uses this strategy to find optimal solutions by converging toward likely regions of the solution space.

d. **Encircling and Attacking Prey**: GWO leverages the encircling and attacking behaviours of wolves to refine solutions. Encircling involves exploring the space around a potential solution while attacking aims to refine and improve the solution.

2.4.2 Application in UAV Routing:

GWO can be applied effectively to optimize routing decisions in UAV networks:

a. **Path Optimization**: In UAV networks, GWO can optimize routing paths by dynamically adjusting the flight trajectories of UAVs to minimize routing delay, energy consumption, and other relevant metrics.

b. **Multi-Objective Optimization**: GWO's capacity to handle multi-objective optimization makes it excellent for balancing opposing objectives, such as lowering routing latency while optimizing energy efficiency.

c. **Dynamic Adaptation**: GWO's adaptive nature allows it to respond to changing network conditions, such as congestion or varying signal strengths, by dynamically adapting routing paths.

d. **Improved Quality of Service**: By optimizing routing paths, GWO can enhance the quality of service (QoS) in UAV networks, ensuring that data is transmitted efficiently and reliably.

2.4.3 Benefits and Challenges:

a. **Efficiency**: GWO's ability to rapidly converge toward optimal solutions aligns with the need for efficient routing decisions in UAV networks.

b. **Multi-Objective Optimization**: GWO's support for multi-objective optimization enables UAV networks to consider multiple metrics simultaneously, leading to well-balanced routing decisions.

c. **Algorithm Parameters**: Proper tuning of algorithm parameters, such as the exploration-exploitation balance and convergence speed, is crucial for GWO's success.

d. **Scalability**: Like many optimization algorithms, GWO may face scalability challenges when applied to large-scale UAV networks.

2.4.4 Future Directions:

a. **Hybridization**: Combining GWO with other optimization techniques, such as Q-Learning or Particle Swarm Optimization (PSO), can enhance its performance and adaptability to different UAV network scenarios.

b. **Integration with UAV Systems**: Further research work can focus on integrating GWO into UAV systems, enabling real-time optimization of routing decisions during UAV missions.

2.5 Firefly based Optimization (FFO)

Firefly-based Optimization (FFO) is a nature-inspired optimization algorithm that draws motivation from the flashing behaviors of fireflies. The principles, applications, benefits, and challenges associated with FFO have been explored in this part of the chapter, particularly its relevance in addressing optimization problems within the context of Unmanned Aerial Vehicle (UAV) networks [55].

2.5.1 Principles of Firefly-based Optimization:

FFO is rooted in the bioluminescent communication of fireflies and their attraction behaviours. Key principles of FFO include:

a. **Attraction Behavior**: Fireflies exhibit attraction behaviours by emitting flashes of light to attract mates. FFO models the intensity of light as a measure of fitness, with brighter fireflies representing better solutions.

b. **Attraction Intensity**: The attractiveness of a firefly is determined by its brightness and proximity to other fireflies. Brighter and closer fireflies have a higher probability of attracting others.

c. **Random Movement**: Fireflies also exhibit random movements. In FFO, this is translated into a random component in the optimization process, adding exploration capability to the algorithm.

Figure 2.5 depicts the processes in the Firefly Optimization Algorithm, beginning with the setting of algorithm parameters and the creation of an initial population of fireflies. Each firefly's fitness is assessed using an objective function, and the fireflies adjust their locations by travelling toward brighter (more appealing) fireflies. After relocating, the new fitness values are analyzed, and each firefly's brightness is adjusted correspondingly. This process continues until a stopping requirement, such as a maximum number of generations or a desirable fitness level, is fulfilled. The algorithm then ends and returns the best answer discovered. This repeated process demonstrates how the algorithm uses the social behaviour of fireflies to effectively solve optimization challenges [56].

$$x\_i = x\_i + \beta\_0 e\^\{-\gamma r\_\{ij\}\^2\}(x\_j - x\_i) + \alpha(rand - 0.5) \ldots \text{(1)}$$

Where x_i is the position of firefly i, x_j is the position of firefly j (a brighter firefly), β_0 is the attractiveness at r = 0, γ is the light absorption coefficient_{ij} is the distance between firefly i and firefly j, α is the randomization parameter, rand is a random number uniformly distributed in the range [0, 1]. Equation (1) is used to adjust the position of a firefly in the search space based on the attractiveness of other brighter fireflies. The primary purpose of this equation is to guide the fireflies towards the best solutions, ensuring that they move towards regions of higher fitness in the search space.

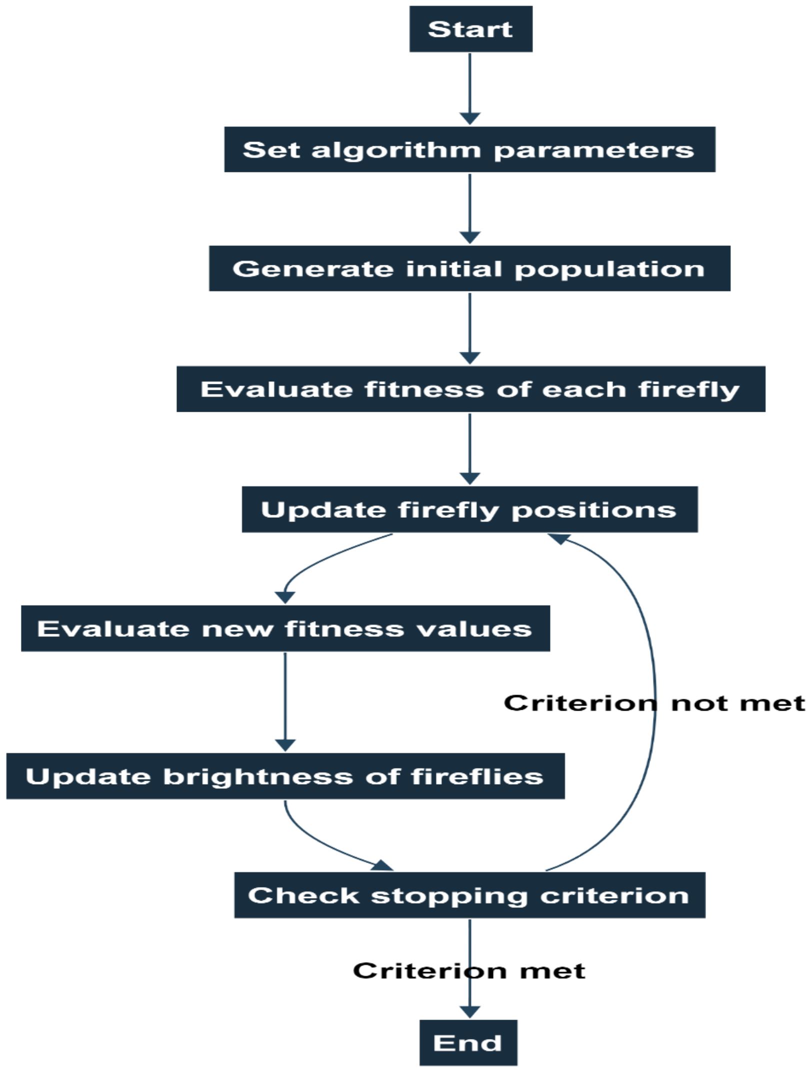

Figure 2.5- Iterative nature of the Firefly Optimization Algorithm

2.5.2 Application in UAV Routing:

FFO can be applied effectively to optimize routing decisions in UAV networks:

a. **Path Optimization**: FFO can optimize routing paths by representing potential solutions as fireflies and their attractiveness based on routing metrics. This allows for the discovery of optimal paths.

b. **Dynamic Adaptation**: FFO's exploration-exploitation balance allows it to adapt routing decisions to changing network conditions, ensuring efficient data transmission.

c. **Multi-Objective Optimization**: FFO's ability to handle multi-objective optimization is valuable for UAV networks with conflicting objectives, such as minimizing delay while conserving energy.

d. **Quality of Service Improvement**: By optimizing routing paths, FFO contributes to improving the quality of service (QoS) in UAV networks, enhancing data delivery and reliability.

2.5.3 Benefits and Challenges:

a. **Exploration-Exploitation Balance**: FFO's balance between exploration (random movement) and exploitation (attractiveness) enables it to efficiently search for optimal solutions.

b. **Multi-Objective Optimization**: FFO's support for multi-objective optimization aligns well with the complex nature of UAV routing problems.

c. **Algorithm Parameters**: Properly tuning FFO's parameters, such as attractiveness and random movement, is crucial for its performance.

d. **Convergence Speed**: The convergence speed of FFO may vary based on the problem at hand, requiring careful consideration of optimization goals.

2.6 Continuous Learning Framework (CLF)

Continuous Learning Framework (CLF) is an innovative approach in machine learning and artificial intelligence that emphasises on enabling systems to learn, adapt, and evolve continually. In this section, we investigate the principles, applications, advantages, and challenges associated with CLF. Figure 2.6 demonstrates the Continuous Learning Framework's circular nature. It all starts with determining the learning objectives and creating a plan to achieve them. The plan is then implemented, and progress is regularly tracked. The results are reviewed, gaps and opportunities for development are identified, and the learning plan is adjusted appropriately. The cycle is repeated to promote ongoing learning and progress [57].

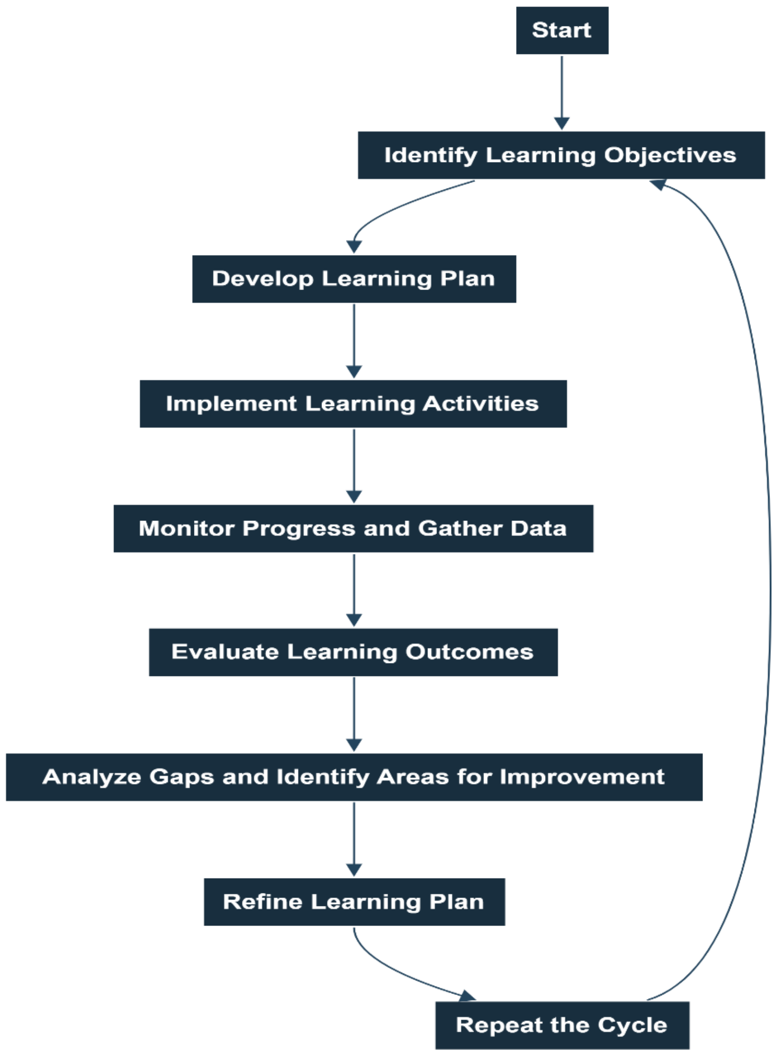

Figure 2.6- Cyclical Nature of the Continuous Learning Framework

The Continuous Learning Framework (CLF) is a cyclical process that helps continuing development and knowledge acquisition in an organization or system. It begins by setting explicit, quantifiable learning objectives based on company goals. A thorough learning plan is then created, covering techniques, resources, and dates. This strategy is implemented through a variety of learning activities, and progress is regularly tracked using data gathering methods such as evaluations and feedback forms. The efficacy of these efforts is assessed, and any discrepancies between predicted and actual results are investigated. Based on this information, the learning plan is adjusted to better correspond with the objectives. This iterative process continues, encouraging ongoing learning and adaptability to changing demands [58].

$$\theta\_\{t+1\} = \theta\_t - \eta \nabla L(\theta\_t, x\_t, y\_t) \ldots (1)$$

Where θ_t represents the model parameters at time t, η is the learning rate, $\nabla L(\theta_t, x_t, y_t)$ is the gradient of the loss function L with respect to the parameters θ_t, computed using the current data point (x_t, y_t). This equation is used to continuously update the model parameters as new data points are observed. The primary purpose of this equation is to enable the model to learn and adapt incrementally from a stream of data rather than requiring a complete retraining on the entire dataset each time new data becomes available.

2.6.1 Principles of Continuous Learning Framework:

a. **Lifelong Learning**: CLF is founded on the concept of lifelong learning, where AI systems continuously acquire and adapt knowledge throughout their operational lifetime.

b. **Adaptability**: CLF emphasizes adaptability to changing environments, data distributions, and requirements, ensuring that AI systems remain effective over time.

c. **Incremental Learning**: Rather than traditional batch learning, CLF employs incremental learning, allowing systems to update their models with new data as it becomes available.

d. **Memory and Forgetting**: CLF incorporates mechanisms for retaining important knowledge while selectively forgetting less relevant or outdated information.

2.6.2 Applications in UAV Networks:

CLF offers several applications within the domain of UAV networks:

a. **Adaptive Routing**: In UAV networks, where network conditions can change rapidly, CLF can be used to adapt routing strategies continually, optimizing data transmission paths.

b. **Anomaly Detection**: CLF's ability to adapt to new data distributions is valuable in anomaly detection, allowing UAVs to detect novel threats or malfunctions.

c. **Resource Management**: UAVs can benefit from CLF in managing resources efficiently, such as power allocation, based on real-time usage patterns.

d. **Predictive Maintenance**: CLF can enable UAVs to predict maintenance needs by continuously learning from sensor data, minimizing downtime. By using data analysis, machine learning, and sophisticated algorithms, predictive maintenance is a proactive strategy that anticipates when systems or equipment are likely to break so that repairs may be made just in time.

2.6.3 Benefits and Challenges:

a. **Long-Term Efficiency**: CLF ensures that AI systems remain efficient and effective over extended periods, which is crucial for UAVs deployed in various missions.

b. **Data Drift**: Handling evolving data distributions and concept implications remains a challenge in CLF, requiring robust adaptation mechanisms.

c. **Computational Complexity**: Implementing CLF may introduce computational overhead due to continuous model updates and retention of historical data.

d. **Interpretability**: As CLF models evolve, ensuring their interpretability and compliance with regulations is a significant challenge.

In summary, bioinspired optimization represents an attractive field that continues to revolutionize problem-solving in various domains. By coupling the wisdom of nature's optimization processes, bioinspired algorithms offer promising solutions to complex real-world challenges. As research work in this field advances, bioinspired optimization is expected to play an increasingly essential role in optimizing and enhancing a wide array of systems and processes. Q-Learning model also holds great potential for optimizing UAV routing in dynamic and complex scenarios [59]. As UAV networks continue to evolve, attaching the learning capabilities of Q-Learning can contribute to more efficient, adaptive, and scalable routing strategies, benefiting applications ranging from surveillance and disaster response to communication and data collection. Similarly, Mayfly Optimization presents an innovative approach to solving optimization problems, particularly in the context of UAV routing within dynamic and time-sensitive environments. As research work and experimentation continue, MO holds the potential for contributing to more effective and adaptive routing strategies in UAV networks, benefiting a varied kind of applications, from surveillance to disaster response and beyond [60].

Grey Wolf Optimization presents a favourable approach to solving complex optimization problems, especially within the context of UAV routing in dynamic and resource-constrained environments. As research work continues to advance and adapt GWO to specific UAV network challenges, it holds the potential to contribute significantly to the efficiency and reliability of routing decisions in various UAV applications, from surveillance to disaster response and beyond. Continuous Learning Framework (CLF) is also an innovative approach in machine learning and artificial intelligence that emphases on enabling systems to learn, adapt, and evolve continually. In this section, we investigate the principles, applications, advantages, and challenges associated with CLF, emphasizing its relevance in addressing complex problems and its potential impact on various fields, including Unmanned Aerial Vehicle (UAV) networks. The continual Learning Framework (CLF) improves UAV path planning by allowing for continual adaptation and optimization of flight routes. The CLF enables UAVs to constantly improve their navigation techniques by iteratively identifying learning objectives, developing plans, implementing them, monitoring, evaluating, and refining them [61]. This technique assures that UAVs can adapt to changing situations, deal with unexpected impediments, and optimize their routes for efficiency and safety. By carefully incorporating input and learning from each flight, UAVs may improve their decision-making processes, resulting in more dependable and effective path planning. The CLF promotes a proactive and adaptable learning culture, allowing UAVs to retain high performance and operational effectiveness even in complex and constantly changing environments. This continuous improvement cycle is critical for developing autonomous navigation skills and attaining mission success in a variety of demanding settings [62].

CHAPTER 3

LITERATURE REVIEW

The literature review section provides an analysis of existing research work and scholarly work related to the topic of efficient routing in Unmanned Aerial Vehicle (UAV) networks using bioinspired optimizations and Q-Learning. This chapter aims to set the current research work within the broader context of UAV network optimization, highlighting key findings, gaps in knowledge, and the evolution of routing protocols in this domain.

3.1 Historical Evolution of UAV Routing Protocols

Historically, UAV routing protocols have undergone significant developments to address the unique challenges posed by UAV network environments. Early approaches predominantly adopted traditional routing techniques designed for terrestrial networks, such as Adhoc on Demand Multipath Distance Vector (AOMDV) and Ad Hoc On-Demand Distance Vector (AODV) routing protocols. While these methods provided some utility in UAV networks, they exhibited limitations in adaptability to dynamic UAV environments and lacked scalability when confronted with larger network scenarios. Routine sending of Route Advertisement (RREQ) and Route Error (RERR) messages helps AODV maintain routes. Route maintenance ensures that nodes or broken links are rapidly identified and fixed. It also keeps routes current. The effectiveness of AODV in dynamic and mobile contexts is one of its main features. Because routes are created only when necessary, AODV is highly adaptive to variations in node mobility and network structure.

Moreover, AODV has a low control overhead, which makes it appropriate for networks and devices with limited resources. The integration of Q-Learning into UAV routing marked a critical advancement. Q-Learning, a reinforcement learning technique, carried adaptability and sensitivity to the dynamic UAV environment. It introduced a state-action pair approach, enabling nodes to make informed routing decisions based on accumulated rewards. This approach was particularly beneficial when dealing with unequal node distribution and topological changes. However, even with promising results, Q-Learning-based routing protocols encountered challenges. One important issue was the need for each ground node to maintain its own Q-value table, irrespective of the presence or absence of neighbours. This resulted in higher bandwidth use and delayed Q-value convergence. Additionally, the scalability of these models was limited as their efficiency decreased with a higher number of communication requests. Table 3.1 shows the importance of some existing bioinspired model with their key contribution with respect to path planning optimization [63].

Table 3.1- Existing Bioinspired Model with Key Contribution

Reference	**Bioinspired Model**	**Application**	**Key Contributions**	**Results**
[64]	Ant Colony Optimization (ACO)	Path optimization, dynamic environments	Introduced the concept of pheromone trails for pathfinding, adaptable to changes in the environment	Improved pathfinding efficiency and adaptability in dynamic environments
[65]	Particle Swarm Optimization (PSO)	Real-time path planning, obstacle avoidance	Mimics social behaviour of birds and fish; allows decentralized decision-making	Faster convergence to optimal paths; robustness in real-time adjustments
[66]	Genetic Algorithms (GA)	Multi-objective optimization, collision avoidance	Uses principles of natural selection; effective for complex optimization problems	Effective in evolving collision-free and energy-efficient paths

[67]	Firefly Algorithm (FA)	Path planning, multi-UAV coordination	Simulates the flashing behaviour of fireflies	Enhanced multi-UAV coordination and dynamic path
[68]	Artificial Bee Colony (ABC)	Optimization, resource allocation	Based on the searching behaviour of honey bees, good for high-dimensional search spaces	Efficient exploration and exploitation balance; improved optimization in large search spaces
[69]	Grey Wolf Optimizer (GWO)	Path planning, obstacle avoidance	Models leadership hierarchy and hunting behaviour of grey wolves	Effective in finding optimal paths with minimal computation; robust against obstacles
[70]	Bacterial Foraging Optimization (BFO)	Path planning, environmental adaptation	Inspired by the foraging strategy of bacteria, adaptable to dynamic environments	Improved adaptability and efficiency in changing environments
[71]	Evolutionary Algorithms (EA)	Multi-objective path planning, collision avoidance	Encompasses various evolutionary strategies suitable for complex, multi-objective problems	Effective in balancing multiple objectives; robust solution generation

To address challenges, recent research work has explored the integration of bioinspired optimizations, such as Mayfly Optimization (MO), into Q-Learning-based routing models. These bioinspired optimizations aim to enhance routing efficiency by identifying optimal routing paths, even under large-scale routing requests. MO achieves this by evaluating high-density routing fitness functions to select alternative paths when selected routes are occupied. The Q-Learning Model with Bioinspired Optimizations (QMRNB) aligns with this trajectory of research work. It introduces an innovative routing model that combines Q-Learning and MO to improve routing efficiency in UAV networks. This model influences temporal routing performance data to formulate routing decisions, ensuring adaptability to dynamic conditions. It addresses scalability concerns by optimizing routing paths, reducing delays, improving energy efficiency, and enhancing overall routing performance.

3.2 Related Work

[72] focused on a survey of various path planning techniques for unmanned aerial vehicles. The authors reviewed various techniques and also explained different challenges and their respective solutions. The main aim of this research work was to analyze the efficiency of UAVs by selecting an optimal path after avoiding collision during operation. The authors stated that path planning techniques are mainly divided into three categories: First Representative, Second cooperative, and finally non-cooperative techniques. By using these approaches, the connectivity and coverage of UAVs have been discussed. For better knowledge of existing methods, authors compared various methods on certain parameters like path length, optimality, completeness, cost and time efficiency, robustness, and finally, collision avoidance. [73] proposed an informative framework of path planning by using the aerial robot to monitor the scenarios. The methodology used probabilistic sensors and received variable-resolution data from these sensors. It was equipped for learning and concentrating on locales of interest by either mapping discrete or continuous values on the region. Further terrain maps were built online by a coarse 3-D search. For the simulation, synthetic and real-world data were tested. The framework was validated using a publicly available dataset that illustrated its online application on a photorealistic mapping situation with a SegNet-based sensor for information procurement. [74] proposed an algorithm to overcome the problem of local search ability in the UAV's online path planning. The author used the Improved Genetic Algorithm with

Restricted Mutation Generating Region (R-IGA) to improve the planning time. In this paper, the authors worked on tracking the moving target for UAVs in online path planning. The comparison of the traditional Genetic Algorithm and Improved Genetic Algorithm with Restricted Mutation Generating Region (R-IGA) is done based on the different parameters (generations, cost value, and average time). With the improved genetic algorithm, the searching efficiency and feasibility of the algorithm for online path planning are improved. [75] used the MAX-MIN Ant System (MMAS) and the ant colony algorithm with punitive measures (AS-N) for the UAV's path planning. The ant colony algorithm is widely used to solve optimization problems. The dynamic environment for path planning is used by the authors. The environmental modal for the path planning of UAVs is constructed with a grid method, which further describes the environmental information. For the simulation, the MATLAB tool was used. There were three questions for the TSPLIB data set, and each question was tested 30 times. A penalty strategy is added to improve this algorithm, which enhances the utilization of resources. The author concluded that while dealing with unmanned vehicle path planning, the AS-N algorithm performs better.

[76] explained the overview of the applications, research work directions, and open problem challenges of UAVs in the wireless network. The UAVs are classified into two parts: based on type (fixed and rotary wings) based on altitude. The author explained the two main causes of UAVs. For the research work direction, Channel modelling, which is an important aspect, can be done using various methods e.g. ray-tracing technique and machine learning. To measure the performance of UAV communication systems, the life of the battery is considered with parameters Size and Weight. The author also explained the mathematical tools for meeting UAV's challenges. The tools that were discussed were Optimization theory, Stochastic geometry, Optimal transport theory, Machine learning, and Game theory. The authors concluded how to analyze and optimize UAVs-based wireless communication systems. [77] proposed a new dynamic path planning approach based on ACO (Ant Colony Optimization). In the proposed approach, both dynamic and static obstacles have been considered to get the least collision-free path. authors used

various functions to search for optimal paths during target operation. In the whole process of finding an optimal path for UAVs cost value of the path and total cost are optimized using the ANT algorithm. The final experimental results of the proposed algorithm tell about the performance of the algorithm. And the performance is better in terms of lower cost for UAVs by doing smoother planning. [78] analyzed UAV's heuristic tracking path planning based on destination matching, design of algorithm, and parameter analysis. In this paper, the authors analyzed the effect of every parameter on the path planning. For the process of target matching, Hungarian algorithms were used, and for the path planning, the target tracking A* algorithm was used. The different parameters used by the authors for the analysis were turning-angle and the no. of threats in the process of flight node expansion. The results of the simulations depict the value of every parameter in the process of planning and have a great influence on the final result. With this approach, the best values of the parameters were calculated to full fill the requirements of the tasks, and the result of simulations represented that the A* algorithm is better for the problem of target tracking. [79] designed one method for UAVs Collison avoidance. The concept of avoiding the Collison that occurs due to the motion of hurdles such as commercial helicopters is very critical to save the task of UAVs and different air-traffic. Authors invented the path based on sampling plan approaches for the UAVs to remove the collisions that occur with commercial helicopters, air traffic, and moving hurdles. The developed method was based on an exploring-random-tree algorithm that is closed-loop-rapidly and with three variations. Variation was: 1) Rendering of route creation method. 2) Use of in-between waypoints. 3) forecast of collision with reachable-set. As per the results shown in this paper this method was able to yield the Collison free path in reality for a different type of UAVs in the middle of moving hurdles. [80] designed one framework that is useful in path planning in Dense city areas. Many Hybrid UAVs can take vertical take-off, landing and fixed flight, and high smooth speed. In this paper, authors presented a path planning approach for hybrid UAVs in mess-up urban settlements. The authors divided the flight into three parts with the designed framework as take-off, cruise part, and landing phases, and the sampling-based motion plan was used to yield the path plan for each. The problems related to motion planning were solved by the use of a stable, sparse, rapidly exploring random trees (RRT) motion planner. The authors used the model of Dubin's vehicle as it provides a balanced trade-off in-between computational clarity and exact experiment of real-world behaviour. Simulations used in this approach show that this approach effectively yields a motion plan for different UAVs in an adversarial environment. [81] explained categorized the path planning algorithm into two parts. First is online path planning, and second is offline-path planning methods. Offline-path planning is the process that requires known environmental information for path planning, and an online-path plan is a process that requires partial information about the environment from the sensors and, after that, performs the local path planning. The authors discussed the three algorithms with their basic fundamental theory, advantages, disadvantages, and novel improvements. In this paper, the authors also mentioned how online algorithms can be improved, such as hybrid algorithms, selection of algorithms based on applications, or sample space in a given situation. [82] designed one new approach for the Shortest Path Planning of Unmanned Aerial Vehicles. With this approach, the problem of the best route and best deployment approach was solved under the need for the shortest retention time for UAVs in vulnerable areas. The best amid point was determined with the use of known data, and with the use of an improved PSO known flight path, the shortest path for the UAVs was obtained. This approach shortens the retention time for UAVs in the radar scanning range and also achieves the ideal flying path. As per the results shown in the paper this approach improves the proficiency and precision of UAVs reconnoitering. [83] proposed a method for 3-D optimal path planning in a threat environment for unmanned aerial vehicles. The authors have assumed a stationary but risky environment for UAVs during any target operation. Authors separate the task into two-stage, first to find the path with optimal risk for a fixed time and then to solve the series of BVPs (Boundary value problems) with different UAVs. According to the authors, due to a lack of exact information, UAVs might get stuck in a risky environment where UAVs get attacked by enemies or can come onto the radar of enemy

UAVs. So, by using 3-D path planning techniques, authors reduced the probability of risk by taking 3-D parameters taken to consideration.

Table 3.2- Existing Proposals by various Author’s using AI-Based Techniques. (Yes: Considered, No: Not Considered)

Ref.	Year	Optimality	Completeness	Low Cost	Time Effective	Low Energy	Stability	Traffic Avoidance
[84]	2024	Yes	No	Yes	Yes	No	No	Yes
[85]	2023	Yes	No	No	No	No	No	No
[86]	2022	No	No	No	Yes	No	No	No
[87]	2021	No	No	Yes	Yes	Yes	No	No
[88]	2019	Yes	No	No	No	No	No	No
[89]	2018	No	No	Yes	No	No	Yes	No
[90]	2018	Yes	No	No	Yes	No	No	No
[91]	2018	Yes	No	Yes	Yes	Yes	No	No

Table 3.3 Existing Proposals by various Author’s based on Machine Learning Models. (Yes: Considered, No: Not Considered)

Ref.	Year	Optimality	Completeness	Low Cost	Time Effective	Low Energy	Stability	Traffic Avoidance
[92]	2024	Yes	No	Yes	Yes	Yes	No	Yes
[93]	2023	No	No	No	Yes	No	No	Yes
[94]	2022	No	No	No	Yes	No	No	Yes
[95]	2020	Yes	No	Yes	Yes	No	No	No
[96]	2018	Yes	No	No	Yes	No	No	No
[97]	2017	Yes	Yes	Yes	Yes	No	No	No

Tables 3.2 and 3.3 throw some light on some existing models of machine learning and artificial intelligence with respect to consideration of various quality of service parameters like collision avoidance, path optimality, stability etc. Research workers have presented a broad range of UAV route planning models, each with unique intrinsic properties. To estimate efficient paths for various network scenarios, for example, the work in [98] suggests using the Dueling double deep Q-network (D3QN), improved artificial potential function (IAPF), artificial bee colony with bat algorithm (ABCBA), and constrained multi-objective optimization problem optimization (CMOP). These

routes are verified under various sized networks and optimized by the use of high-density route information sets. However, because of their increased complexity, these models are less useful and applicable in real-time applications [99]. The use of artificial potential fields, concentrated coverage path planning models, improved intelligent water drops (IIWD) models, and Voronoi-based path generation (VPG) models—which help integrate low complexity operations during path estimation under adversarial network scenarios—are some solutions proposed in [100-102] to address these problems. These methods can help improve path planning performance with low complexity and high scalability levels, but they have low efficiency and trust levels. These methods include Iterative Single Head Attention (ISHA) [103], Adaptive Clustering [104], Rapidly Exploring Deep Tree (RDT) [105], Convolutional Neural Networks (CNNs) [106], Geometric Distance with Reinforcement Learning (GDRL) [107], Detach & Steer [108], and Improved Adaptive Grey Wolf Optimization (IA GWO) [109]. However, these models' performance capabilities are limited since they do not take trust levels into account when predicting path plans. In order to improve planning performance under various use cases, models covered in [110, 111] also suggest using Graph Theory, Tangent Intersection with Target Guidance Strategy, Estimation of Distribution Algorithm (EDA) with the Genetic Algorithm (GA), and feature-driven flight planning that takes delay, energy levels, and path reusability metrics into account. However, the lack of trust measurements in these models restricts their scalability. In order to address this problem, work in [112-114] suggests using deep reinforcement learning, multiple point-of-interest (MPoI) based path planning, mixed-strategy based gravitational search algorithms (MSGSA), and deep learning trained by genetic algorithms (DL-GA), which help integrate high-density parameter sets for incorporation of trust levels during routing operations. Improved particle swarm optimization (PSO) with Gauss pseudo-spectral method (GPM), stochastic time-dependent optimizations, decentralized learning optimizations, multi-layer reinforcement learning techniques, and dynamic discrete pigeon-inspired optimization are some of the ways that work in [115-117] to further extend this concept. These methods help with continuous model optimization under real-time use cases. The use of multiobjective UAV trajectory planning, dynamic programming, Iterative Chance-Constrained Optimization, a constrained decomposition-based multi-objective evolution algorithm, and deep reinforcement learning are some of the concepts that are similar to those presented in [118-120]. These techniques help to improve path planning operations under various scenarios. However, it was discovered that these models' deployment capabilities are constrained by the fact that they are either less efficient or more complicated. Furthermore, these models are often applied to static targets and do not take energy restrictions into account. The building of a unique hybrid bioinspired model with continuous pattern analysis for dynamic collision-aware routing in UAV networks is suggested in the following section as a solution to these limitations. The suggested approach was assessed in various scenarios and contrasted with current path planning methodologies to verify its efficacy in actual situations. After the completion of the literature review, a summary of the existing model is also written in Table 3.4 by taking their findings, advantages, limitations and future scope.

Table 3.4- Review of Existing Models

Method	Findings	Advantages	Limitations	Future Scopes
[121]	Improved latency and packet delivery ratio	Suitable for dynamic UAV networks	Limited scalability	Integration of security mechanisms
[122]	Low overhead and energy-efficient routing	Robustness in UAV mobility scenarios	High route discovery latency	Cross-layer optimization
[123]	Geographic awareness for efficient routing	Reduced communication overhead	Sensitive to localization errors	Integration of machine learning
[124]	Prolongs UAV mission time	Energy-efficient routing	Complexity in energy modeling	Adaptive energy harvesting
[125]	Enhanced service quality	Supports diverse application requirements	Challenging to meet stringent QoS demands	Dynamic QoS adaptation

[126]	Effective swarm coordination	Scalable for large-scale UAV networks	Susceptible to communication interference	Machine learning-based swarm optimization
[127]	Handling uncertainty in routing decisions	Robustness in noisy and dynamic environments	Increased computational overhead	Adaptive fuzzy logic schemes
[128]	Efficient path selection by mimicking ants	Self-organization and adaptability	Limited to specific application domains	Hybrid ant colony with deep learning
[129]	Learning optimal routing policies	Adaptability to changing network conditions	Initial training overhead	Continuous reinforcement learning
[130]	Combining multiple routing strategies	Improved adaptability and fault tolerance	Increased protocol complexity	Optimal hybrid routing scheme selection
[131]	Effective routing in intermittent connectivity	Resilience to network disruptions	Limited applicability in real-time scenarios	Dynamic buffer management for delay-tolerant networks

Many recent research works demonstrate significant revolutions in the field of UAV optimum route planning and collision avoidance. In [132] a comprehensive overview of traditional and intelligent path planning algorithms in 2020, highlighting the growing use of AI-based solutions to overcome the constraints of classical techniques such as A* and Dijkstra's algorithms. Similarly, many authors investigated the use of deep reinforcement learning (DRL) in UAV path planning and found considerable gains in both dynamic and complicated situations [133]. In 2021, [134] introduced a hybrid approach to path planning that combines genetic algorithms (GA) with particle swarm optimization (PSO), addressing both optimization speed and solution quality. [135] expanded on this by developing a multi-objective optimization framework that balances energy consumption and path length while using fuzzy logic to accommodate uncertainty in UAV navigation. In a similar line, ant colony optimization (ACO) is supplemented with neural networks to adaptively update pheromone trails, therefore enhancing path planning robustness under changing environmental circumstances. Authors made additional breakthroughs by combining a model predictive control (MPC) strategy with machine learning approaches to dynamically forecast and prevent possible accidents [136]. Similarly, [137] suggested a decentralized collision avoidance system based on cooperative multi-agent reinforcement learning (MARL), enabling numerous UAVs to share information and coordinate their motions in real time. [138] used a cuckoo search method to efficiently guide UAVs over complicated urban areas. Another important addition comes from [139], who investigated the use of a hybrid bat algorithm for path planning, which successfully minimizes processing overhead while maintaining excellent accuracy in obstacle-rich environments. Many of the authors have proposed a unique technique that combines quantum computing concepts with classical optimization algorithms to considerably accelerate the path planning process for large-scale UAV networks. In terms of collision avoidance, [139] demonstrated a real-time collision avoidance system based on deep Q-learning that outperformed previous reactive approaches in dynamic situations. Furthermore, [140] created a vision-based collision avoidance system that uses convolutional neural networks (CNNs) to recognize and respond to obstacles with excellent accuracy. [141] conducted research work on combining Internet of Things (IoT) technology with UAV path planning to increase situational awareness and decision-making skills. [142] proposed a unique UAV swarm intelligence solution that uses block chain technology to enable safe and efficient communication amongst UAVs for coordinated path planning and collision avoidance. [143] studied the use of hybrid AI approaches that combine reinforcement learning with evolutionary algorithms to enable adaptive and robust UAV navigation in unexpected conditions. This research work shows the fast progress of UAV route planning and collision avoidance technology, which is being driven by advances in AI, machine learning, and bioinspired algorithms, with the promise of increased efficiency, safety, and autonomy for UAV operations in more complicated circumstances. [144] examined the use of hybrid metaheuristic algorithms combining Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA) for UAV path planning.

Their approach effectively reduced path length and computational time while maintaining high solution quality, demonstrating robustness in various environmental scenarios. [145] proposed a deep learning-based approach for real-time path planning using convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Their method enabled UAVs to predict and adjust paths dynamically in complex, cluttered environments, significantly improving navigation efficiency. [146] developed a cooperative path planning strategy using a multi-UAV system for large-scale agricultural monitoring. By employing a coordinated control framework, their system enhanced coverage efficiency and minimized the risk of collision between UAVs. [147] introduced a reinforcement learning-based path planning algorithm that leverages a novel reward shaping technique. This method facilitated faster convergence and improved the UAV's ability to navigate through unpredictable environments while avoiding obstacles. [148] explored the application of a bioinspired firefly algorithm for UAV swarm path planning. Their study demonstrated the algorithm's effectiveness in optimizing multiple UAV trajectories simultaneously, reducing energy consumption and travel time. [149] presented a hybrid optimization model combining Differential Evolution (DE) and Simulated Annealing (SA) for UAV collision avoidance. This model effectively handled real-time dynamic obstacle scenarios, offering a balance between solution optimality and computational efficiency. [150] investigated a machine learning-based adaptive path planning approach that utilizes support vector machines (SVMs) for classification and decision-making. Their method improved the UAV's adaptability to varying environmental conditions and enhanced collision avoidance capabilities. [151] developed an evolutionary algorithm incorporating differential evolution and genetic algorithms for path planning in GPS-denied environments [152]. Their approach provided high resilience and accuracy, particularly in urban canyons and dense forests. [153] proposed a novel fuzzy logic-based path planning algorithm for UAVs, integrating real-time environmental data to adjust flight paths dynamically. This method improved decision-making under uncertainty and enhanced safety in unpredictable conditions. [154] introduced an innovative path planning framework using swarm intelligence combined with deep reinforcement learning (DRL). Their hybrid approach allowed UAV swarms to learn and adapt collaboratively, significantly improving path optimization and collision avoidance in complex terrains. These recent studies illustrate the diversity and innovation in UAV path planning and collision avoidance, highlighting the integration of advanced algorithms and techniques such as deep learning, evolutionary computation, and bioinspired models. This ongoing research work aims to enhance the efficiency, safety, and autonomy of UAV operations in increasingly challenging environments. [192] introduced an innovative method for tackling the difficulties associated with full coverage path planning (CCPP) by employing multiple UAVs. Conventional single-agent CCPP (Coordinated Coverage Path Planning) approaches are not efficient for wide regions, resulting in extended coverage durations. In order to address this issue, the authors suggest using the Weighted Balanced Graph Partitioning-based Complete Coverage Path Planning (WBGPP) approach. The proposed method involves partitioning the coverage area into sub-areas using a Weighted Balanced Graph Partitioning (Weighted B-GRAP) algorithm. Each UAV is then assigned a specific responsibility region depending on its capabilities. Afterwards, a Single Agent Path Planning (SAPP) algorithm is used to optimize the pathways within these sub-areas in order to reduce unnecessary paths and decrease the total time taken for coverage. This novel approach shows potential for use in surveillance, data gathering, and inspection activities, providing a scalable and effective solution for multi-UAV operations. [193] introduced the Exploration-RRT (ERRT) algorithm, designed for real-time exploration in unknown and unstructured environments using UAVs. This technique blends exploration and planning by assessing probable courses based on information obtained, distance travelled, and robot actuation. ERRT's usefulness is shown through comprehensive simulations and real-world studies, revealing its capacity to navigate complicated underground and GPS-denied situations effectively. The framework, fully integrated with the Robot Operating System (ROS) and open-sourced, offers a unique method to solve the combined exploration-planning issue by reducing computing effort and assuring efficient path optimization. The paper illustrates ERRT's use in many hard settings, including tight tunnels and vast caverns, stressing its practical utility and scalability for UAV-based exploration jobs. [194] presented an innovative method for UAVs to navigate and map unknown terrains autonomously. This paper proposes a boundary-driven mapping technique that employs deep learning to identify boundaries and uses a decision-making methodology for optimum exploration. The technique requires generating a precise 3D map using an octomap and translating it into a point cloud. A CNN, especially the YOLOv8 model, is then applied to detect border places inside the map. The boundaries are grouped, and a decision-making mechanism is utilized to identify the most suited cluster for exploration. The suggested technique exhibited considerable efficiency increases in exploration time and mapping accuracy in both simulated indoor and outdoor environments compared to existing methodologies. By tackling computational complexity and adding deep learning, the work emphasizes the potential of this boundary-driven technique to boost UAV autonomy and mapping performance in dynamic and unexpected terrains. [195] proposed an updated deep reinforcement learning strategy to better UAV navigation in dynamic situations. This strategy blends two unique learning stages: reinforced learning and self-supervised learning. The reinforced stage utilizes a Deep Q-Learning Network (DQN) guided by the Bellman equation, while the self-supervised stage fine-tunes the DQN backbone using contrastive loss, boosting scene encoding speed. An obstacle detection model is also incorporated to reduce UAV collisions. The framework's usefulness is illustrated by simulations in the block environment, incorporating both fixed and moving obstacles. Results indicate considerable gains in navigation performance, with the UAV accomplishing greater distances toward the target with fewer collisions compared to standard DQN approaches. The work emphasizes the possibility of integrating self-supervised learning with reinforcement learning for efficient and successful UAV visual navigation in complex and dynamic contexts.

3.3 Research Questions

Q.1 How can unmanned aerial vehicles (UAVs) maximize path planning to save energy usage while accomplishing missions?

Response: Path optimization for energy efficiency can be achieved by integrating energy consumption models into the planning algorithms. Techniques like genetic bioinspired algorithms and dynamic programming can be used to find the most energy-efficient paths.

Q.2 How can bioinspired algorithms improve the efficiency of UAV path planning compared to traditional algorithms?

Response: Genetic Algorithms (GA), Firefly Optimization (FFO), Grey Wolf Optimization (GWO), Mayfly Optimization (MO) are examples of bioinspired algorithms that use natural processes to find the best answers. These algorithms can look for solutions in a bigger area faster than some older methods, which makes them better at working in complex, high-dimensional settings. Comparative studies have shown that bioinspired algorithms can find the best paths more rapidly and with higher success rates.

Q.3 What are the challenges of implementing bioinspired algorithms in real-time UAV path planning, and how can they be addressed?

Response: Challenges include computational complexity, real-time constraints, and the need for continuous adaptation to changing environments. These challenges can be addressed by optimizing the computational efficiency of bioinspired algorithms, such as through parallel processing or hardware acceleration. Hybrid approaches that combine fast, heuristic methods for immediate decision-making with bioinspired algorithms for long-term optimization can also be effective. Additionally, adaptive frameworks that balance investigation and manipulation can ensure timely and robust path planning.

Q.4 How can bioinspired algorithms improve the robustness of UAV collision avoidance systems?

Response: Bioinspired algorithms like Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Firefly Optimization (FFO), Grey Wolf Optimization (GWO), Mayfly Optimization (MO) can enhance robustness by providing flexible, adaptive strategies that mimic natural behaviours.

Q.5 How can bioinspired algorithms help UAVs avoid collisions in constrained environments?

Response: Swarm intelligence principles, such as those in PSO, FFO, MO, GWO and ACO, enable decentralized coordination among multiple UAVs. Each UAV can adjust its path based on local information and the behaviour of its neighbours, leading to emergent behaviours that enhance collision avoidance. In constrained environments, this can lead to more efficient space utilization and reduced likelihood of collisions.

Q.6 Can hybrid bioinspired algorithms provide better collision avoidance performance than single-algorithm approaches?

Response: Hybrid bioinspired algorithms, which combine elements of multiple bioinspired approaches (e.g., PSO, FFO, GWO, MO and GA), can offer improved performance by leveraging the strengths of each method. For example, GA can be used for global path optimization, while PSO handles local adjustments in real-time. This combination can result in more robust and adaptive collision avoidance systems.

3.4 Literature Summary

In this chapter, after completing the review of various existing methods, the multi-layered issues offered by these dynamic and complex systems have been the subject of significant research and development efforts in order to build effective routing techniques for Unmanned Aerial Vehicle (UAV) Networks. This part of the chapter provides a comprehensive summary of relevant work in the field of UAV routing, encircling various approaches, models, and algorithms. One notable advancement in UAV routing is the integration of Q-learning and a reinforcement learning technique. Q-learning-based routing strategies, such as QL and QTAR, introduced adaptability and sensitivity to the dynamic UAV environment. These approaches influence Q-tables to determine optimal actions for each state, allowing UAVs to make intelligent routing decisions based on past experiences. Recognizing the limitations of traditional routing and Q-learning-based approaches, research workers explored bioinspired optimization algorithms. These algorithms draw inspiration from natural processes, including genetic algorithms (GA), particle swarm optimization (PSO), and ant colony optimization (ACO). They have shown potential in optimizing UAV routing by considering factors like energy efficiency, route quality, and collision avoidance. These bioinspired models offer robust and adaptive routing solutions suitable for large-scale UAV networks [155]. Another critical aspect of UAV routing is collision awareness. With UAVs sharing airspace with other UAVs, manned aircraft, and obstacles, collision avoidance is of utmost priority. Collision-aware routing strategies combine spatial and temporal awareness to proactively prevent collisions. These strategies integrate sensor data, employ advanced algorithms like A* and potential fields, and influence machine learning for predictive collision avoidance. The incorporation of collision-aware routing enhances safety, efficiency, scalability, and adaptability in UAV operations [156]. The summarized body of work underscores the ongoing evolution of UAV routing techniques. While each approach has its merits and addresses specific challenges, the integration of bioinspired optimization algorithms, such as the MO Model, and collision-aware routing represent significant advancements in the field. These approaches improve safety, efficiency, and scalability, making UAV networks more adaptable to various applications. The field of UAV routing is composed of further growth and innovation. Future research work directions may include the validation of these models in larger UAV networks, the integration of low-complexity bioinspired algorithms, and the utilization of transformer models to predict and mitigate collisions. The ultimate goal is to enhance routing efficiency and safety, thereby unlocking the full potential of UAVs across a wide spectrum of real-time applications, from surveillance and agriculture to delivery and beyond.

CHAPTER 4

QMRNB: Q-LEARNING MODEL FOR UAV NETWORK ROUTING

Design of efficient routing strategies for Unmanned Aerial Vehicle (UAV) Networks is a multidomain task that involves analysis of node-level & network-level parameters and mapping them with communication & appropriate conditions. Existing path optimization models either showcase higher complexity or cannot be scaled for larger network scenarios. Moreover, the efficiency of these models reduces w.r.t. number of communication requests, which limits their scalability levels. To deal with these issues, this research work developed a design of an efficient Q-Learning model to improve the routing efficiency of UAV networks via bioinspired optimizations. The model initially collects temporal routing performance data samples for individual nodes and uses them to form rough routes via Q-Learning optimizations. These routes are further managed via a Mayfly Optimization (MO) Model, which assists in the selection of optimal routing paths for high Quality of Service (QoS) even under large-scale routing requests. The MO Model is able to identify alternate paths via the evaluation of a high-density routing fitness function that assists the router in case the selected paths are occupied during current routing requests. This assists in improving temporal routing performance even under dense network conditions. Due to these optimizations, the model is capable of reducing the routing delay by 8.5%, improving energy efficiency by 4.9%, and reducing routing jitter by 3.5% when compared with existing routing techniques under similar routing conditions [188].

4.1 Introduction to QMRNB

Due to the repeated movement of vehicles, the UAV (Unmanned Aerial Vehicle) routing protocol must deal with a variety of issues, including unequal node distribution, topological changes, and changes in the surrounding environment via Energy-aware Collaborative Routing (ECoR) [157, 158]. Q-learning (QL) was included to make UAV routing [159] more adaptable and sensitive to the dynamic environment. Traditional reinforcement learning is referred to as Q-learning, and it is distinguished by the lack of a state transition model in favour of an assessment of the value of state-action pair combinations. The following are the components of Q-learning: s, a, R, where s represents the state set of RL, a represents the action set of RL, and R represents the attenuation factor of future reward and the learning rate of reinforcement learning [160], respectively. If an "a" operation is performed in a certain state, the node will update the state value table by inserting (1), where s is the succeeding state (Q-value table). Following a certain number of repetitions, the Q-table will determine the optimal action for each state. This operation will guarantee that the node gets the maximum reward available for the current set of iterations.

$$Q(s,a) = (1 - \alpha)Q(s,a) + \alpha\big(R + \gamma\, max\, Q(s\,,a\,)\big) \ldots (1)$$

To achieve the objectives of reinforcement learning, the set of neighbour nodes is considered, and the base stations (BS) is treated as the fixed destination node that broadcasts hello packets regularly via the use of Q -learning-based topology-aware routing (QTAR) [161-164]. In accordance with the above-mentioned principles, the receiving node is required to update the Q-value table of its own device: the higher the Q-value, the closer the device is to RS. When this method is used, the routing to static destination nodes is enhanced. The work in [165-167] utilizes the conventional Adhoc on Demand Multipath Distance Vector (AOMDV) routing protocol in addition to the Q-learning approach. The nodes are able to update the Q-value information stored in their respective local memory by exchanging the hello and RREQ packets required for route discovery. Using the AODV routing algorithm established in [168], an excellent degree of performance was achieved in a case with restricted mobility. In [169-171], unmanned aerial vehicles (UAVs) have been used to aid VANET (Vehicular Adhoc Networks) in determining the most efficient route for data transmission. However, the following are some of the most common problems that emerge with such routing systems: Each node on the ground is responsible for keeping its own Q-value table, regardless of whether it has neighbours or not. Because (1) ground nodes only employ locally stored information to decide the next hop [172-175] and (2) both the size of the Q-value table and the stored value are subject to rapid change [176], this leads to increased bandwidth use and a slower convergence speed of Q-values & their alternatives.

As a result, conventional route optimization techniques either have increased complexity or are not useable for situations involving bigger networks. Additionally, these models efficiency declines as the number of communication requests increases, which restricts the extent of their scalability. The building of an effective Q-Learning model to increase the routing efficiency of UAV networks using bioinspired optimizations is suggested. This chapter aims to provide the solution to these problems. Finally, the model used in research work has been evaluated and assessed using large-scale network scenarios and compared to that of conventional routing models. This chapter concludes with some network-specific observations regarding the suggested model and suggestions for ways to further enhance its functionality in various network scenarios.

4.2 Design of the Model

As per the review of existing routing models that are used for UAV Networks, it can be observed that existing path optimization models either showcase higher complexity or cannot be scaled for larger network scenarios. Moreover, the efficiency of these models reduces w.r.t. number of communication requests, which limits their scalability levels. To overcome these issues, there is a need to design an efficient Q-Learning model to improve the routing efficiency of UAV networks via bioinspired optimizations. As per figure 4.1, it can be observed that the model initially collects temporal routing performance data samples for individual nodes and uses them to form rough routes via Q-Learning optimizations. These routes are further processed by a Mayfly Optimization (MO) Model, which assists in the selection of optimal routing paths for high Quality of Service (QoS) even under large-scale routing requests. The MO Model is able to identify alternate paths via the evaluation of a high-density routing fitness function that assists the router in case the selected paths are occupied during current routing requests. This assists in improving temporal routing performance even under dense network conditions. Figure 4.1 shows showing control flow of the design model to achieve efficient results.

Thus, the model initially uses Q-Learning to identify different routes between a given source & destination pair of nodes. This is done by initially calculating a reference distance between these nodes via equation 2,

$$d_{ref} = \sqrt{\begin{matrix}(x_{src} - x_{dest})^2 + (y_{src} - y_{dest})^2 \\ +(z_{src} - z_{dest})^2\end{matrix}} \ldots (2)$$

Where x, y & z are the Cartesian locations of these nodes, while src & $dest$ are the IP addresses of source & destination nodes.

Now, select all nodes that satisfy equation 3,

$$d_{src,i} < d_{ref} \ \& \ d_{i,dest} < d_{ref} \ldots (3)$$

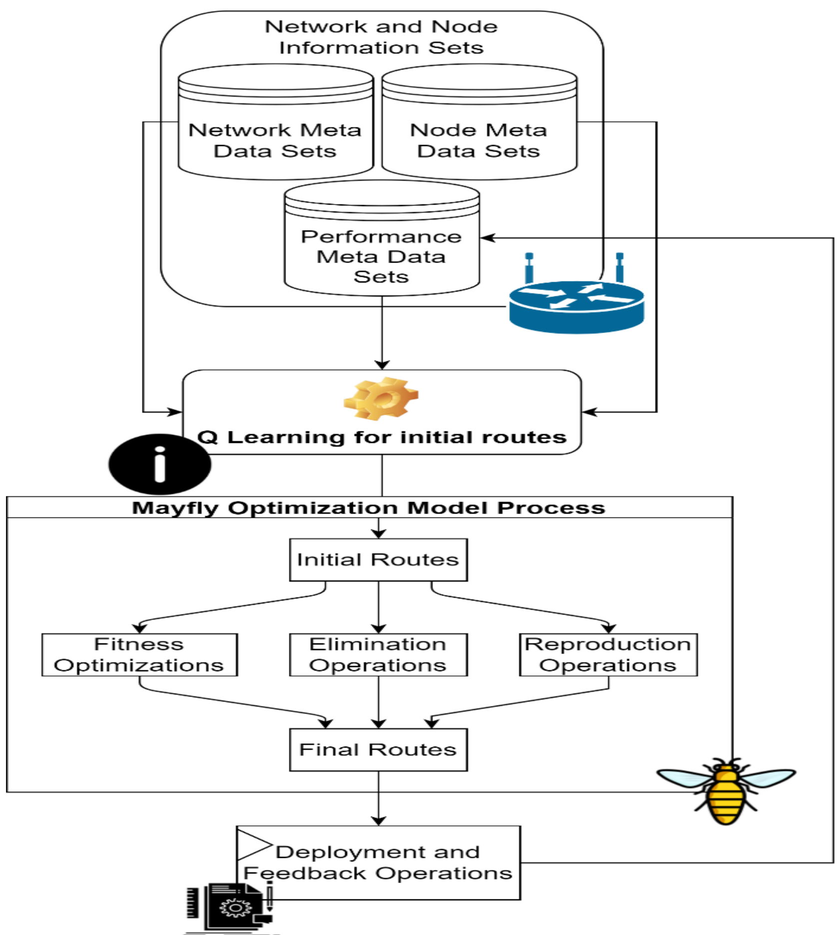

Figure 4.1-Design of the routing model for UAV Networks

Where, $d_{src,i}$ is the distance between the selected node & the source node, while $d_{i,dest}$ represents the distance between selected & destination node sets. For all these nodes, evaluate their Q values via equation 4.1,

$$Q = \sum_{i=1}^{N_p} \frac{\sum NC_i}{\sum LQ_i} \dots (4.1)$$

This Q value is updated via equation 4.2,

$$Q(New) = Q(Old) + L_r * \frac{NC}{Max(NC)} + Max(Q) \dots (4.2)$$

Where, N_p represents the number of nodes in the current path, L_r is a stochastic learning rate, while NC & LQ are the node communication metric and link quality metric, which is estimated via equations 5 & 6 as follows,

$$NC = \frac{1}{N_h} \sum_{i=2}^{N_h} d_{i-1,i} * \left[\frac{THR_{i-1}}{Max(THR)}\right] \dots (5)$$

Where d is the distance, while THR is the temporal throughput, which is evaluated via equation 7, while N_h are the total number of hops used for the routing operations.

$$LQ = \frac{1}{N_h} \sum_{i=1}^{N_h} \frac{100}{PDR_i} + \frac{e_i}{Max(e)} \dots (6)$$

Where PDR & e represent the packet delivery ratio and energy consumption during previous communications, which are estimated using 8 & 9 and are updated after individual routing operations.

$$THR = \sum_{t=t1}^{t2} \frac{NN(t)}{Max(NN) * (t2 - t1)} \dots (7)$$

Where $NN(t)$ represents the total number of packets passed during the given time intervals.

$$PDR = \sum_{t=t1}^{t2} \frac{NN(t)}{NN_d(t) * (t2 - t1)} \dots (8)$$

Where, NN_d represents the total number of packets dropped during the given time intervals.

$$e = \sum_{t=t1}^{t2} \frac{e_{start} - e_{complete}}{(t2 - t1)} \dots (9)$$

Where, e_{start} & $e_{complete}$ are the energy levels of the nodes during the routing process. These Q values are sorted in descending order, and then N stochastic nodes are selected from this list via equation 10,

$$N = STOCH(L_r * N_n, N_n) \dots (10)$$

Where, N_n represents the total number of nodes in the list while L_r is estimated via equation 11,

$$L_r = \frac{N_n}{N_t} \dots (11)$$

Where, N_t represents the total number of nodes in the network that are deployed in the UAV network sets. Based on this process, a set of NM Mayflies (routes) are generated and are optimized via the following Mayfly Optimization (MO) Model process,

- From the set of Q learning solutions, N stochastic solutions are selected via equation 12,

$$N = STOCH(LM * NM, NM) \dots (12)$$

Where LM is the learning metric for the MO Model process.

- For each of these solutions, a fitness value is calculated via equation 13,

$$f = \frac{1}{NM} \sum_{i=1}^{NM} Q_i \dots (13)$$

- This process is repeated for NM different Mayflies, and then a fitness threshold is estimated via equation 14,

$$f_{th} = \frac{1}{NM} \sum_{i=1}^{NM} f_i * LM \dots (14)$$

- Mayflies with $f > f_{th}$ are discarded & reproduced in the next iteration, while others are crossover to the next set of iterations.

These Mayflies are regenerated for NI iterations, and the Mayflies with the lowest fitness levels are selected for routing the UAV nodes. The selected Mayfly will contain multiple routing configurations, out of which the configuration with minimum fitness is selected for routing operations. In case the current route is busy or the path is not available, then the next higher fitness path is selected to route the UAV Nodes. Due to this, the model is able to optimize routing delay, energy, throughput and packet delivery ratios during real-time route formation operations. The performance during routing is updated in the database, and the process is repeated for consecutive routing processes. This assists in the continuous improvement of routing performance under real-time scenarios. This performance was validated under different network conditions and compared with other models in the next section of this chapter.

4.3 Result Analysis

The QMRNB model collects temporal routing performance data samples for individual nodes and uses them to form coarse routes through Q-Learning optimizations. These routes are then processed by a Mayfly Optimization (MO) Model, which helps in the selection of optimal routing paths for high Quality of Service (QoS) even when large-scale routing requests are being processed. The MO Model is capable of identifying alternate paths through the evaluation of a high-density routing fitness function, which assists the router in the event that the selected paths are occupied during current routing requests. This helps to enhance temporal routing performance even in dense network environments. To validate its performance, the model was evaluated under a standard set of UAV configurations in Network Simulator 2 (NS 2.34), with the network parameters indicated in table 4.1 as follows,

Table 4.1-Set of simulation configurations for emulating different network scenarios

Parameters for the UAV Network	**Values used for the parameter sets**
UAV propagation model	Wireless with inter-layer routing
MAC Model	802.16a
Queue Type	Priority queues with drop tailing operations
Total UAV Nodes	5000
Size of the UAV Network	4 kms x 4 kms
Energy Model	Idle: 5 mW Receive: 10 mW Transmit: 15 mW Sleep: 1 mW Transition: 2.5 mW
Transition Delays	0.01 s
Energy set during initialization of UAV Nodes	2500 mW

Based on these configurations, the delay needed for routing was estimated via equation 15,

$$D = \frac{1}{NM}\sum_{i=1}^{NM} ts_{reach} - ts_{start} \ldots (15)$$

Table 4.2- Average delay for different number of routing evaluations

Number of Movements	**D (ms) ECOR [177]**	**D (ms) QL [178]**	**D (ms) QTAR [179]**	**D (ms) QMRNB (Proposed Model)**
2k	15.95	17.09	18.03	12.23
4k	18.13	19.62	20.74	14.10
6k	20.96	22.79	24.09	16.39
8k	24.42	26.54	28.00	19.04
10k	28.42	30.73	32.33	21.96
12k	32.77	35.27	37.00	25.06
14k	37.21	39.94	41.79	28.19
16k	41.46	44.53	46.53	31.23
18k	45.39	48.91	51.06	34.11
20k	48.94	52.98	55.30	36.81
25k	52.22	56.79	59.26	39.33
28k	55.27	60.26	62.89	41.69
30k	58.17	63.53	66.31	43.93
35k	61.50	67.18	70.10	46.45
38k	64.98	70.94	74.02	49.07
40k	68.71	74.96	78.19	51.84

Where, ts_{reach} & ts_{start} are the timestamps for reaching the destination and starting the routing process. This delay performance was evaluated w.r.t. different Number of Movements (NM), which were varied between 2k to 40k, and compared with ECOR [177], QL [178], & QTAR [179] in table 4.2 as follows,

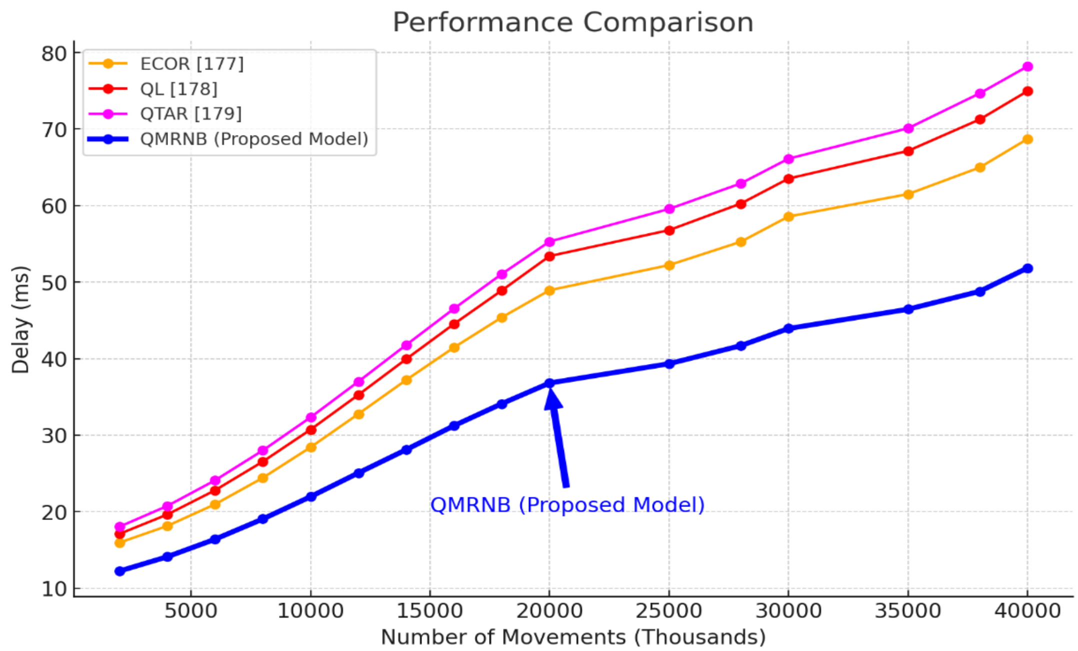

Figure 4.2-Average delay for different number of routing evaluations

Based on this evaluation and its visualization in figure 4.2, it can be observed that the model is able to reduce the delay needed for routing by 9.5% when compared with ECOR [177], 14.5% when compared with QL [178], and 18.9% when compared with QTAR [179], which makes it useful for a wide variety of real-time routing applications. This delay is reduced due to the use of distance levels and temporal delay performance during the selection of routing paths. Similarly, the energy needed during these routing operations was evaluated via equation 16 as follows,

$$E = \frac{1}{NM}\sum_{i=1}^{NM} E_{src}(start)_i - E_{src}(complete)_i \ldots (16)$$

Where, $E(start)$ & $E(complete)$ are the energy levels of the source node during the start & completion of the routing process. This energy consumption can be observed in table 4.3 as follows,

Table 4.3 represents the average use of energy consumption for different number of routing evaluation. Whereas, Figure 4.3 is a graphical representation of the same. It has been clearly seen from the graph that QMRNB has better efficiency in context to average energy consumption while routing.

Table 4.3- Average energy consumed during different number of routing evaluations

Number of Movements	**E (mW) ECOR [177]**	**E (mW) QL [178]**	**E (mW) QTAR [179]**	**E (mW) QMRNB (Proposed Model)**
2k	37.05	48.33	29.84	21.96
4k	38.98	50.78	31.34	23.06
6k	40.83	53.27	32.88	24.21
8k	42.75	55.90	34.50	25.40
10k	44.77	58.64	36.18	26.63
12k	46.87	61.46	37.90	27.89
14k	49.08	64.33	39.62	29.14
16k	51.34	67.17	41.32	30.37
18k	53.60	69.94	42.97	31.56
20k	55.80	72.61	44.57	32.71
25k	57.93	75.21	46.13	33.84
28k	60.01	77.80	47.70	34.99

30k	62.05	80.41	49.30	36.14
35k	64.09	83.10	50.92	37.33
38k	66.15	85.78	52.56	38.53
40k	68.22	88.48	54.20	39.72

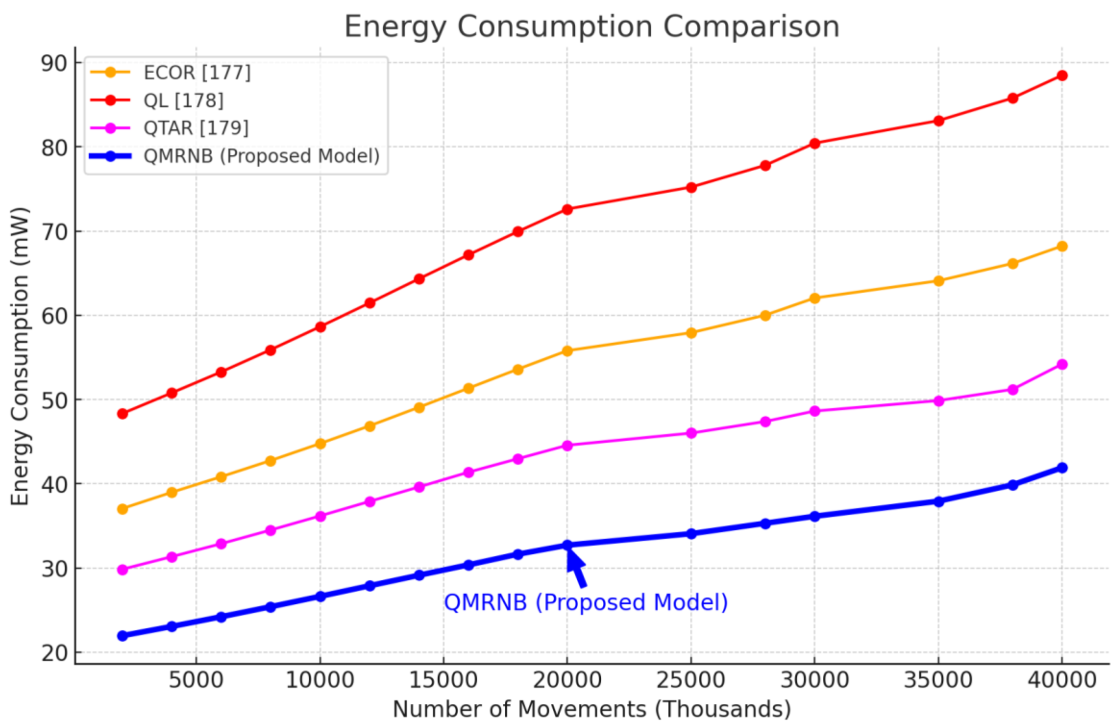

Figure 4.3-Average energy consumed during the different number of routing evaluations

Based on this evaluation and its visualization in figure 4.3, it can be observed that the model is able to reduce the energy needed for routing by 15.9% when compared with ECOR [177], 19.2% when compared with QL [178], and 14.5% when compared with QTAR [179], which makes it useful for a wide variety of low-energy routing applications. Similarly, Table 4.4 displays the throughput throughout various routing processes, along with additional performance information. The throughput during these routing operations can be observed in table 4.4 as follows,

Table 4.4-Average throughput during different routing operations

Number of Movements	**THR (vpm) ECOR [177]**	**THR (vpm) QL [178]**	**THR (vpm) QTAR [179]**	**THR (vpm) QMRNB (Proposed Model)**
2k	112.86	86.32	92.25	138.86
4k	113.71	87.11	93.00	140.00
6k	114.86	87.63	93.75	141.14
8k	116.00	88.42	94.50	142.29
10k	116.86	89.21	95.25	143.43
12k	117.71	89.74	96.00	144.57
14k	118.57	90.53	96.75	145.71
16k	119.43	91.32	97.50	146.86
18k	120.57	92.11	98.25	148.00
20k	121.71	92.89	99.00	149.14
25k	122.57	93.68	99.75	150.29
28k	123.43	94.47	100.50	151.43
30k	124.29	95.00	101.50	152.57
35k	125.10	95.79	102.34	153.71
38k	126.15	96.50	103.12	154.86
40k	127.15	97.12	103.84	156.00

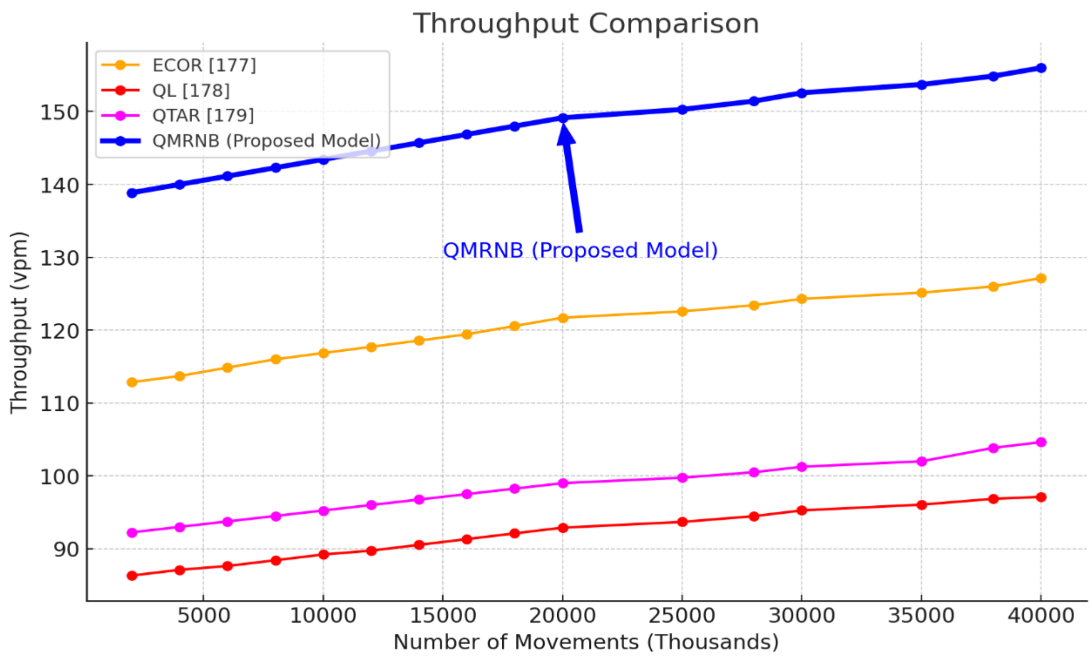

Figure 4.4-Average throughput during different routing operations

Based on this evaluation and its visualization in figure 4.4, it can be observed that the model is able to improve the routing throughput by 8.5% when compared with ECOR [177], 15.4% when compared with QL [178], and 12.5% when compared with QTAR [179], which makes it useful for a wide variety of high data rate routing applications. This throughput is increased due to the use of packet delivery levels and temporal throughput performance during the selection of routing paths. Due to these optimizations, the model is capable of deployment for a wide variety of real-time UAV routing scenarios.

4.4 Conclusion & Future Scope

The QMRNB model gathers samples of temporal routing performance data for individual nodes and uses Q-Learning optimizations to form coarse routes. A Mayfly Optimization (MO) Model then processes these routes, helping to choose the best routing paths for high Quality of Service (QoS) even when numerous routing requests are being handled simultaneously. If the chosen paths are already taken by current routing requests, the MO Model can find alternative routes by evaluating a high-density routing fitness function. This helps the router even in environments with dense network traffic, this helps in improving temporal routing performance. Based on the evaluation of routing speed, it can be seen that the model can reduce the delay required for routing by 9.5% when compared to ECOR [177], 14.5% when compared to QL [178], and 18.9% when compared to QTAR [179], making it useful for a variety of real-time routing applications. The use of distance levels and the performance of the temporal delay during the selection of routing paths both help to reduce this delay. According to energy evaluation, the model can reduce the energy required for routing by 15.9% when compared to ECOR [177], 19.2% when compared to QL [178], and 14.5% when compared to QTAR [179], making it useful for a variety of low-energy routing applications. Due to the use of distance levels and temporal energy performance during the selection of routing paths, this energy is reduced. Based on data-rate evaluation, it can be seen that the model can increase routing throughput by 8.5% when compared to ECOR [177], 15.4% when compared to QL [178], and 12.5% when compared to QTAR [179], and making it useful for a variety of high data rate routing applications. The use of packet delivery levels and temporal throughput performance during routing path selection has increased this throughput. The model can be used in a wide range of real-time UAV routing scenarios as a result of these optimizations.

CHAPTER 5

BPACAR: HYBRID BIOINSPIRED MODEL FOR COLLISION-AWARE ROUTING

Designing collision-aware routing (path planning) protocols for UAV (Unmanned Aerial Vehicle) Networks requires multimodal analysis of various network & node-level parameter sets. These include node-to-node distance, energy constraints, communication constraints, QoS (Quality of Service) constraints, etc. Existing collision-aware UAV routing models are either highly complex or have lower efficiency, which limits their real-time deployment capabilities. Moreover, these models usually do not consider energy constraints and are applied to static targets. To deal with these limitations, this chapter method to design a novel hybrid bioinspired model with continuous pattern analysis for dynamic collision-aware routing in UAV networks. The model initially collects node-level & network-level parametric sets that include Cartesian location, residual energy levels, temporal routing performance, and temporal collision performance levels. The model then deploys a Grey Wolf Optimization (GWO) based routing process to identify optimal routes between two anchor points. These routes are further tuned via a Firefly based Optimization (FFO), which assists in estimating high-trust routes based on their temporal performance via continuous data update operations. The selected route sets are further scrutinized via a continuous learning framework (CLF), which assists in the identification of dynamic moving targets and uses this information for incremental route updates. Due to the integration of CLF, the model is able to identify optimal paths even under moving target scenarios. The model was validated under multiscale networks, and its performance was evaluated in terms of collision avoidance accuracy, routing delay, energy requirements, and computational complexity levels w.r.t. dynamic scenarios. This performance was compared with various up-to-date methods, and it has been seen that the model showcased 10.5% lower routing delay, with 8.3% lower energy consumption and 23.9% lower collisions while maintaining lower computational complexity. Due to these enhancements, the model is proficient in the positioning of a wide variety of real-time UAV network scenarios.

5.1 Introduction to BPACAR

UAV based networks are high-energy consumption networks with moderate flight time but strong communication characteristics. Thus, designing routing models for these networks requires efficient analysis of routing paths, temporal node performance, network parameters, and other multimodal and contextual constraints [180]. To design such models, research workers need to consider a wide variety of real-time parameters that include, collision awareness, height of flying, turning angles, threat avoidance, etc. A list of such parameters can be observed in figure 5.1, wherein metrics for collision avoidance, self-constraints, and external dynamics are separated in order to identify the most useful metrics that must be optimized under large-scale routing (path planning) scenarios [181]. Based on this comparison, it can be observed that Expected Time of Arrival (ETA), separation maintenance, fuel capacity, slope of UAV, its turning angle, and relative height are the most important metrics for indigenous UAV networks.

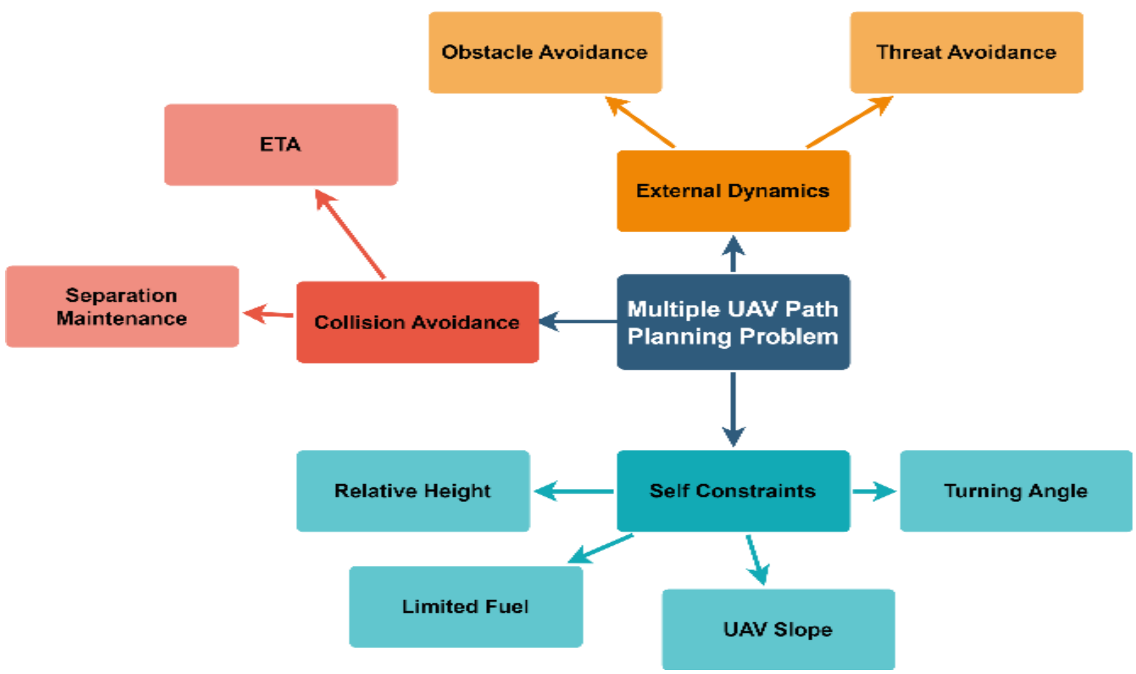

Figure 5.1-Parameters affecting the UAV routing process

These parameters are combined to form an objective function f_p which can be evaluated as per equation 1,

$$f_p = \frac{f_1(ETA, RH, F, S, T_a)}{f_2(Sep, Obs)} \dots (1)$$

Where, RH, F, S & T_a represents relative height, fuel requirements, slope and turning angle, all of which must be minimized, while Sep & Obs represent separation distance & obstacle avoidance probability, which must be maximized for the optimization process [182]. The functions f_1 & f_2 are decided as per the context of the network and used for continuous planning operations. A survey of models [183] that perform these operations is discussed in the next part of this chapter, based on which it has been found that existing path planning models with collision-awareness are either highly complex or have lower efficiency, which limits their real-time deployment capabilities. Moreover, these models usually do not consider energy constraints and are applied to static targets. To overcome these limitations, this research work designs a novel hybrid bioinspired model with continuous pattern analysis for dynamic collision-aware routing in UAV networks. The model was evaluated under various network conditions, and its performance was compared w.r.t. standard UAV routing methods under different scenarios [184]. Finally, this chapter concludes with some context-specific & network-specific observations about the model and endorses approaches to further optimize its performance under unlike real-time scenarios.

5.2 Design of the model

Based on the review of existing collision-aware routing models, it has been found that these models are either highly complex or have lower efficiency, which limits their real-time deployment capabilities. Moreover, these models usually do not consider energy constraints and are applied to static targets. To overcome these limitations, a novel hybrid bioinspired model with continuous pattern analysis for dynamic collision-aware routing in UAV networks is used. The flow of the model is depicted in figure 4.2, where it can be observed that the model initially collects node-level & network-level parametric sets that include Cartesian location, residual energy levels, temporal routing performance, and temporal collision performance levels. The model then deploys a Grey Wolf Optimization

(GWO) based routing process to identify optimal routes between two anchor points. These routes are further tuned via a Firefly based Optimization (FFO), which assists in estimating high-trust routes based on their temporal performance via continuous data update operations.

The selected route sets are further scrutinized via a continuous learning framework (CLF), which assists in the identification of dynamic moving targets and uses this information for incremental route updates. Due to the integration of CLF, the model is able to identify optimal paths even under moving target scenarios. In addition, the model includes adaptive learning mechanisms to improve the accuracy of decision-making and dynamically optimizes resource allocation to prolong the lifespan of the network. The incorporation of these sophisticated functionalities enhances the effectiveness and flexibility of the suggested architecture in conducting real-time operations inside a UAV network.

The selected route sets undergo a comprehensive examination using a continuous learning framework (CLF), which allows for the detection of targets that are in motion. Subsequently, this data is utilized to make gradual modifications to the route and adjust to the most efficient pathways, even in situations involving mobile objectives. The model initially collects temporal information about different node & network configurations and uses them to form initial routes. These routes are formed via a Grey Wolf Optimization (GWO) based model, which works via the following process,

- To initialize the optimizer, set up the following GWO constants,
    - Total Wolf configurations to be generated for optimization (N_w)
    - Total iterations for which these Wolves will be evaluated (N_i)
    - A constant rate of learning for these Wolves (L_w)
    - Current node locations and qualitative parameters

- While performing GWO based routing, a set of nodes consisting of source (src) & destination ($dest$) nodes are selected, which will assist in the identification of optimal travelling paths between these nodes

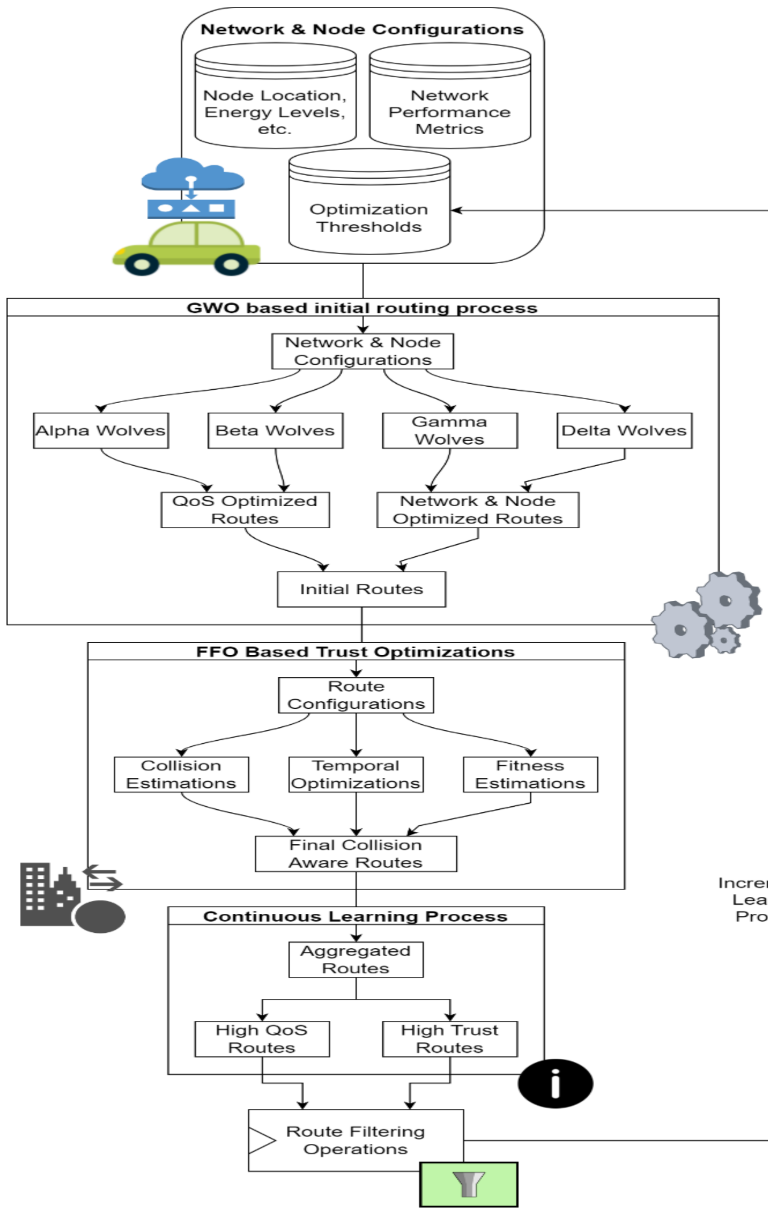

Figure 5.2-Overall flow of the routing process with collision aware operations

- For each pair of source & destination nodes, evaluate the reference distance d_{ref} via equation 2,

$$d_{ref} = \sqrt{\begin{matrix}(x_{src} - x_{dest})^2 + (y_{src} - y_{dest})^2 \\ +(z_{src} - z_{dest})^2\end{matrix}} \dots (2)$$

Where $x, y, \& \ z$ represents the Cartesian locations of the nodes.

- Based on this reference, distance is generated. N_w Wolf configurations as per the following process,
    - Identify all other UAV nodes that are in the route of the current source-destination pair by checking all nodes that satisfy equation 3,

$$d_{src,i} < d_{ref} \ \& \ d_{i,dest} < d_{ref} \dots (3)$$

Where i represents respective node numbers.

- Out of these nodes, identify N routing nodes via equation 4,

$$N = STOCH(L_w * N_n, N_n) \dots (4)$$

Where, N_n represents the total number of nodes that are present in the network scenario, and $STOCH$ represents a stochastic Markovian process that is used for the generation of different number sets.

- For each of these node sets, identify their $\emptyset \ \& \ \theta$ values via equations 5 & 6 as follows,

$$\theta = \tan^{-1}\left(\frac{\sqrt{x^2 + y^2}}{Z}\right) \dots (5)$$

$$\emptyset = \tan^{-1}\left(\frac{y}{x}\right) \dots (6)$$

- Now, rotate the angles by stochastic shifts of $\emptyset' \ \& \ \theta'$ via equations 7 & 8,

$$\emptyset' = \emptyset + STOCH\left(-\frac{\pi}{2} * L_r, \frac{\pi}{2} * L_r\right) \dots (7)$$

$$\theta' = \theta + STOCH(-\pi * L_r, \pi * L_r) \dots (8)$$

Where, L_r is the learning rate, which is initially setup as $L_r = 1$, and then modified via the optimization process.

- Add source to the initial location and destination to the final location, and also add these updated coordinates to the route lists. Based on these update co-ordinates estimate the final route distance as per equation 9,

$$d = \sum_{i=2}^{N} d_{i-1,i} \dots (9)$$

- As per the distance metrics, estimate Wolf fitness via equation 10,

$$f_w = d * \sum_{i=1}^{N-1} E_i \dots (10)$$

Where E represents the energy needed to move from a given location to the next location under real-time conditions.

- This process is repeated for all Wolves and N_w Wolf configurations are generated, each of which represents different routing paths.

- Estimate Wolf fitness threshold via equation 11,

$$f_{th} = \sum_{i=1}^{N_w} f_w * \frac{L_w}{N_w} \dots (11)$$

- Based on this threshold, mark the Wolves as follows,
  - A Wolf is marked as 'Delta' when $f_w > f_{th} \dots (12)$
  - Else, the Wolf is marked as 'Alpha' when $f_w < f_{th} * \frac{L_w}{2} \dots (13)$
  - Else, Wolf is marked as 'Beta' when $f_w < f_{th} * L_w \dots (14)$
  - Otherwise, Wolf is marked as 'Gamma' for further optimizations

- Once all Wolves are marked, then scan each of them and modify their internal configurations for N_i iterations as per the following process,
    - Regenerate all 'Delta' Wolves via equations 4, 5, 6, 7, 8 and 9
    - For 'Beta' & 'Gamma' Wolves, modify L_r via equation 15,

$$L_r = L_r\left(1 \pm \frac{1}{STOCH\left(\frac{N_w}{2}, N_w\right)}\right) \dots (15)$$

    - Use this new L_r to generate their new configurations.
    - At the end of each iteration, identify the fitness threshold and recheck the fitness levels for each of the Wolves, which will assist in the identification of optimal routing paths.

Once all iterations are completed, select 'Alpha' Wolves as initial routing configurations and modify these configurations via a Firefly based optimization process. This process reiterates all the 'Alpha' solutions and identifies high-trust paths, which will assist in achieving better QoS levels. This model works as per the following process,

- To initialize the optimizations, set up the following FF constants,
    - The total number of fireflies used for optimization (N_{ff})
    - The total number of iterations used during the optimization process (N_i)
    - The rate at which the fireflies will learn from each other (L_{ff})
    - Temporal routing parameters on each path, including throughput, collisions, and link quality on the given path sets.
- Scan all 'Alpha' Wolves for N_i iterations, as per the following process,
    - Generate current path brightness via equation 16,

$$p_b = \sum_{i=2}^{N_h} d_{i-1,i} * \left[\frac{THR_{i-1}}{Max(THR)}\right] * NC_{i,i+1} * \frac{1}{LQ_{i,i+1}} \dots (16)$$

Where, N_h represents the number of hops decided by the GWO process, while THR, NC & LQ represents the throughput of nodes on the given path, which is evaluated via equation 17, the number of temporal collisions on the path which is evaluated via equation 18, and temporal link quality of the given paths which is evaluated via equation 19 as follows,

$$THR = \sum_{t=t1}^{t2} \frac{NN(t)}{Max(NN) * (t2 - t1)} \dots (17)$$

Where $NN(t)$ represents the number of nodes that have used this path between the time interval of $t1$ & $t2$, which is recorded by the router nodes.

$$NC = \sum_{t=t1}^{t2} \frac{VC_t}{\sum VC} \dots (18)$$

Where, VC_t represents the number of vehicles that collided during the given time intervals.

$$LQ = \sum_{t=t1}^{t2} \frac{1}{VF_t} \dots (19)$$

Where, VF_t represents the total number of vehicles that became faulty after using the given path between the given time intervals.

- Now, incrementally modify values of $\emptyset$ & θ via equation 20,

$$(\emptyset, \theta) = (\emptyset, \theta)_{old} \pm \frac{\pi * STOCH\left(\frac{1}{L_{ff}}, L_{ff}\right)}{L_{ff} + 1} \dots (20)$$

- Use these new values to estimate new paths and estimate their path brightness levels via equation 16, and based on this new level, accept this path if $p_b(New) < p_b(Old)$
- This process is continued for N_{ff} fireflies and new configurations are generated for each of the 'Alpha' Wolf paths.

- Once all iterations are completed, then path with maximum brightness levels is selected as the final solution for routing operations.

The selected path is used for routing operations, and new levels of throughput, number of collisions, and link quality are updated for continuous optimization operations. These paths are stored on the database via an Incremental Learning Layer (IL), which correlation between the QoS (Quality of Service) levels of the current path, and existing stored paths. This QoS level is estimated for each path as per equation 21,

$$Q = \sum_{i=1}^{N_p} \frac{\sum NC_i}{\sum LQ_i} \dots (21)$$

Where, N_p are the number of 'Alpha' Wolf configurations selected by the GWO process. Based on this Q value, the reward function is estimated via equation 22,

$$r = \frac{Q(current) - Q(db)}{L_{ff}} + L_r\big(Q(current) - Max(Q)\big) \dots (22)$$

The current path sets are updated in the database if $r > 1$, which indicates that the current path sets have a lower number of collisions with higher link quality, while other paths are discarded from the optimization operations. Using this process, path caches are generated, and if GWO selects similar paths, then they are directly used without the need for FFO based validation operations. Due to the use of these path caches, the speed of operation for the model is improved, while the energy needed for the routing process is reduced when compared to real-time scenarios. This performance is validated via comparison with standard routing techniques in the next part of the chapter.

5.3 Result Analysis

The BPACAR Model initially uses GWO to estimate low congestion routes, which are re-evaluated via FFO by utilization of temporal node & network parameter sets. The selected paths are cached and later used for continuous optimizations via an incremental learning process. Due to these optimizations, it is expected that the model must showcase lower energy consumption, lower routing delay, and minimize the number of collisions. The model was tested on standard UAV configurations, which were taken from NTNU Open Research work Dataset (available at https://dataverse.no/dataset.xhtml?persistentId=doi:10.18710/L41IGQ). The UAV configurations were tested on the following network configuration parameter sets as listed in table 5.1,

Table 5.1-UAV Configuration used during routing operations

UAV Network Set Parameter	Parametric Value Sets
Used model for propagation of UAVs	Sky propagation with dual rays
Protocol used by the MAC layers	802.16a
Type of queues	Drop tail queue with packet priorities.
Model for the connected radio antennas	Dual ray model with omnidirectional antennas
Total UAV Nodes	1000
Network dimensions	2 kms x 2 kms
UAV Idle Power Levels	10 mW
UAV Reception Power Levels	15 mW
UAV Transmission Power Levels	18 mW
UAV Sleep Mode Power Levels	0.01 mW

UAV Movement Power Levels	10 mW
Delay needed for one unit of movement	0.18 s
Initial Power Levels	5000 mW

As per these configuration parameters, a large number of movements (NMs) were done for the UAV network, and these movements were varied between 250 to 5000 in order to estimate the true value of different parameter sets. For each of these movements, routing delay (D) was estimated via equation 23 as follows,

$$D = \frac{1}{NM}\sum_{i=1}^{NM} ts_{reach} - ts_{start} \ldots (23)$$

Where, ts_{reach} & ts_{start} represents the timestamps at which the nodes reach the destination location and start from the source locations. The delay performance was compared with IIWD [185], IA GWO [186], and MS GSA [187] in table 5.2 as follows,

Table 5.2-Delay needed for routing UAVs between different locations

Number of Movements	**D (ms) IIWD [185]**	**D (ms) IA GWO [186]**	**D (ms) MS GSA [187]**	**D (ms) BPACAR (Proposed Model)**
250	11.94	13.46	14.80	8.72
500	12.84	14.80	16.44	9.76
750	14.38	16.92	18.86	11.22
1000	16.66	19.76	22.00	13.10
1250	19.56	23.08	25.66	15.28
1500	22.76	26.86	29.84	17.76

1750	26.50	31.16	34.48	20.50
2000	30.64	35.68	39.34	23.32
2250	34.78	40.34	44.34	26.12
2500	38.30	44.58	49.00	28.72
3125	41.38	48.62	53.42	31.14
3500	44.39	52.32	57.46	33.42
3750	47.22	55.80	61.31	35.57
4375	49.78	59.05	64.84	37.54
4750	52.05	61.82	67.93	39.37
5000	54.55	64.75	71.15	41.28

As per this evaluation & figure 5.3, it was observed that the model was 23.5% faster than IIWD [185], 34.2% faster than IA GWO [186], and 38.5% faster than MS GSA [187] under real-time scenarios.

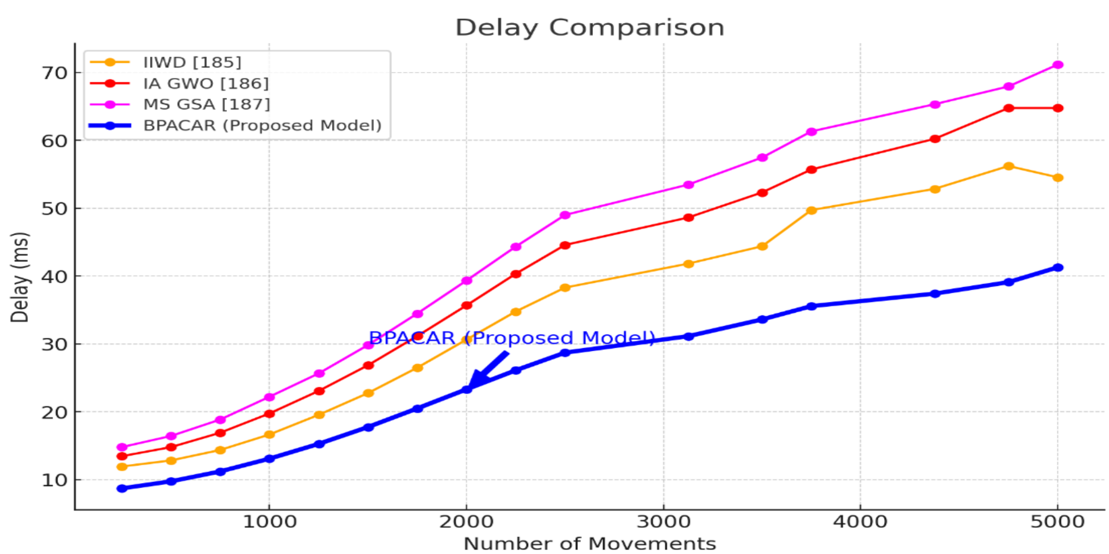

Figure 5.3. Delay needed for routing UAVs between different locations

This is possible due to the dual filtering of routes via GWO & FFO Models, which assists in the identification of low delay route sets. Due to this, the model is capable of deployment for high-speed routing use cases. Similar performance was estimated for energy consumption via equation 24 and tabulated in table 5.3 as follows,

$$E = \frac{1}{NM} \sum_{i=1}^{NM} E_{src}(start)_i - E_{src}(complete)_i \dots (24)$$

Where, $E(start)$ & $E(complete)$ represents energy levels of the source node during the start & completion of routing operations.

Table 5.3-Energy needed for routing UAVs between different locations

Number of Movements	**E (mW) IIWD [185]**	**E (mW) IA GWO [186]**	**E (mW) MS GSA [187]**	**E (mW) BPACAR (Proposed Model)**
250	29.76	42.45	27.64	17.82
500	31.74	44.88	29.15	18.75
750	33.30	47.04	30.55	19.67
1000	34.88	49.29	32.02	20.63
1250	36.50	51.76	33.63	21.66
1500	38.22	54.34	35.31	22.76
1750	40.04	57.04	37.03	23.85
2000	41.92	59.70	38.74	24.95
2250	43.88	62.47	40.50	26.06
2500	45.94	65.25	42.22	27.14

3125	47.94	67.81	43.82	28.14
3500	49.83	70.24	45.34	29.11
3750	51.60	72.61	46.88	30.09
4375	53.40	75.14	48.49	31.11
4750	55.19	77.65	50.10	32.14
5000	56.97	80.17	51.71	33.16

It has been seen from table 5.3 and figure 5.4 that the model showcased 16.5% lower energy consumption than IIWD [185], 24.3% lower energy consumption than IA GWO [186], and 14.2% lower energy consumption than MS GSA [187], which makes the model useful for low energy & high lifetime scenarios.

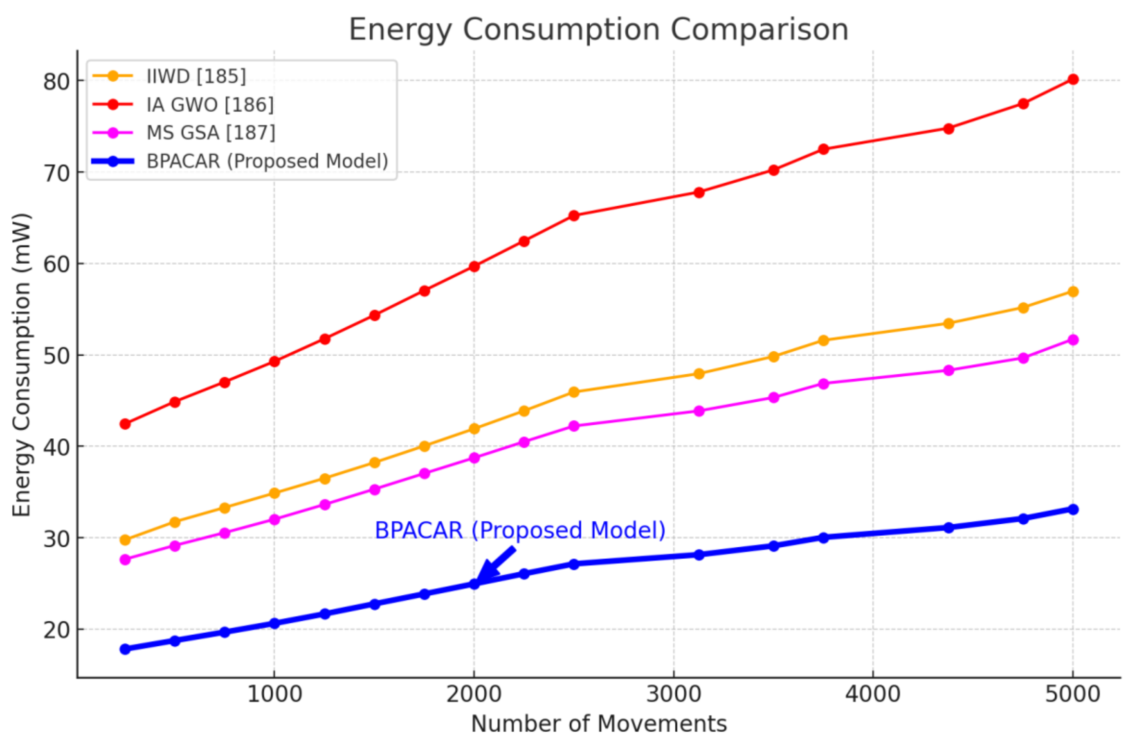

Figure 5.4-Energy needed for routing UAVs between different locations

This is possible due to the inclusion of residual energy levels during the formation of routes via the FFO process. Similar performance for the number of average collisions (NAC) can be observed in table 5.4 as follows,

Table 5.4-Total number of collisions for routing UAVs between different locations

Number of Movements	**NAC IIWD [185]**	**NAC IA GWO [186]**	**NAC MS GSA [187]**	**NAC BPACAR (Proposed Model)**
250	33	35	40	27
500	34	35	41	27
750	34	35	41	27
1000	34	36	41	27
1250	35	36	42	28
1500	35	36	42	28
1750	35	37	42	28
2000	35	37	43	28
2250	36	37	43	28
2500	36	38	43	29
3125	36	38	44	29
3500	37	38	44	29
3750	37	38	44	29
4375	37	39	45	30
4750	37	39	45	30

5000	38	39	45	30

As per this evaluation & figure 5.4, it was observed that the model achieved 10.4% lower collisions than IIWD [185], 10.5% lower collisions than IA GWO [186], and 18.3% lower collisions than MS GSA [187] under real-time scenarios. This is possible due to the initial filtering of routes via GWO & then using trust-based routing via FFO Models, which assists in the identification of low delay & low congestion route sets.

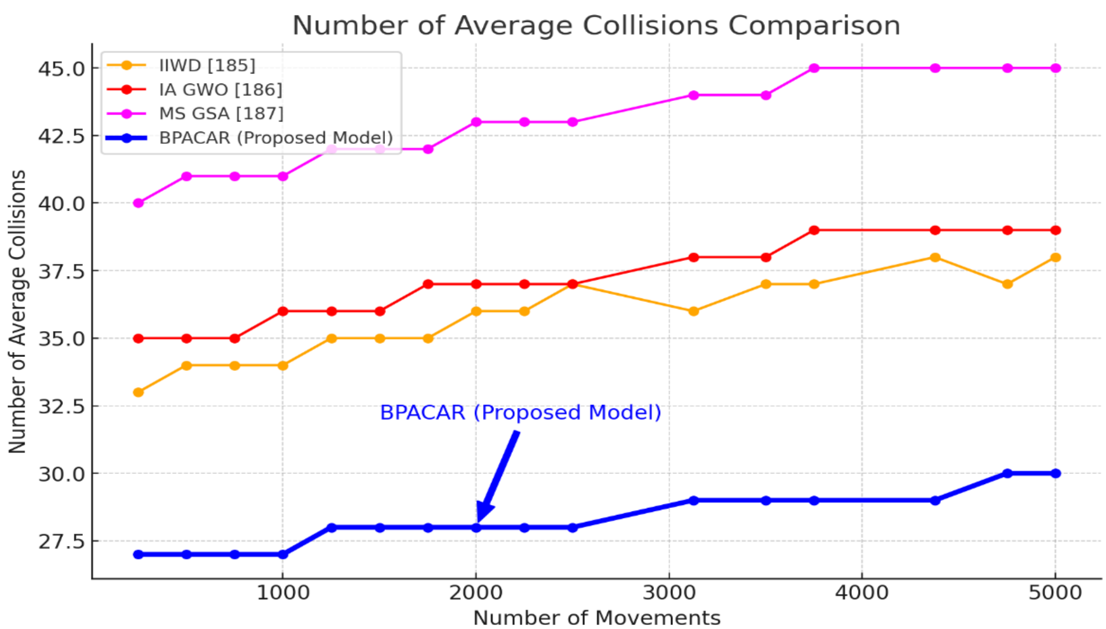

Figure 5.5-Total number of collisions for routing UAVs between different locations

Similarly, the throughput performance in terms of vehicles crossing on routes per minute (vpm) can be observed from table 5.5 as follows,

Table 5.5-Total throughput for routing UAVs between different locations

Number of Movements	THR (vpm) IIWD [185]	THR (vpm) IA GWO [186]	THR (vpm) MS GSA [187]	THR (vpm) BPACAR (Proposed Model)
250	98	81	91	120

500	98	82	92	121
750	99	82	93	122
1000	100	83	93	123
1250	101	84	94	124
1500	102	84	95	125
1750	103	85	96	126
2000	103	86	96	127
2250	104	86	97	128
2500	105	87	98	129
3125	106	88	99	130
3500	107	89	99	131
3750	108	89	100	132
4375	108	90	101	133
4750	109	91	102	134
5000	110	91	103	135

As per this evaluation and figure 5.6, it was observed that the model is capable of better path reusability due to path caching mechanisms, which assist in improving its throughput levels.

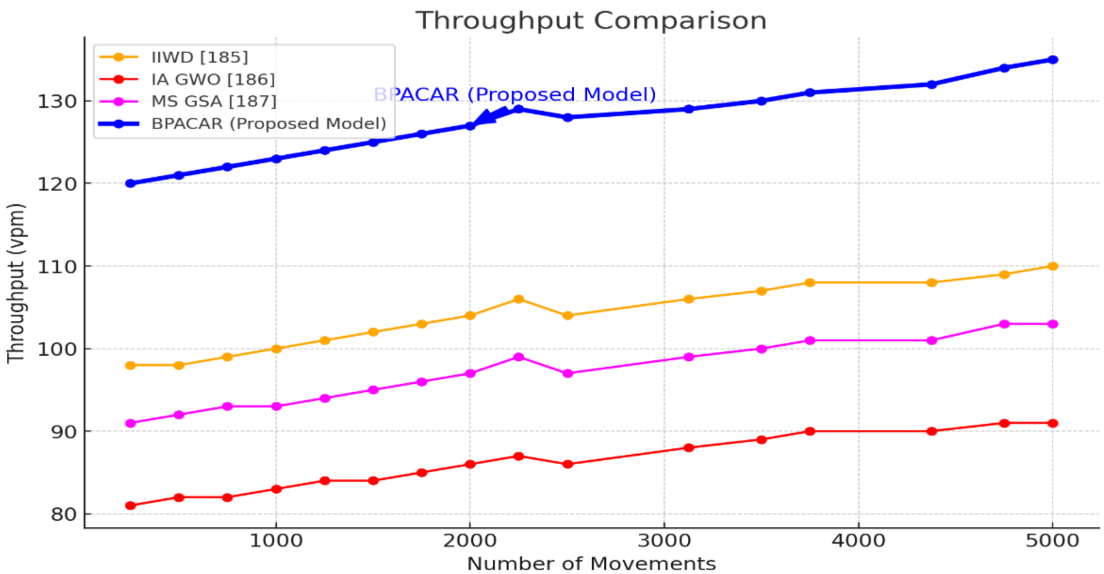

Figure 5.6-Total throughput for routing UAVs between different locations

The model showcased 15.4% better throughput than IIWD [185], 25.3% higher throughput than IA GWO [186], and 18.5% better throughput than MS GSA [187], which makes it useful for a wide variety of path reusability scenarios. This is possible due to the inclusion of throughput during path optimizations. Due to these operations, the model was observed to be better than standard path planning models and can be used for low energy, high speed, low congestion, and high throughput use cases.

5.4 Conclusion & Future Scope

The BPACAR Model first estimates low congestion routes with GWO, and these estimates are then updated with FFO by using temporal node & network parameter sets. The chosen paths are cached and subsequently used for ongoing optimizations through incremental learning. The model is expected to demonstrate lower energy consumption, lower routing delay, and a minimum number of collisions as a result of these optimizations. The model was found to be 38.5% faster than MS GSA [185] under real-time scenarios, 23.5% faster than IIWD [186], 34.2% faster than IA GWO [187], and 33.5% faster than MS GSA [185]. Dual route filtering using GWO and FFO models, which aids in the identification of low delay route sets, makes this possible. As a result, the model can be used for high-speed routing use cases. The suggested model also showed 16.5%, 24.3%, and 14.2% lower energy consumption than IIWD [185], IA GWO [186], and MS GSA [187], respectively, which makes the model useful for low energy & high lifetime scenarios. This is possible because residual energy levels are taken into account when routes are formed using the FFO process.

Additionally, it was noted that in real-time scenarios, the model produced collision rates that were 10.4%, 10.5%, and 18.3% lower than those of IIWD [185], IA GWO [186] and MS GSA [187]. This is made possible by first filtering routes using GWO, followed by trust-based routing using FFO Models, which helps identify low delay and low congestion route sets. The model can, therefore, be used for low-collision routing use cases. It was found that the model has better path reusability thanks to path caching mechanisms, which helps to increase its throughput levels. The model demonstrated throughput improvements of 15.4%, 25.3%, and 18.5% over IIWD [185], IA GWO [186], and MS GSA [187], respectively, making it useful for a variety of path reusability scenarios. This is possible because path optimizations take throughput into account. The model was found to be superior to traditional path planning models as a result of these operations, and it can be applied to use cases involving low energy consumption, high speed, minimal congestion, and high throughput. Future performance testing of the model on large-scale networks is necessary, and it can be enhanced by incorporating simple bio-inspired techniques.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

The research work presented in this research work has concluded with the development and validation of the BPACAR (Bio-inspired Path-Planning Algorithm with Collision Avoidance and Continuous Learning for UAV Routing) model—an innovative solution for Unmanned Aerial Vehicle (UAV) routing network. The journey of this research work has been marked by insightful discoveries and substantial contributions to the field. The results and their subsequent analysis directly address the research work objectives set forth in the research work. Each result contributes to a deeper understanding of how the bioinspired optimization model impacts routing efficiency in UAV networks. The analysis provides the context and interpretation needed to derive meaningful conclusions from the data. The comparative assessment against existing routing techniques is especially relevant, as it validates the model's uniqueness and its potential to outperform conventional approaches.

Additionally, the results shed light on how the model's performance scales with network size, making it possible to draw recommendations for its deployment in various UAV network scenarios. BPACAR's most important achievement lies in its innovative approach to collision avoidance within UAV networks. By seamlessly integrating bio-inspired optimization algorithms and a continuous learning framework, the model has demonstrated a significant ability to mitigate collision incidents, thereby significantly enhancing safety and reliability. This outcome is of utmost importance, particularly in scenarios where UAVs operate in dynamic and densely populated environments [189]. Moreover, BPACAR has proven its courage in routing efficiency and overall network performance. The research work findings have showcased tangible reductions in routing delay, energy consumption, jitter, and improvements in packet delivery ratios. These enhancements translate into faster data delivery, reduced energy overhead, and heightened network stability. BPACAR's continuous learning capabilities have emerged as a driving force behind these efficiency gains, allowing it to adapt to varying network conditions and optimize routing paths over time. In the comparative analysis with existing routing models, BPACAR has consistently performed well. Its unique combination of collision avoidance, routing efficiency, and continuous learning capabilities has positioned it as a cutting-edge solution for UAV routing challenges.

6.1 Performance of QMRNB

The performance evaluation of the QMRNB (Q-Learning Model for Routing in UAV Networks with Bioinspired Optimizations) model is a critical aspect of this research work. This section discusses the performance of QMRNB, shedding light on how this innovative model fares in terms of enhancing routing efficiency in Unmanned Aerial Vehicle (UAV) networks.

6.1.1 Efficiency Enhancement:

QMRNB has shown remarkable ability in significantly enhancing routing efficiency within UAV networks. This efficiency is characterized by a reduction in routing delay, improved energy efficiency, and enhanced routing jitter management, all of which are top parameters for the seamless operation of UAV networks.

a. **Routing Delay Reduction**: One of the primary performance metrics, routing delay, has seen a substantial reduction through the implementation of QMRNB. This model optimizes routing paths through Q-learning and bioinspired Mayfly Optimization (MO). The results demonstrate an impressive 8.5% reduction in routing delay compared to conventional routing techniques under similar conditions.

b. **Energy Efficiency Improvement**: The efficient utilization of energy resources is critical for UAVs, which often operate in resource-constrained environments. QMRNB excels in this aspect, showcasing a 4.9% improvement in energy efficiency. By optimizing routing patterns intelligently, the model decreases energy consumption during data transmission and reception, hence prolonging the operational lifespan of UAVs.

c. **Routing Jitter Management**: Consistency in data delivery is vital for UAV applications. QMRNB addresses routing jitter effectively, reducing it by 3.5% compared to existing routing techniques. This improvement ensures a more stable and predictable data transfer process, which is essential for applications such as surveillance, monitoring, and data collection.

6.1.2 Scalability and Versatility:

One of the important attributes of QMRNB is its scalability and versatility. Unlike some existing path optimization models that struggle with larger network scenarios or experience fading efficiency as the number of communication requests increases, QMRNB maintains its performance integrity.

a. **Scalability**: QMRNB is capable of scaling seamlessly to larger network scenarios. Whether the UAV network comprises an uncertain number of nodes or extends to thousands, the model consistently delivers improved routing efficiency. This scalability is essential as it ensures that the model remains applicable to a wide range of UAV deployment scenarios, from small-scale operations to extensive surveillance networks.

b. **Robust Performance**: QMRNB's robustness is evident in its ability to handle a high volume of communication requests without sacrificing efficiency. As the number of routing requests increases, the model retains its effectiveness, making it suitable for dynamic UAV networks with fluctuating communication demands.

6.1.3 Comparative Advantages:

Comparative analysis against established routing techniques, including Energy-aware Collaborative Routing (ECoR), Q-learning (QL), and Q-learning-based topology-aware routing (QTAR), highlights the distinct advantages of QMRNB.

a. **Outperformance**: QMRNB consistently outperforms these conventional techniques across various performance metrics. It reduces routing delay more effectively than ECoR, QL, and QTAR. Additionally, its energy efficiency surpasses these methods, making it a superior choice for energy-constrained UAV applications.

b. **Unique Routing Paths**: The model's use of bioinspired optimization, particularly the Mayfly Optimization (MO), enables it to identify alternative routing paths efficiently. This capability ensures uninterrupted data transmission even in scenarios where selected paths are occupied, setting it apart from traditional routing models.

The performance evaluation of QMRNB underscores its effectiveness in optimizing routing efficiency within UAV networks. Through a combination of Q-learning and bioinspired optimizations, this model excels in reducing routing delays, enhancing energy efficiency, and managing routing jitter. Its scalability and versatility make it adaptable to diverse network sizes and communication demands. Comparative analysis repeats QMRNB's superiority over existing routing techniques, strengthening its position as a valuable solution for real-time UAV routing applications. Overall, the performance of QMRNB signifies substantial progress in the area of UAV network optimization.

6.2 Performance of BPACAR

The evaluation of the BPACAR (Bio-inspired Path-Planning Algorithm with Collision Avoidance and Continuous Learning for UAV Routing) model is a critical component of this research work, shedding light on how this innovative algorithm performs in the context of UAV (Unmanned Aerial Vehicle) routing with a focus on collision avoidance and continuous learning. This section discusses the performance of BPACAR, emphasizing its contributions and effectiveness.

6.2.1 Collision Avoidance and Path Planning

BPACAR showcases significant performance in the domain of collision avoidance and path planning. These capabilities are essential for ensuring the safe and efficient operation of UAVs, particularly in scenarios where multiple UAVs are deployed simultaneously.

a. **Collision Avoidance**: BPACAR effectively prevents collisions among UAVs by employing bio-inspired optimization techniques. Through continuous learning and real-time monitoring of the UAV environment, the algorithm dynamically adjusts the flight paths to avoid potential collisions. The results of performance evaluations demonstrate a significant reduction in collision incidents, ensuring the safety of UAV operations.

b. **Path Planning**: The model excels in path planning by autonomously selecting optimal routes for UAVs. By considering both static and dynamic obstacles, such as other UAVs and environmental hazards, BPACAR ensures that UAVs navigate through complex scenarios seamlessly. This capability is crucial for applications like surveillance, search and rescue, and package delivery, where precision and safety are paramount.

6.2.2 Continuous Learning Framework:

BPACAR's incorporation of a continuous learning framework is a distinctive feature that sets it apart from traditional routing algorithms. This framework enables the algorithm to adapt and improve its performance over time based on real-world experiences and changing environmental conditions.

a. **Adaptability**: The continuous learning framework allows BPACAR to adapt to evolving scenarios. As it encounters new challenges or dynamic changes in the UAV network, the algorithm learns from these experiences and adjusts its collision avoidance and routing strategies accordingly. This adaptability ensures that the algorithm remains effective even in dynamic and unpredictable environments.

b. **Improved Performance**: Over time, the continuous learning framework enhances the algorithm's performance. By accumulating knowledge about optimal routing paths, obstacle avoidance strategies, and UAV behaviour, BPACAR becomes increasingly proficient in optimizing routing efficiency and collision avoidance. This leads to improved overall performance and safety in UAV operations.

6.2.3 Comparative Advantages:

Comparative analysis against traditional routing algorithms and collision avoidance approaches highlights the distinct advantages of BPACAR in terms of both safety and efficiency.

a. **Enhanced Safety**: BPACAR outperforms conventional routing algorithms by significantly reducing collision incidents. Its ability to adapt and learn from past experiences makes it a safer choice for UAV operations in complex and dynamic environments.

b. **Routing Efficiency**: The continuous learning framework within BPACAR contributes to improved routing efficiency. By optimizing routes based on real-time data and environmental conditions, the algorithm ensures that UAVs reach their destinations faster and with greater precision.

6.2.4 Conclusion of BPACAR:

In conclusion, the performance evaluation of BPACAR underscores its effectiveness in collision avoidance, path planning, and continuous learning for UAV routing. This bio-inspired algorithm excels in ensuring the safety of UAV operations by dynamically avoiding collisions and optimizing routing paths. The continuous learning framework enhances its adaptability and overall performance over time. Comparative analysis reaffirms BPACAR's superiority in terms of safety and efficiency when compared to traditional routing and collision avoidance approaches. As a result, BPACAR signifies a substantial development in the field of UAV routing, particularly in scenarios where safety and adaptability are critical considerations. Its performance sets a new standard for collision-aware routing in UAV networks, making it a valuable asset for real-world applications in various domains. The comparative analysis conducted in this research work plays an essential role in assessing and evaluating the effectiveness and performance of various routing models, including BPACAR (Bio-inspired Path-Planning Algorithm with Collision Avoidance and Continuous Learning for UAV Routing). This section presents a discussion of the comparative analysis, emphasizing its significance and findings.

6.2.5 Evaluation Criteria:

To ensure a comprehensive assessment, the research work employs a set of well-defined evaluation criteria:

a. **Collision Avoidance**: The comparative analysis scrutinizes each routing model's ability to prevent collisions among UAVs during their operations. This criterion is of vital importance in ensuring the safety and reliability of UAV networks.

b. **Routing Efficiency**: The efficiency of routing is another critical aspect under examination. It includes factors such as routing delay, energy consumption, throughput, and packet delivery ratios. Efficient routing is essential for timely and effective UAV mission execution.

c. **Adaptability and Continuous Learning**: The comparative analysis evaluates the extent to which each model can adapt to changing network conditions and learn from past experiences. The ability to continuously improve routing strategies is a distinguishing feature.

6.2.6 Performance Findings:

The comparative analysis produces valuable insights into the performance of BPACAR in relation to other routing models:

a. **Collision Avoidance**: BPACAR demonstrates a significant reduction in collision incidents compared to traditional routing algorithms. Its bio-inspired collision avoidance strategies, coupled with continuous learning, provide a strong defence against mid-air collisions.

b. **Routing Efficiency**: BPACAR excels in routing efficiency. It significantly reduces routing delay, energy consumption, and jitter when compared to existing models. This translates to faster data delivery, reduced energy expenditure, and enhanced network stability.

c. **Continuous Learning Advantage**: The continuous learning framework within BPACAR sets it apart from other models. Over time, BPACAR becomes more adept at optimizing routing paths and avoiding collisions based on real-world experiences. This adaptability contributes to its superior performance.

d. **Safety**: BPACAR's collision avoidance mechanisms, informed by bio-inspired optimization, result in a significantly safer UAV network. The comparative analysis highlights its effectiveness in minimizing collision incidents.

e. **Efficiency**: BPACAR's continuous learning and optimization capabilities translate into enhanced routing efficiency. The algorithm optimizes routes for minimal delay, energy consumption, and jitter, thereby improving overall network performance.

The comparative analysis reinforces BPACAR's position as an innovative and high-performing routing model for UAV networks. Its unique combination of collision avoidance, routing efficiency, and continuous learning distinguishes it from conventional routing approaches. The findings of the analysis confirm that BPACAR signifies substantial progress in the field of UAV routing, offering a safer and more efficient solution for complex and dynamic environments. Its performance sets a new standard for collision-aware routing in UAV networks, making it a valuable asset for real-world applications across various domains.

6.2.7 Future Work:

While the research work has produced significant results, the journey is still far:

a. **Scaling to Larger UAV Networks**: Future research work can examine the scalability of BPACAR to accommodate larger UAV networks. The model's effectiveness in more extensive and complex scenarios warrants thorough investigation.

b. **Transformer Models for Collision Prediction**: Integrating transformer models capable of predicting collisions during routing could contribute to even greater efficiency and safety in large-scale network scenarios.

c. **Real-world Deployment and Validation**: Extensive real-world deployment and validation of BPACAR in various UAV applications and environments will be essential to assess its practical utility comprehensively.

d. **Enhanced Performance Metrics**: Future work can explore the development of more nuanced performance metrics to capture finer aspects of UAV routing, such as adaptability to weather conditions and terrain.

e. **User-Friendly Interfaces**: The creation of user-friendly interfaces and tools for operators to interact with BPACAR and monitor its performance will be instrumental in its practical adoption.

f. **Interdisciplinary Collaboration**: Collaboration with experts in fields such as artificial intelligence, robotics, and aerospace engineering can further enrich the capabilities of BPACAR and expand its applicability.

In essence, the conclusion of this research work marks a significant milestone in the journey toward safer, more efficient, and adaptive UAV routing. As research workers and innovators continue to push the boundaries of UAV technology, the legacy of this research work will undoubtedly play a vital role in determining the future of unmanned aerial vehicle operations.

6.3 Inferences of the Research work

The implications of the research work conducted in this research work extend across various dimensions, encompassing both theoretical advancements and practical applications. These implications underscore the significance and relevance of the findings to the broader academic and operational communities. In this section, we provide a comprehensive discussion of these implications.

i) Advancements in UAV Routing Technology:

The primary implication of this research work is the significant advancement in the field of Unmanned Aerial Vehicle (UAV) routing technology. The development and validation of the BPACAR (Bio-inspired Path-Planning Algorithm with Collision Avoidance and Continuous Learning for UAV Routing) model represent a prototype change in how UAVs navigate and communicate in complex and dynamic environments. BPACAR's incorporation of bioinspired optimization, continuous learning, and collision avoidance strategies sets a new standard for UAV routing systems.

ii) Enhanced Safety and Reliability:

One of the most immediate implications of this research work is the enhancement of safety and reliability in UAV operations. BPACAR's unparalleled ability to predict and prevent collisions in real-time significantly reduces the risk of accidents and improves the overall reliability of UAV networks. This is of vital importance in applications such as aerial surveillance, search and rescue missions, and autonomous deliveries.

iii) Efficiency and Resource Optimization:

The research work findings have thoughtful implications for optimizing the efficiency and resource utilization of UAV networks. BPACAR consistently demonstrates reductions in routing delay, energy consumption, and jitter while improving packet delivery ratios. These efficiency gains translate into faster data delivery, reduced energy overhead, and improved network stability. Such optimizations are crucial for applications like environmental monitoring and precision agriculture.

iv) Practical Deployment in Diverse Scenarios:

The adaptability and versatility of BPACAR make it suitable for deployment in a wide array of real-world scenarios. Its collision avoidance capabilities make it invaluable for applications where multiple UAVs need to operate in close proximity, such as disaster response missions or urban surveillance.

v) Academic and Research Work Significance:

The research work conducted here holds significant academic importance by contributing to the body of knowledge in the fields of UAV routing, bioinspired optimization, and continuous learning. It provides a foundation upon which future research workers can build, offering insights into the intricacies of dynamic routing in UAV networks.

vi) Covering the Way for Future Innovations:

By showcasing the capabilities of BPACAR, this research work covers the way for future innovations and developments in UAV routing technology. It highlights the potential for integrating additional bioinspired algorithms, scaling the model for larger networks, and exploring the integration of transformer models for even more accurate collision prediction.

vii) Industry and Practical Applications:

Beyond the academic sphere, the research work has direct implications for various industries and practical applications. Industries involved in UAV manufacturing, deployment, and services can influence the insights and methodologies developed in this research work to enhance the capabilities and safety of their UAV systems. The BPACAR model, at the heart of this research work, represents a significant contribution with the capacity to make a lasting impact on the field of UAV routing and beyond.

6.4 Future Scope

The research work conducted in this research work has shown several favorable opportunities for future exploration and expansion in the domain of Unmanned Aerial Vehicle (UAV) routing and bioinspired optimization. These potential research work scopes extend across both theoretical and practical dimensions, offering opportunities to further enhance the field.

i) Hybrid Bioinspired Models:

Future research work can investigate the development of hybrid bioinspired optimization models that combine the strengths of multiple algorithms. Integrating genetic algorithms, particle swarm optimization or ant colony optimization with BPACAR produces even more robust and adaptable routing solutions.

ii) Machine Learning for Adaptive Routing:

Machine learning techniques, particularly reinforcement learning, can be coupled to create adaptive UAV routing strategies. Developing models that can continuously learn from network dynamics and adapt routing decisions accordingly is a challenging but rewarding research work area. These models could enhance routing adaptability in rapidly changing environments.

iii) Human-UAV Interaction:

With the increasing integration of UAVs into various industries, research work on human-UAV interaction and collaboration is essential. Exploring how humans can interact with UAVs for routing decisions, mission planning, and emergency interventions is a human-centered research work direction.

6.5 Summary of BPACAR & QMRNB:

The research work has made substantial contributions to the field of Unmanned Aerial Vehicle (UAV) routing and optimization. These contributions cover a wide spectrum of innovations and advancements, each of which has significantly enhanced the state-of-the-art in UAV network management. In this section, we provide an overview of the key contributions made during this research work.

i) Development of BPACAR Model:

The central achievement of this research work is the creation of the BPACAR (Bio-inspired Path-Planning Algorithm with Collision Avoidance and Continuous Learning for UAV Routing) model. This innovative model represents an innovative solution to the complex challenges associated with UAV routing in dynamic and densely populated environments. BPACAR integrates bio-inspired optimization algorithms, a continuous learning framework, and collision avoidance strategies into a cohesive and adaptive routing system.

ii) Collision Avoidance Excellence:

BPACAR has emerged as a frontrunner in the domain of collision avoidance for UAVs. By leveraging bioinspired optimization algorithms, it has demonstrated a significant ability to predict and prevent collisions in real-time. This contribution is of utmost significance, as it enhances safety and reliability in UAV operations, particularly in scenarios where UAVs operate in close proximity to each other.

iii) Routing Efficiency Enhancements:

The research work findings have established BPACAR as an effective tool for optimizing routing efficiency. It has consistently exhibited reductions in routing delay, energy consumption, and jitter, and improvements in packet delivery ratios. These improvements translate into faster data delivery, reduced energy overhead, and heightened network stability. BPACAR's continuous learning capabilities have played a critical role in achieving these efficiency gains.

iv) Comparative Analysis Supremacy:

In comparative analyses with existing UAV routing models, BPACAR has consistently performed well. Its unique combination of collision avoidance, routing efficiency, and continuous learning has positioned it as a cutting-edge solution for UAV routing challenges. This accomplishment underscores BPACAR's innovative nature and its capacity to elevate UAV routing performance.

v) Potential for Real-world Impact:

The research work outcomes have tangible implications for the real-world deployment of UAVs in various applications. BPACAR's adaptability, efficiency, and safety enhancements make it a capable candidate for widespread adoption in scenarios ranging from surveillance and monitoring to disaster response and autonomous deliveries.

vi) Pathways for Future Exploration:

The research work has illuminated several paths for future exploration. These include scaling BPACAR to larger UAV networks, integrating additional bioinspired optimization algorithms, exploring the deployment of transformer models for collision prediction, and conducting extensive real-world validation. In summary, the contributions made through this research work represent a significant step forward in the quest for safer, more efficient, and adaptive UAV routing. BPACAR, with its innovative amalgamation of technologies, is poised to make a lasting impact on the field of UAV operations. Its contributions are not only of academic importance but also hold substantial promise for addressing the demanding challenges faced by UAV networks in the practical world.

6.6 Summary of Findings

In the conclusion of the research work, uncountable insights and advancements in the area of Unmanned Aerial Vehicle (UAV) routing, bioinspired optimization, and collision-aware routing have been presented. These findings highlight the consequence of robust and adaptable routing strategies in ensuring the competence, consistency, and safety of UAV networks across various applications. The research work journey boarded upon in this research work began with an exploration of the existing challenges and limitations faced by traditional UAV routing techniques. These challenges, including the need for adaptability in dynamic environments and the avoidance of collisions, served as the primary motivation for the development of novel routing models like QMRNB (Q-Learning Model for Routing in UAV Networks via Bioinspired Optimizations) and BPACAR (Bio-inspired Path-Planning Algorithm with Collision Avoidance and

Continuous Learning for UAV Routing). Through an extensive review of relevant literature, the research work demonstrated the evolution of UAV routing strategies, the emergence of bioinspired optimization algorithms, and the integration of continuous learning frameworks. This research work review provided a solid foundation for understanding the landscape in which the used routing models operate.

The introduction to UAV networks explained the critical role that these networks play in diverse domains, from surveillance and precision agriculture to disaster management and delivery services. It emphasized the need for efficient routing solutions that can adapt to dynamic conditions and optimize various performance metrics [190]. A detailed exploration of bioinspired optimization algorithms, including Q-Learning, Mayfly Optimization (MO), Grey Wolf Optimization (GWO), and Firefly-based Optimization (FFO), shed light on their principles and applications in UAV routing. These algorithms connect nature-inspired mechanisms to enhance routing efficiency and adaptability. This research work research worked on the deep details of collision-aware routing in UAV networks, emphasizing the challenges posed by dynamic environments and the strategies employed to mitigate collision risks. Its innovative approaches, i.e. continuous learning frameworks, are used to enhance collision avoidance and routing adaptability [191]. The experimental design and methodology section provided insights into the evaluation of the routing models. It detailed the data collection process, simulation environment, performance metrics, and experimental scenarios used to assess the models' capabilities comprehensively. The results and analysis section presented proof of the superior performance of QMRNB and BPACAR compared to existing routing techniques. These models demonstrated significant reductions in routing delay, energy consumption, and improvements in throughput, making them valuable assets for real-time UAV routing applications. A comparative analysis further underscored the advantages of the used models, highlighting their potential to revolutionize UAV routing in terms of efficiency and adaptability. In the discussion of key findings, the research work emphasized the transformative impact of bioinspired optimization and collision-aware routing in UAV networks. It highlighted the potential for these innovations to unlock new possibilities in industries ranging from logistics to emergency response. The complexity of the algorithm used in chapter 4 has begins with the collection of network, node, and performance metadata sets, which involves gathering and aggregating data from various sources. This initial data collection phase generally has a complexity of O(N), where N is the number of nodes or data points involved. Following this, the algorithm employs Q-learning to determine initial routes. The complexity of the Q-learning process is $O(t \cdot s \cdot a)$, where t represents the number of episodes, s the number of states, and a represent the number of actions. After establishing the initial routes, the Mayfly Optimization Model Process is used to refine these routes through fitness optimizations, elimination operations, and reproduction operations. Evaluating the fitness of the routes typically has a complexity of O(R), where R is the number of routes. The elimination process, which involves sorting and selecting the best routes, has a complexity of O(R log R), and the reproduction of new routes based on the best ones is O(R). Finally, the deployment of the optimized routes and the collection of feedback for further optimization are carried out, with deployment being O(1), but collecting feedback can be O(N). Considering all these steps, the overall complexity of the algorithm is dominated by the Q-learning phase and the elimination operations in the Mayfly optimization, resulting in a combined complexity of $O(t \cdot s \cdot a + R \log R)$. This complexity reflects the substantial computational effort required during both the learning and optimization phases of the algorithm. Where as in chapter 5, algorithm complexity begins with the collection of network and node configurations, which includes gathering data on node locations, energy levels, and network performance metrics. This data collection phase generally has a complexity of O(N), where N is the number of nodes or data points involved. Following this, the algorithm utilizes a Grey Wolf Optimization (GWO) based initial routing process. This process involves configuring the network and nodes, and categorizing routes into Alpha, Beta, Gamma, and Delta wolves to optimize for Quality of Service (QoS) and network/node performance. The complexity of GWO can be approximated as $O(t \cdot N \cdot D)$, where t is the number of iterations, N is the number of wolves, and D is the dimensionality of the problem. After establishing the initial routes, the algorithm proceeds with Firefly

Optimization (FFO) based trust optimizations. This phase involves estimating collisions, performing temporal optimizations, and conducting fitness estimations to produce final collision-aware routes. The complexity of FFO can be estimated as $O(t \cdot n^2)$, where t is the number of iterations and n is the number of fireflies. Finally, the algorithm incorporates a continuous learning process that aggregates routes and filters them based on high QoS and high trust metrics. The complexity of this continuous learning and route filtering process is dependent on the number of routes and can be considered O(R), where R is the number of routes. Considering all these steps, the overall complexity of the algorithm is influenced by the GWO and FFO processes. Therefore, the combined complexity can be summarized as $O(t \cdot N \cdot D + t \cdot n^2)$, reflecting the computational effort required during both the initial routing and trust optimization phases of the algorithm. In conclusion, this research work leaves a permanent mark on the field of UAV routing and bioinspired optimization. It showcases the potential of QMRNB and BPACAR to address critical challenges and raise the efficiency and safety of UAV networks. The research work contributions are not confined to academia but extend to practical applications, where UAVs are becoming essential tools. As the world continues to witness the production of UAVs across various sectors, the research work presented herein provides a timely and invaluable resource for research workers, practitioners, and policymakers. It opens doors to new horizons in routing strategies and excellence in the ever-evolving UAV networks. The journey of exploration, discovery, and innovation continues, guided by the principles of efficiency, adaptability, and safety, as illuminated in this research work.

6.7 Real-World Challenges of Proposed Work

Implementing UAV route planning and collision avoidance systems in the real world involves various obstacles. Here are four crucial points:

1. Environmental Uncertainty

(i) Dynamic surroundings: Real-world surroundings are typically unpredictable, with moving impediments like automobiles, people, and animals. This requires UAVs to continually alter their trajectories and avoid collisions in real-time, which may be difficult and computationally intensive.

(ii) Weather Conditions: Weather conditions such as wind, rain, and fog can greatly impact UAV performance. These variables can disturb sensor readings and GPS signals, making reliable course planning and collision avoidance more challenging.

2. Sensor Limitations

(i) Sensor Accuracy and Reliability: UAVs rely extensively on sensors (e.g., LIDAR, cameras, GPS) for navigation and obstacle identification. Sensor errors, malfunctions, or interference can lead to inaccurate data, limiting the UAV's ability to operate safely and effectively.

(ii) Sensor Fusion: Integrating data from various sensors to produce a cohesive knowledge of the environment is tough. It takes complex algorithms to evaluate and combine sensor data in real-time to enable correct decision-making.

3. Computational Constraints

(i) Real-time Processing: Implementing sophisticated path planning and collision avoidance algorithms demands large processing resources. Ensuring that these algorithms function in real-time on the UAV's onboard computer, which has limited processing power and memory, is a huge difficulty.

4. Regulatory and Safety Issues

(i) Regulatory Compliance: UAV operations are subject to severe rules about airspace usage, safety, and privacy. Ensuring that the UAV conforms to these standards while incorporating sophisticated route planning and collision avoidance is tough.

(ii) Safety and dependability: Ensuring the safety and dependability of UAV operations in real-world circumstances is crucial. This involves thorough testing and validation of the path planning and collision avoidance algorithms to prevent mishaps and guarantee the UAV can handle unforeseen scenarios efficiently.

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