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INTELLIGENT ROUTE PLANNING METHOD FOR UAV BASED ON SWARM INTELLIGENCE AND DEEP LEARNING TECHNOLOGY

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Abstract. Due to its potential applications in numerous industries, Unmanned Aerial Vehicles (UAVs) have gained considerable attention recently. UAV networks that are autonomous and decentralized have various practical uses, such as in disaster recovery, environmental monitoring, and security surveillance. Due to frequent route distractions and traffic congestion at high node speeds, the performance of routing systems in these networks drops considerably. UAVs with a mission to gather sensory data from various sources require meticulous route planning to decrease traffic congestion effectively. Due to flight time, range, and coverage area limitations, efficient route planning is crucial for maximizing the efficiency of UAV data collection. Optimal route planning and a delicate balancing act between these critical parameters are two of the biggest obstacles in sensory data gathering. This study presents a new method for dealing with these issues by developing an Intelligent Route Planning for Sensory Data Collection (IRP-SDC) system to optimize autonomous UAV route planning with congestion-aware modelling by considering time, distance, and area coverage limits. The IRP-SDC framework uses Multi-Objective Grey Wolf Optimization and Deep Q-Learning (MOGWO-DQL) for smart UAV route planning. The MOGWO algorithm, developed after observing the hunting techniques of grey wolves, can perform a worldwide search, which helps determine the most efficient paths to take after gathering information. DQL, on the other hand, has adaptive learning capabilities that can modify the UAV's flight path in response to alterations in its external environment. The suggested framework combines the two techniques to maximize the usefulness of UAVs in gathering sensory data. Extensive trials were carried out to prove the efficacy of the proposed technique. The IRP-SDC system beats previous approaches concerning time, distance, and area coverage by providing an ideal route for a UAV to acquire sensory data.

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Keywords: Autonomous UAVs, intelligent route planning, sensory data, swarm intelligence, Deep-Q-Learning, multi-objective grey wolf optimization, congestion-aware modeling

1 INTRODUCTION

Unmanned aerial vehicles (UAVs) have changed the data collection game entirely, which has resulted in widespread economic growth and new opportunities. They have far-reaching effects and many facets, revolutionizing industries and opening new horizons [1]. Tracking, mapping, transportation, and data collecting are all made more accessible by their capacity to function autonomously and cover large regions rapidly [2, 3]. As the goal is to collect sensory data from several sites, efficient route planning is crucial in optimizing UAV operations [4]. Considering aspects like journey duration, coverage area, and energy consumption, the UAV must be guided along a specified course encompassing all target areas to collect sensory data [5]. As there are many destinations, the UAV must find the most efficient path that balances these three goals (coverage area, journey duration, and power consumption) [6]. Several factors make solving the challenge of efficient route planning for UAVs carrying out sensory data collection difficult. Since the UAV must travel to numerous places quickly, determining the fastest route between them is essential for reducing data gathering lag [7]. Second, increasing the coverage area's efficiency is crucial for gathering as much helpful information as possible from each target location [8]. Many current methods for planning UAV routes need to consider many restrictions at once [9] or prioritize the optimization of a single aim. As a result, it is possible for there to be inefficient pathways, longer trip times, less thorough coverage, and more power consumption [10]. As a result, cutting-edge approaches are required [11] to effectively manage the complexity of the route planning problem considering various objectives and restrictions. Communication between UAVs is challenging to maintain because of the high dynamism of the nodes engaged in the network and the high risk of loss owing to incompatible timings, congestions, collisions, or excessive energy consumption. When drones begin communicating with one another to aid ground users, these concerns become much more apparent. Intermittent communication between the drones and the users makes the network more likely to experience delays. Constraints on communication and processing, such as security and congestion, are brought about by the widespread use of the Internet of Drones (IoD). Any emergency may include sensitive and crucial information. Drones may exchange messages with other drones through radio transmission. Congestion is caused by drones constantly sending and receiving signals and packets [12].

Effective route planning, considering trip time, coverage area, and energy consumption constraints, is crucial to optimizing the data-gathering process [12]. Sensory data gathering utilizing UAVs presents considerable problems, including striking a balance between these parameters and guaranteeing optimal route planning [4]. This study offers a new method dubbed the IRP-SDC system. Multi-objective Grey Wolf Optimization (MOGWO) [13] and Deep Q-Learning (DQL) [14, 15] are two essential technologies used by the proposed system to optimize UAV route planning under time, distance, and area coverage constraints. It uses a reward system in which the UAV is rewarded for optimal behaviour and punished for substandard or undesirable behaviour. The algorithm improves its route planning efficiency through trial and error as it learns to correlate different activities with different rewards. The MOGWO algorithm, developed partly to mimic the hunting techniques of grey wolves, is a strong global search tool that may be used to pinpoint the most efficient ways to gather data. The program effectively explores the solution space and identifies pathways that satisfy the numerous objectives of the problem by modelling the intelligent cooperation and teamwork seen in wolf packs [16]. The suggested framework uses DQL to supplement the MOGWO algorithm to improve the flexibility of UAV route planning in uncertain situations. DQL uses a reinforcement learning strategy to teach the UAV from its mistakes and create judgments suitable for its changing surroundings. Because of its ability to learn from experience, the UAV may instantly modify its route planning technique to select the most efficient routes for data collection.

The proposed approach incorporates the MOGWO algorithm with DQL to optimize route planning, allowing for more effective sensory data collection using UAVs. Extensive experiments were performed on both simulated and actual scenarios to evaluate the efficacy of the proposed approach. As shown by the experiments, the IRP-SDC system is superior to the contemporary in terms of computing efficiency, coverage effectiveness, and route optimization. The main objectives of this research:

- Creating an IRP-SDC system that enhances navigation for UAVs collecting sensory data-based on Congestion-aware modelling.
- The IRP-SDC system reveals optimal paths for UAVs that make gathering sensor data more accessible, which combines the MOGWO algorithm with DQL.
- Experiments show that the IRP-SDC system is superior to other methods in route optimization, coverage improvement, and computing efficiency, all of which are necessary for efficient sensor data gathering.

The rest of the article follows: Section 2 analyzes various studies in the UAV route planning methodologies by analyzing their contributions and research gaps. Section 3 discusses the essential components of the IPR method: Problem formulation, route planning with MOGWO-DQL, and objective functions. Section 4 presents the experimental results of the proposed method and their performance in finding optimal routes analyzed and discussed. Finally, the paper concludes with the concluding note in Section 5 with the recommendation for future enhancements in this field of research.

2 LITERATURE SURVEY

Pan et al. [17] proposed a Deep Learning trained by Genetic Algorithm (DL-GA) algorithm to combat the inefficiency of gathering data from dispersed sensors under challenging environments. According to the findings, the DL-GA method outperforms GA under some scenarios and displays a more incredible solving velocity than GA, with a low loss of optimization capacity. The average DL-GA solution time is 300–2 000 times faster than the GA solution time, demonstrating DL-GA's superiority. However, there are significant research gaps and restrictions to consider, including but not limited to energy usage, expansion, and real-time adaptability. The study does not deal with these restrictions and instead verifies the algorithm's performance in more challenging settings and more practical contexts.

Bayerlein et al. [18] proposed a multi-agent reinforcement learning (MARL) approach to collect information from widely dispersed Internet of Things (IoT) devices. The suggested network design merges global and local map depictions of the environment and uses convolutional layers to facilitate efficient cooperation, adaptation to novel surroundings, and well-informed movement decisions. The method does not require any prior familiarity with the specifics of wireless channels in highly populated areas. The proposed method showed a 99.4 % success rate in landing, an 88.0 % collection rate, and an 87.5 % success rate in both landing and collecting. The experimental outcome of the proposed method shows the efficacy and flexibility in various settings. However, depending on the state of the channel, the proposed method may not provide the best possible results.

The route planning problem for UAVs gathering sensory input has been the focus of Shi and Xu [19]. The study suggests using a Particle Swarm Optimization (PSO) technique in conjunction with route encoding and local search to get an answer. The numerical simulations examine the influence of the area dimension and D2D link on the required number of UAVs and their flight time to prove the method's viability. According to the study, streaming data network quality of service and total area coverage is guaranteed, but flying costs are optimized – the findings for a vast, 80-by-80-inch region. There is no way to complete the mission with less than 6 UAVs. The PSO procedure uses six UAVs to locate workable solutions. The longest flying time among them is for dmax = 1, at 164 epochs. The new algorithms will need to be developed, or the current technique will need to be modified to successfully design routes for UAVs across regions with complicated geometries.

Wang et al. [20] suggested an Intelligent UAV-based Data Aggregation Algorithm (IDAA) to guarantee safety and energy conservation in the data gathering method in the 5G-enabled IoT. The results show that the suggested IDAA algorithm has many benefits over the status quo, including enhanced security, more thorough data collecting, and lower energy use. At DCR = 340 120 bit/s, IDAA's sinking ratio is at its maximum; at DCR = 260 bit/s, it is at its lowest. There is a general decrease in sinking ratios across all baselines compared to IDAA. The time and effort spent gathering information is optimized due to this. However, the study does not discuss implementing or testing the IDAA method.

He et al. [21] focused on the problem of small Unmanned Aerial Vehicles (UAVs) navigating autonomously across surroundings with which they were unfamiliar. The results demonstrated the effectiveness of the simulation-trained deep neural network-based route planner suggested in this work. Constructing saliency maps to provide more thorough visual and textual explanations of the strategic activities is recommended. Illustration of a Real-World Action in Three Time Intervals and the steering velocity is negative 23.3 degrees per second at duration $t = 10$ seconds, indicating a sharp left turn. The UAV began its left turn at $t = 11\,\mathrm{s}$ after the steering output decreased from 23.3 to 10.2 deg/s. The obstruction disappeared from view at time $t = 12\,\mathrm{s}$. The next step is to make a right turn. The critical reasons for this are the CNN4 feature and the angle error to the objective. The model descriptions should be used to develop the path planner further and improve its effectiveness in practical settings.

UAV swarm routing and distributed collaboration inference request modelling were developed by Dhuheir et al. [22]. A digital approach based on deep RL is presented to test the efficacy of the suggested model and compare it to prior state-of-the-art research. The proposed model is tested through extensive simulations and compared to earlier, advanced research. In terms of reducing average latency per demand to 0.26 seconds and increasing accuracy while still maintaining limits, the findings showed that the suggested model outperformed competing models. However, improving the dependability of communication networks in UAV swarms has not been the primary focus of the study.

In the framework of 6G-based smart Internet of Things (IoT) networks, Li et al. [23] suggested a unique deep learning with a genetic algorithm for data collecting from various sensor devices. Extensive tests were performed to evaluate the proposed method, and the outcomes show that the approach can significantly enhance the coverage ratio of data collected while simultaneously lowering collecting expenses. The genetic vehicle selection strategy outperformed the rest, increasing collection efforts by 19.015 % and increasing the coverage ratio of data by 14.961 %. Compared to alternative systems, the DRL-based routing strategy significantly shortened collection paths, resulting in a 33.33 % to 60 % reduction in collection expenses. While dealing with an increasing amount of sensor devices and rising network complexity, the scalability of the proposed approach is essential but has yet to be explored.

Koushik et al. [24] investigated the optimum locations for UAVs to communicate inside a manned and unmanned (MUM) network in the sky. To examine the quality of service that may be achieved in multi-hop communication settings, researchers have developed an innovative queueing model called MHQ-PNP. Optimal linkages between UAV nodes are determined using a Deep Q-learning (DQN) model, and UAV node positions are optimized using an optimization technique. The DQN algorithm performs dramatically better than the Q-learning method, with a maximum normalized throughput of close to 0.65. Simulation results verify the throughput efficacy of the DQN-based UAV location technique.

UAV path planning in challenging and dangerous environments was addressed by a hybrid approach presented by Qu et al. [25]. It balances exploration and exploitation by simplifying the Grey Wolf Optimizer (SGWO) and tweaking the Symbiotic Organisms Search (MSOS). The resultant flight path is smoothed using a cubic B-spline curve and convergence analysis based on linear differential equations. The algorithm's efficacy in acquiring a practical and efficient route for UAVs in complicated and hazardous environments is demonstrated by simulation trial results. The proposed algorithm outperforms the competition in terms of convergence impact. In iteration 20, the HSGWO-MSOS finds the globally optimal solution. It is necessary to examine the algorithm's sensitivity to its parameters to evaluate the reliability and consistency of the proposed method.

This review of the relevant literature sheds light on the research designs, data collection procedures, and data analysis strategies used in prior investigations. Even though the studies presented significant advances in UAV collecting information and planning routes, they need to be investigated. These include energy efficiency, scalability, real-time flexibility, optimization, algorithm appropriateness for different scenarios, dependability in UAV swarms, and the endurance of proposed approaches. This study puts forth the unique IRP-SDC framework, based on congestion-aware modelling, which facilitates sensory data collecting by devising an ideal route for the UAVs using the MOGWO and DQL algorithms. This section examines the methodology used, results obtained, research gaps, and potential areas for future research into UAV route planning to propose the IRP-SDC framework [26].

3 OPERATIONAL STRUCTURE OF THE PROPOSED WORK

3.1 Problem Specification

A few limitations hamper real-world applications for UAV swarms. With their varied objectives and limited sensing and communication capabilities, UAVs often only have a local understanding of the whole network. UAVs cannot suddenly fail in a hazardous situation; instead, they have to anticipate possible risks and implement countermeasures in advance. A drone operator uses wireless communications to exchange control and information packets with the drones. Videos, audio, sensor data, processed information, and other forms of information are all often found inside data packets. Commands, such as mission inquiries and responses, different instructions, and so on, are typically included in data packets. In contrast, control information, such as a heartbeat, system status, position data, neighbourhood discovering things configuration, management of the fleet, and so on, is typically included in control packets for UAV systems and networks. Wireless networks are more prone to disruption because their available capacity fluctuates more often than wired networks. Drones' great degree of mobility also makes communication less secure. Drones' flight stability is compromised if packet communications are substantially delayed or lost due to poor communication quality. In particular, the operator must be able to maintain track of the drones' status and regulate their actions by receiving control packets on time without interruption.

Route planning for UAV and data gathering activities are some areas that the IRP-SDC architecture tries to improve by considering variables like journey time, distance, and coverage area. Suboptimal routes, longer trip times, distance to reach the destination, and ineffective coverage are typical results of the lack of optimization and consideration of numerous constraints simultaneously that characterize many conventional systems. Through efficient flight time, distance and complete coverage, and the capacity to adapt to changing environmental circumstances, the IRP-SDC framework based on congestion-aware modelling seeks to enhance UAV route planning for sensory data collecting. It can instantly adjust to new possibilities while balancing priorities like journey time, distance and coverage area. This study presents a congestion-aware routing protocol that is adaptive and effective mobility for decentralized and autonomous UAV networks.

3.2 System Model

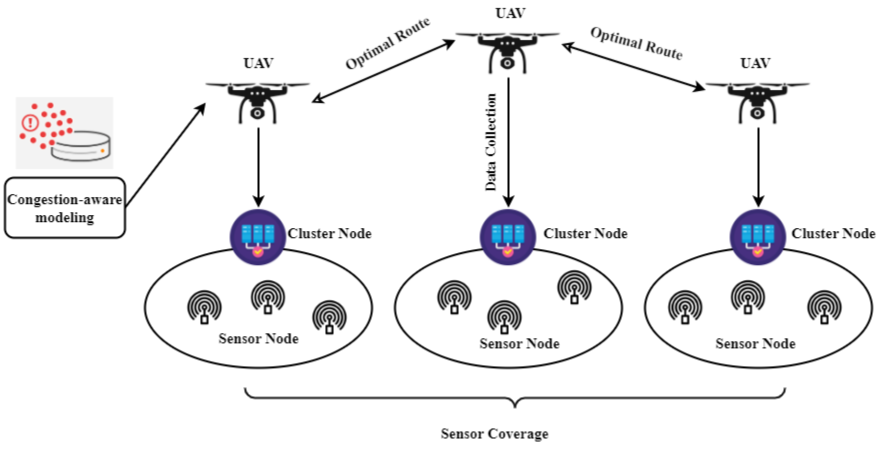

Figure 1. System model

Figure 1 shows the system model. This study assumes one or more UAVs are deployed over an Area of Interest, which consists of numerous targets, e.g., a person, the location of a vehicle, or any entity of interest. Every UAV is prepared at least with

1. sensor nodes,
2. a single radio for communication; and
3. computational units.

The edge servers are equipped with low-latency hardware for deep learning computation.

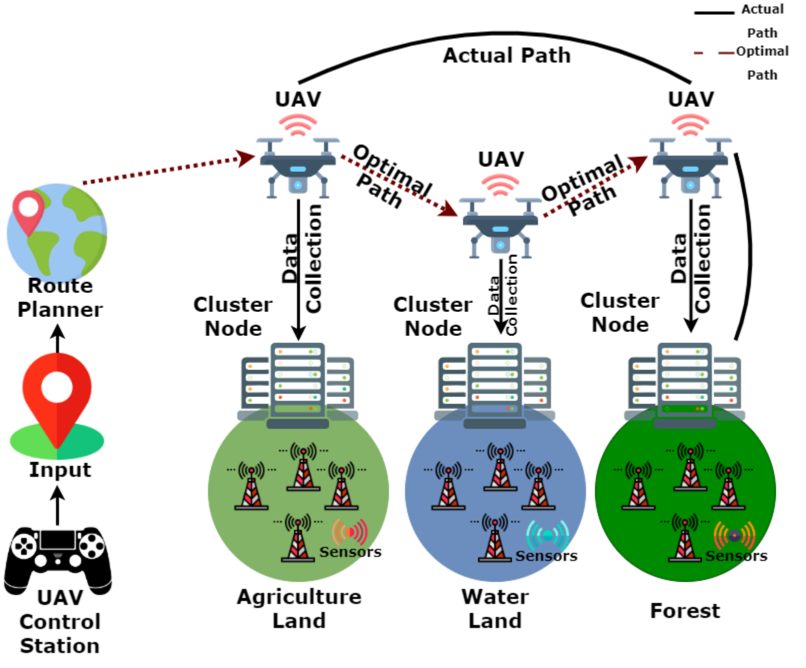

Figure 2. Architecture of the IRP-SDC system

As shown in Figure 2, the architecture of Intelligent Route Planning for UAVs to collect sensor data consists of several interrelated parts that work together to ensure effective data collection.

3.2.1 UAV Control Station

The Intelligent Route Planning architecture for UAV sensor data collection relies heavily on the UAV Control Station. It is a control centre for controlling and communicating with the UAVs flying about during the data-collecting phase. It facilitates mission preparation, live monitoring, operator-UAV interaction, and data visualization. It allows operators to remotely control UAVs, issue orders, and get real-time feedback or status updates; the interaction between UAVs within the UAV Control Station is paramount. Because of this connection, operators can more easily manage a UAV activity, improving communication and efficiency. Insights from the acquired data, well-informed judgments, and rapid responses to emergent circumstances are all facilitated by data visualization for operators. This functionality allows operators to handle and maximize UAV operations through a ground-based control station, increasing the data-collecting process's efficiency, safety, and efficacy.

3.2.2 Route Planner Using MOGWO-DQL Algorithm

As shown in Figure 2, the IRP-SDC framework's combined design of MOGWO and DQL uses MOGWO's global search and optimization capabilities to probe the solution space and pinpoint Pareto-optimal paths. Meanwhile, DQL offers advanced learning capabilities to improve the UAV's ability to make decisions in response to a dynamic environment and to maximize the payoffs associated with data collecting [27, 28]. The synergy between MOGWO and DQL allows for determining more reliable and efficient data-gathering routes. Because DQL excels at leveraging known expertise and making decisions according to learned experiences, MOGWO is well-known for its capacity to delve into the search space and uncover varied answers. By combining the two, a synergy is formed that improves data collecting by taking advantage of the strengths of each algorithm.

A. Multi-Objective GWO Algorithm (MOGWO)

The MOGWO algorithm enhances the GWO algorithm for solving optimization problems with multiple objectives. Both algorithms take cues for success from the hunting techniques of grey wolves. On the other hand, MOGWO is an expansion of GWO that allows it to deal with issues involving many competing goals. Initially proposed for use in single-objective optimization, the GWO algorithm instead models its processes after those of a pack of grey wolves, complete with a social hierarchy and hunting strategies. However, MOGWO develops this concept further to optimize several different goals to find the best possible solution; it iteratively adjusts the wolves' locations [29].

The MOGWO method is implemented to solve the problem of determining the best path for a UAV to collect sensor data from numerous sites, considering objectives like minimizing travel time and area cover.

1. Defining the problem: Identify the problem's objectives, constraints, and decision variables. The decision variables could, for instance, stand in for the GPS coordinates of waypoints or the order in which those sites should be visited.
2. Initialization: Set the starting locations of the grey wolves (the solutions) in the search space at random. Position-based starting fitness values are assigned to each grey wolf.
3. Dominance sorting: The evaluation of the grey wolves' fitness levels using the Pareto principle. Based on their fitness levels, grey wolves are sorted into non-dominated and dominated groups throughout the dominance sorting process. By classifying them, we may find the solutions on the Pareto-optimal front, the set of options for which there is no way to improve upon one aim without negatively impacting another.

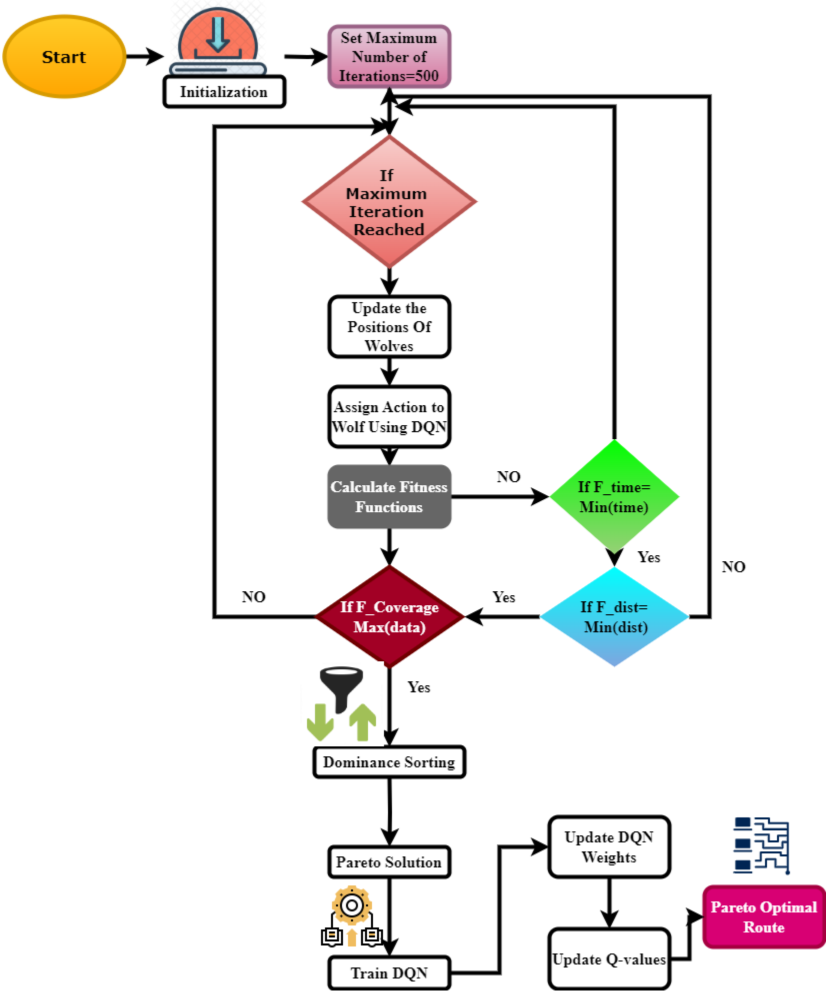

Figure 3. MOGWO-DQL in IRP-SDC system

4. Update the best solution set: Choose the grey wolves that are not under human dominance to make up your updated best-case scenario set. The Pareto-optimal solutions developed so far strike a balance between the competing goals.
5. Search iteratively: Repeat processes till a desired solution is found. Integrate exploration and exploitation into the MOGWO equations and use them to update the grey wolves' whereabouts [30]. Use search operators like crossover and mutation to encourage search space exploration. Check if the new positions are a good fit.

6. Dominance sorting and best solution set update: Compare the updated fitness values of the grey wolves based on Pareto dominance. Update the dominance levels and set the best solution accordingly.
7. Check that the solutions have converged according to some predetermined criterion, such as after a certain number of iterations or a specified degree of solution variety.
8. The Pareto-optimal paths for the UAV are represented by the best solution set generated in the end. These paths offer trade-offs between the time a UAV must fly and the amount of data it collects, allowing decision-makers to pick the optimal path depending on their priorities.

To address issues of multi-objective optimization, the MOGWO expands upon the original GWO algorithm. It considers competing priorities like flight time and data coverage aids in revealing ideal paths for UAVs. The algorithm investigates the search space, finds solutions that are not dominated, and presents a set of Pareto-optimal paths to help decision-makers make educated trade-offs. Once Pareto optimality, no additional gains can be made toward one goal without diminishing the effectiveness of another. Pareto-optimal pathways are a class of methods for UAV route planning that offer varying tradeoffs between journey time, total distance, and area covered. The algorithm attempts to find an optimal medium by contrasting potential solutions based on their fitness scores.

B. Deep Q-Learning Algorithm

The IRP-SDC framework uses Deep Q-Learning (DQL), a reinforcement learning approach, to improve UAV route planning to achieve this goal. Adaptive route planning for UAVs is made possible by DQL, which integrates Q-learning and deep neural networks, an exemplary reinforcement learning technique, as shown in Figure 4. The proposed framework has the following phases to train an agent (the UAV) to move between states in a network and choose actions that maximize sensory data collection.

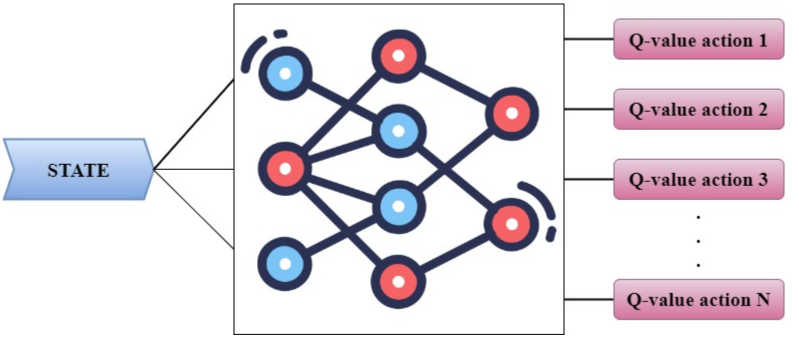

Figure 4. Structure of the deep Q-learning algorithm

Initialize $Q_0(s, a)$ for all pairs (s, a) as in Equation (1), the Q-values represent the estimated value of taking action a in state s.

$$Q_0(s, a) = 0, \tag{1}$$

constant initial value.

The Q-values can be set to zero as a starting point for UAV route planning if it is more convenient. Assuming the agent starts off knowing nothing about the world and has no expectations for gain, setting the initial Q-values to zero is a reasonable starting point. Initialize the iteration counter as in Equation (2); this keeps track of the current iteration of the algorithm.

$$k = 0, \tag{2}$$

iteration counter.

Each iteration of the Deep Q-Learning algorithm is tracked through the iteration counter, denoted by the variable k, which is also used to check the algorithm's state and determine the stopping criteria. Until the agent (UAV) learns an approach for route planning that maximizes the predicted cumulative rewards, the loop-defining Equations (3), (4), (5), (6), (7), (8) will continue to run in the background. Equation (3) represents the selection of an action, denoted by the variable a, that maximizes the Q-value in a given state s.

$$a = \arg\max_a Q(s, a), \tag{3}$$

where $Q(s, a)$ represents the Q-value associated with taking action a in state s. It denotes the agent's (UAV's) anticipated cumulative rewards in the state s if action is chosen. $\arg\max_a$ will always return the action with the highest Q-value among all possible actions a. The change from state s to state s' following intervention is represented by Equation (4).

$$s' = T(s, a). \tag{4}$$

Here s is the current state of the system or environment, a is the action performed by the agent (such as the UAV) in that state, and $T(s, a)$ is the transition function that defines the next state (s') that will be reached after the action (a) was performed in the state (s). After performing an action a, Equation (5) determines whether or not the resulting state s' is a terminal state. The current episode or assignment has concluded if s' is a terminal state.

$$\text{if } (s' \text{ is a terminal state}) : \text{target} = R(s, a, s'). \tag{5}$$

After the agent (UAV) executes action a on the current state s, the state transitions to s'. The value $R(s, a, s')$ indicates the immediate payoff for changing between state s to state s' via the action a. As the new state s' attained after taking action a is a non-terminal state, the target value utilized in the Q-learning update phase is calculated using Equation (6).

$$\text{if } (s' \text{ is a non-terminal}) : \text{target} = R(s, a, s') + \gamma * \max_{a}{}' Q(s', a'). \tag{6}$$

After the agent (UAV) executes action a on the current state s, the state transitions to s'. The value $R(s, a, s')$ denotes the immediate payoff for changing from state s to state s' via the action a. The discount factor (γ) balances immediate and future benefits fairly. The greatest Q-value for all actions a' in the new state s' is denoted by $\max(a', Q(s', a'))$. Since s' is not a terminal state, it signifies that progress can be made toward completing the work or mission through additional steps and transitions. Using $R(s, a, s')$ as an immediate reward and $\gamma * \max(a', Q(s', a'))$ as a discounted maximum future reward, Equation (6) determines the required Q-value for the (s, a) pair. In the Q-learning method, the rule for updating Q-values is represented by Equation (7).

$$Q(s, a) = (1 - \alpha) * Q(s, a) + \alpha * \text{target}. \tag{7}$$

Here, $Q(s, a)$ is the current Q-value for action a in state s; is the learning rate that defines the weight provided to the new information as updating the Q-values; the target is the desired Q-value for the (s, a) pair depending on the observed rewards and future estimates; and s is the state associated with action a. The Q-value approximation for the (s, a) pair is updated by plugging the new target value into the Equation. The learning rate determines the current Q-value's relative importance and the update rule's target value. In the framework of the Q-learning method, the value of the future state s' is substituted for the present state s using Equation (8).

$$s = s'. \tag{8}$$

The agent's (UAV's) current state in the environment is denoted by s, whereas the state at which action causes the agent to make a transition from s to s' is denoted by s'. The agent's internal state representation agrees with its external state transition from the current state s to the new state s', as in Equation (8). The DQL algorithm repeats these procedures until convergence is reached.

By continuously updating the Q-values depending on observed rewards and transition between states, the DQL algorithm seeks to locate optimal paths for the UAV to collect sensor data. It allows the UAV to acquire knowledge and plan its course efficiently and effectively to maximize cumulative rewards.

C. MOGWO-DQL Algorithm for UAV Route Planning

Regarding UAV route planning, MOGWO and DQL algorithms provide a potent answer for multi-objective optimization and reinforcement learning. MOGWO excels at navigating the solution space and was designed specifically for multi-objective optimization issues. It is better able to deal with ambiguity, utilize its faculties of exploration and exploitation, and serve as a foundation for ongoing development. The IRP-SDC framework's integration of MOGWO and DQL is concerned with finding the best paths for UAVs to collect sensory data while covering the most ground in the least amount of time. This fusion takes advantage of deep reinforcement learning to solve the multi-objective optimization issue by combining the strengths of both techniques. UAV data-collection route planning is improved by the MOGWO-DQL method in various ways. The MOGWO is built to tackle such "multi-objective optimization" issues and simultaneously optimize for multiple competing goals.

The method can find a collection of Pareto-optimal solutions, which are tradeoffs between minimizing time, minimizing distance, and maximizing area coverage because of the incorporation of MOGWO. DQL's exploitation capability makes use of the acquired knowledge to make sound decisions, but MOGWO's exploration capability aids in the discovery of novel solutions across the search space. This integration seeks to determine ideal paths for UAVs gathering sensor data to reduce flight time and distance, increasing area coverage. Combining the benefits of MOGWO with Deep Q-Learning (DQL), the MGWO-DQL method provides an effective solution for UAV route planning. It allows for adaptive decision-making, prioritization, and tradeoffs in light of the mission's specific objectives and restrictions and efficient solution space exploration. It also gives decision-makers leeway to set priorities and tradeoffs regarding the mission's requirements. By combining these features, a more complete and efficient route planning solution can be achieved by investigating trade-offs between objectives. The integration yields Pareto-optimal solutions, which offer a variety of possibilities that strike a balance between travel time, total distance, and the total area covered, allowing decision-makers to weigh the pros and cons of each and pick a path that best suits their needs. Algorithm 1 demonstrates the MOGWO-DQL algorithm's operating concept within the IRP-SDC architecture.

Objective Function for Time Calculation. Time is important in calculating the fitness function for UAV route planning and data gathering. The time efficiency of the UAV's mission should be maximized as a primary goal of the fitness function. Before returning to base, the UAV must travel to a series of waypoints, where it will collect data before returning to base. Time efficiency is influenced by the time spent travelling between waypoints, and the time spent collecting data at each waypoint is $W_{\mathrm{TravelTime}}$ and W_{DataTime}, respectively. An iterative optimization procedure could determine the weighting factors. As a starting point, it is reasonable to give travel time and data collecting time the same amount of importance. The weights can then be fine-tuned based on the interest criterion through experimentation and optimization. By iteratively refining the weighting criteria, optimal results can be achieved.

$T(i, j)$ represents the time from point A to point B to determine the travel time score for a given route, and Equation (9) involves adding up the trip times between each waypoint.

$$\text{Route}_{\text{TravelTime}} = \sum T(i, j), \quad \text{for all waypoints in the route.} \tag{9}$$

$D(i)$ represents the duration of the data-collecting process at node i. The data collection time score for a given route can be computed by adding the times it took to collect the necessary information at each route's waypoint, as shown in Equation (10).

$$\text{Route}_{\text{DataCollectionTime}} = \sum D(i), \quad \text{for all waypoints in the route.} \tag{10}$$

Incorporate the weighted sum of the time spent travelling to and collecting the data. Assuming that all factors have the same importance, the fitness function could be determined as follows in Equation (11):

$$\text{time} = W_{\text{TravelTime}} * \text{Route}_{\text{TravelTime}} + W_{\text{DataTime}} * \text{Route}_{\text{DataCollectionTime}}. \tag{11}$$

Optimize the fitness function based on time by determining the optimal path and data collection strategy using the MOGWO-DQL method.

Objective Function for Distance Calculation. In UAV route planning for data collection, the ideal path is determined by calculating a fitness function based on distance – set goals and limitations for the UAV route planning and data collection mission. The amount of ground the UAV covers is the most important factor. Assign a value, given by w_{distance}, to the distance component based on its significance. The distance score between two waypoints i and j is given by $Dt(i, j)$, and the distance score for a given route can be found by adding the distance scores between each pair of waypoints along the route using Equation (12).

$$\text{Route}_{\text{DistanceScore}} = \sum Dt(i, j). \tag{12}$$

The distance score is standardized and multiplied by the distance component's weight according to the formula in Equation (13).

$$\text{distance} = w_{\text{distance}} * \text{Normalized}_{\text{DistanceScore}}. \tag{13}$$

The MOGWO-DQL optimization algorithm can be used to discover the path that will result in the lowest possible fitness cost. Improve the effectiveness of UAV route planning for data collection by finding a path that reduces the total distance travelled by periodically optimizing the fitness function.

Objective Function for Area Coverage. In UAV route planning for data collection, a fitness function based on area coverage considers the performance of the planned UAV path that covers the target region – set goals and limitations for the UAV route planning and data collection mission. The primary factor is the size of the area covered by the UAV's flight path. Assign the area coverage factor a relative relevance weight and refer to the coverage area weight as w_{coverage}. Applying the number of cells in the target area grid (N_{total}) and the number of cells covered by the UAV's flight path (N_{covered}) in Equation (14), determine the area coverage scores of the Grid.

$$\text{Area}_{\text{CoverageScore}}1 = N_{\text{covered}}/N_{\text{total}}. \tag{14}$$

Determine the intersection area ($A_{\text{intersection}}$) that connects the UAV's flight path and the target region (P_{target}) by calculating the area of the polygon marked by P_{target}. Equation (15) provides a formula for determining the area coverage score.

$$\text{Area}_{\text{CoverageScore}}2 = A_{\text{intersection}}/A_{\text{target}}. \tag{15}$$

The area covered by the sensor's FoV (Field of View) over the target region is given by A_{coverage}, which can be calculated. Equation (16) can be used to determine the score for area coverage.

$$\text{Area}_{\text{CoverageScore}} = A_{\text{coverage}}/A_{\text{target}}. \tag{16}$$

The area coverage score can be normalized and multiplied by the component's weight using Equation (17).

$$\text{Weighted}_{\text{AreaCoverageScore}} = w_{\text{coverage}} * \text{Area}_{\text{CoverageScore}}. \tag{17}$$

The MOGWO-DQL method is used to identify the optimal path that optimizes the fitness function using area coverage. UAV route planning for data collection can achieve efficient area coverage by optimizing the fitness function to discover a UAV path and data collection plan that maximizes the area coverage.

Setting Parameters of MOGWO-DQL Algorithm. Important processes and parameter settings are addressed as part of the algorithmic method. An objective function must be defined to minimize flying time and distance while maximizing area coverage, and initial values for waypoints, flight duration, and battery life must be determined. The training parameter sets the optimal number of training iterations, balancing exploration and exploitation. The MOGWO algorithm combines meta-heuristic search with the DQN to adjust positions and choose responses. Time, distance, and area

Algorithm 1 MOGWO-DQL

1. Initialization:
   - Define the problem, decision variables, constraints, and objectives.
   - Initialize the MOGWO population of grey wolves.
   - Initialize the DQN with random weights.
2. Training:
   - Set the maximum number of iterations or stopping criteria.
   - Repeat until convergence:

   (a) Perform MOGWO search iterations:
     - Update the positions of the grey wolves based on MOGWO equations.
     - Use the DQN to select actions (waypoints) for each grey wolf.

   (b) Evaluate fitness values and update dominance levels:
     - Calculate the fitness values of the grey wolves based on the defined objectives in Equations (11), (13) and (17).
     - Perform dominance sorting to classify the grey wolves.
     - Update the best solution set representing the Pareto-optimal solutions.

   - Train the DQN:
     - Update the DQN weights using a batch of experiences from the MOGWO search.
     - Update the Q-values estimation.
3. Output: Return the final best solution set representing the Pareto-optimal routes.

are all factors in determining fitness levels. The DQN learns from a batch of experiences from the MOGWO protocol. These procedures allow for multi-objective optimization in UAV route planning.

The starting points for the tuple of waypoints are set as (i, j).

Initialize the default flight time and battery life for certain destinations.

Set the objective function to minimize time and distance and maximize area coverage.

Set the training parameter, the maximum number of iterations, from 100 to 500. Based on empirical study, 100–500 iterations are used to find an optimal balance between exploration and exploitation. The best number of iterations for a given problem domain can be determined by analyzing convergence and performance characteristics.

Set the number of iterations performed in the MOGWO algorithm between 10 and 100, where grey wolves update their positions and actions are selected using the DQN.

Fitness evaluation and dominance sorting are performed as in Equations (18),

(19) and (20),

$$F_{\text{time}} = \min(\text{time}), \tag{18}$$

$$F_{\text{dist}} = \min(\text{distance}), \tag{19}$$

$$F_{\text{coverage}} = \max(\text{area}). \tag{20}$$

The DQN is trained using a batch of experiences from the MOGWO search. The batch size can be set to a suitable value, such as 32 or 64.
The best solution set represents Pareto-optimal paths for the UAV, noting the trade-offs between travel time, total distance, and the total area covered. The result is a combination of checkpoints and routes that maximize time spent gathering sensor data.

3.2.3 Data Collection with UAV and Cluster Centre

UAVs and sensor nodes communicate and share sensory data as part of the IRP-SDC system. Connectivity between the UAV and sensor nodes is achieved through wireless communication protocols like Wi-Fi or Bluetooth. The UAV initiates the activation of the sensor nodes in the target area. The sensor nodes in the target region are activated once the UAV sends a request or instruction over a wireless communication protocol like Wi-Fi or Bluetooth. The UAV normally activates the sensor nodes by delivering a signal or command for them to begin data gathering. This technique or protocol may vary depending on the implementation.

4 PERFORMANCE EVALUATION OF THE PROPOSED WORK

Time, distance, and area covered by the UAV while collecting sensor data are all factored into an analysis of the effectiveness of the proposed IRP-SDC system. The suggested framework is tested by analyzing the data collected at the hubs of each cluster. The error rate is determined to evaluate the proposed study thoroughly. At last, the results are compared with other models to demonstrate the superiority of the IRP-SDC architecture.

4.1 Simulation Results

The simulation tests are run with the following settings to demonstrate the dominance of the proposed structure. A $5\,000 \times 5\,000$ m area is available for flight planning. Position $(0, 0)$ is used as the origin. The coordinates $(5\,000, 5\,000)$ have been specified as the target. The criteria for weighting have been set at 0.4. Dimension is set at 10, and the maximum number of iterations is 500. The average of 30 separate simulations is presented.

Time, distance, and coverage area are the three primary metrics of the proposed framework. In Figure 5, the time the suggested IRP-SDC takes based on the congestion-aware modelling framework to complete the task is shown. The optimal route revealed by the IRP-SDC algorithm is evaluated at each iteration by calculating and evaluating the time required by the UAV to accomplish the task at each cluster node. The results of estimating the distance of an optimal route for all cluster nodes across multiple iterations are represented in Figure 6. Figure 7 represents the outcomes of the optimal path's coverage of the complete area at different iterations. Figure 8 presents the IRP-SDC system's average response time, average distance revealed for the optimal path to all cluster centres, and total area coverage.

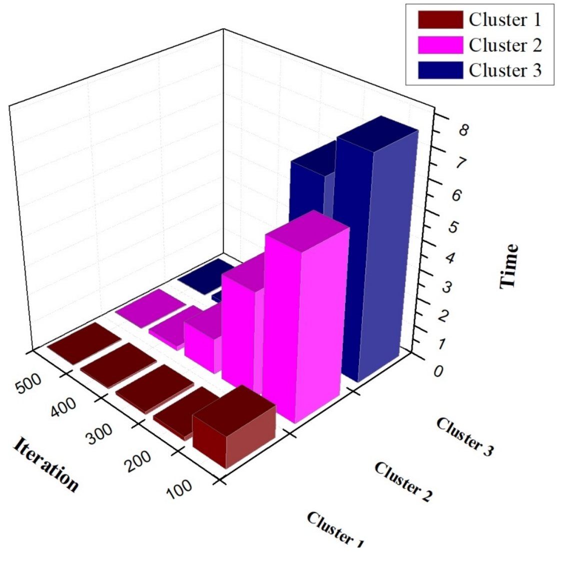

Figure 5. Time taken by the IRP-SDC system at each iteration

Deep Learning and Genetic Algorithm (DL-GA), Q-learning and Genetic Algorithm (DL-GA), and Deep Learning and Multi-objective Particle Swarm Optimization (DL-MOPSO) are some of the available methods used to examine the IRP-SDC system's main indicators. Table 1 displays the outcomes of each cluster node for the suggested and compared approaches. The error rate of the IRP-SDC and other models for the comparatively studied and the results are depicted in Figure 9. The mean and standard deviation have been selected as performance indicators for the IRP-SDC system because they accurately depict the system's error rate. The mean is a common statistic that takes the average of a set of numbers to understand how the system performs. The standard deviation evaluates the consistency and variability of the error rate, while the mean estimates the system's performance. These metrics, taken as a whole, provide the important information on the system's efficiency and reliability in gathering sensor data.

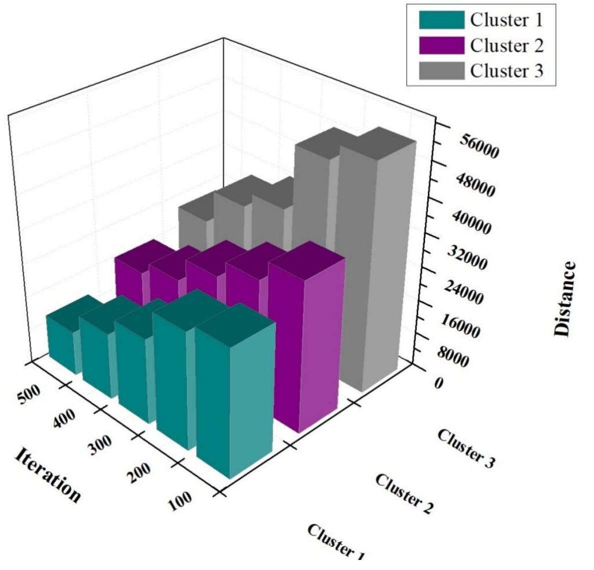

Figure 6. Route distance at each iteration of the IRP-SDC system

4.2 Discussion

In this section, the experimental data that assesses the efficiency of the proposed IRP-SDC setup is studied. Primarily, the performance of the proposed system is assessed in terms of time, distance, and coverage area during data collection by UAV. An error rate analysis was also performed to understand the research plan further. Finally, the comparison demonstrated the IRP-SDC framework's superiority over competing models. Using the ideal results shown in Figure 5, the proposed IRP-SDC system efficiently collects data from clusters 1, 2, and 3 in 0.019, 0.023, and 0.028 iterations, respectively. The distance of the ideal path is determined for all cluster nodes at various iterations to measure the effectiveness of the proposed framework in reducing the total distance travelled by the UAV during data collection. Figure 5 displays the findings, which show that the UAV travelled a total of 10 526, 16 532, and 21 652 m during data collection at the three cluster centres using the maximum number of iterations, respectively, and that the suggested IRP-SDC system is effective in lowering the UAV's journey distance. Figure 7 shows the average time needed by all cluster nodes, the average distance of the optimal path to all cluster centres, and the total area coverage achieved by the IRP-SDC system, all of which are 0.023 seconds, 16 236 meters, and 57 424 square meters, respectively. Figure 8 depicts the typical duration (in seconds), distance (in meters), and surface area (in square meters) covered by the IRP-SDC system.

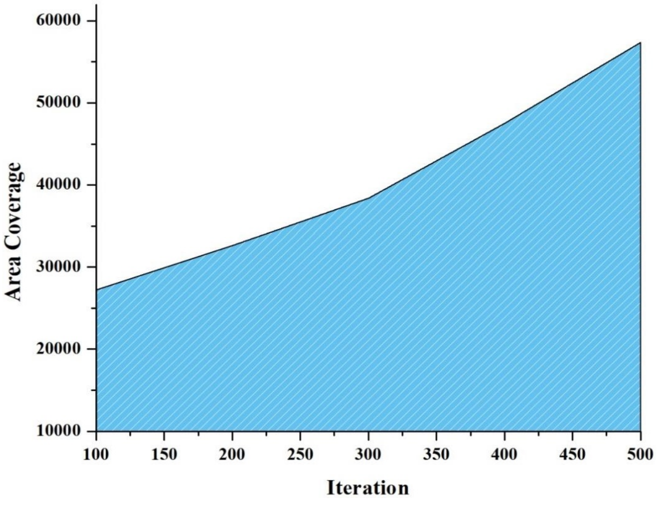

Figure 7. Total area covered at each iteration by the IRP-SDC system

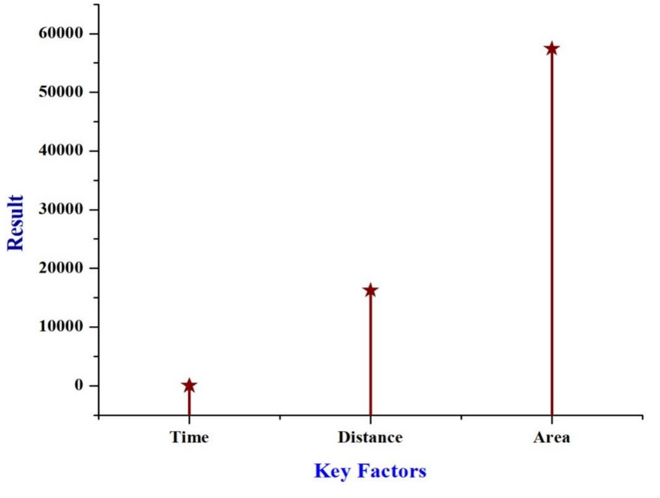

Figure 8. Average time, distance and coverage area of an optimal route by IRP-SDC system for UAV's sensory data collection

The IRP-SDC framework's overall efficacy is evaluated in relation to the state-of-the-art DL-GL, QL-GL, and DL-MOPSO approaches. The proposed system outperforms other methodologies of all key factors, time, distance, and area coverage with values of 0.019, 10 526, and 45 623 for cluster node 1, 0.023, 16 532, and 58 696 for cluster node 2, and 0.028, 21 652, and 67 955 for cluster node 3. These values are summarized in Table 1. The outcomes show that the proposed system is superior to the currently used methods. Figure 9 shows the mean and standard deviation of the error rate for the IRP-SDC system and other existing models; these values are 0.068 and 0.098, respectively, and provide insight into the precision and consistency of the IRP-SDC architecture. The experimental outcome presents that the IRP-SDC system outperforms the contemporary systems for UAV-based sensor data collecting in terms of time efficiency, distance travelled, and coverage area. The comparison results demonstrate that the IRP-SDC framework is superior to the competing models.

Cluster Centre	Methodology	Time	Distance	Coverage Area
Node 1	DL-GA	12.3	12 563	25 647
	QL-GA	4.562	13 654	12 356
	DL-MOPSO	2.432	15 896	25 789
	IRP-SDC	0.019	10 526	45 623
Node 2	DL-GA	23.45	25 689	39 685
	QL-GA	12.96	21 424	38 621
	DL-MOPSO	5.8	19 882	41 256
	IRP-SDC	0.023	16 532	58 696
Node 3	DL-GA	32.56	48 756	45 602
	QL-GA	15.42	35 987	56 231
	DL-MOPSO	4.51	29 782	59 123
	IRP-SDC	0.028	21 652	67 955

Table 1. Cluster-wise performance analysis of an optimal route by the IRP-SDC and other existing methodologies

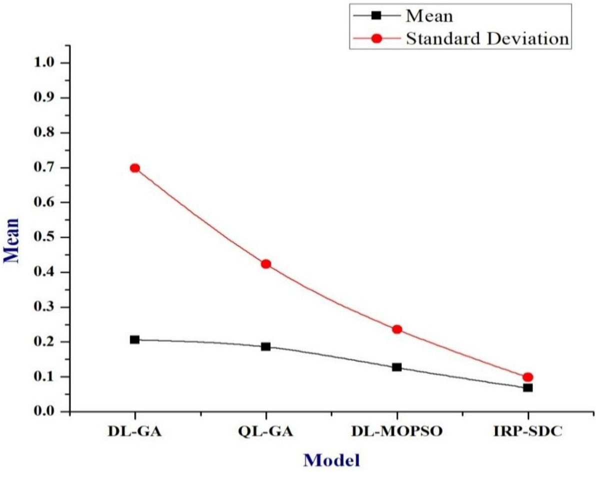

Figure 9. Analysis of mean and standard deviation of an optimal route by the IRP-SDC system and other existing methodologies

In this section the efficacy of the proposed IRP-SDC system is tested by a series of experimental studies. The IRP-SDC system's efficacy is evaluated by contrasting it with previously established methods. The projected error rate is used to evaluate the planned work compared to currently available models. These results prove the efficiency and usefulness of the proposed approach, demonstrating its potential for enhancing route planning during UAV-based sensor data collection.

5 CONCLUSION AND FUTURE SCOPE

The suggested IRP-SDC framework is an innovative method for enhancing autonomous UAV-based data-gathering route planning. Based on congestion-aware modeling, intelligent decisions may be made by autonomous drones and UAVs (unmanned aerial vehicles) without the involvement of a human pilot or operator since they are not limited to a prescriptive algorithm and can instead learn from and adapt to their surroundings. The system surpasses more standard methods, which frequently ignore several limitations, by considering trip time, coverage area, and energy use. UAV Control Stations are integrated into the design to facilitate centralized management of flight operations, mission preparation, real-time monitoring, and data display. With the addition of the MOGWO-DQL algorithm, the Route Planner is better able to perform global searches and optimize routes in light of shifting conditions. The experimental findings show that the IRP-SDC system is the most effective in saving time, reducing travel, and expanding coverage. The superiority of the design over previous models is further validated by comparative analysis. The versatility of the IRP-SDC system and the effectiveness of its route planning in UAV-based data collection make it ideal for use in a wide variety of contexts. Future UAV route planning for sensory data collection will investigate additional constraints like weather, battery life, and obstacle avoidance. In the future, the IRP-SDC will be enhanced using techniques like adaptive route planning enabled by weather forecasting data. These battery management techniques extend flight time, obstacle detection, and avoidance mechanisms that guarantee safe navigation in complex situations.

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