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Dynamic Positioning and Energy-Efficient Path Planning for Disaster Scenarios in 5G-Assisted Multi-UAV Environments

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Abstract: The integration of fifth-generation (5G) and unmanned aerial vehicle (UAV) technologies has become a promising solution for providing seamless communication in applications, such as disaster management, because of its bandwidth availability, cost-efficacy, and mobile nature. The state-of-the-art research in UAV communication concentrates on effective positioning and path planning. Despite this, these systems performed poorly due to a lack of dynamic control and external factors, such as weather. The solution presented in this paper addresses the problems listed above by using dynamic positioning and energy-efficient path planning for disaster scenarios in the 5G-assisted multi-UAV environments (Dynamic-UAV) to maximize the performance metrics. The lightweight gated recurrent unit (LGRU) is used for weather and event prediction to determine the disaster and non-disaster area and the context of the disaster. The density-based optics clustering (DBOC) algorithm is used to achieve reliability during communication with cluster IoT devices in disaster and non-disaster regions. The satellite determines the number of UAVs required and positions the UAVs using the dynamic positioning-based soft actor–critic (DPSAC) algorithm to achieve maximum throughput. Moreover, the UAVs' path planning is performed using the shuffled shepherd optimization with dynamic-window method (SSO-DWM) to reduce energy consumption. The proposed approach is simulated using the NS 3.26 simulator and validated by comparing the results with existing techniques regarding the quality of service (QoS), reliability, and energy efficiency. Experimental results indicate that the proposed method achieved maximum throughput (1.59 bit/s), packet delivery ratio (0.88), coverage probability (0.82), number of collected packets (7109–5875), energy efficiency (1.544), minimum delay (16.4 ms–18.5 ms), and energy consumption (7.48 KJ).

Keywords: UAV; IoT; 5G; positioning; clustering; path planning; QoS; reliability; energy efficiency

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1. Introduction

Unmanned aerial vehicles (UAVs) are highly demanding for various applications, such as rescue operations, surveillance, and disaster monitoring. Besides this, UAVs are also used to recover network facilities in the regions of natural disasters, such as forest fires, floods, cyclones, landslides, and manmade disasters, namely power plant explosions and terrorism, which can control emergencies when action is required [1]. In any area of interest, one or more UAVs are used for monitoring and collecting data from the ground devices equipped in that area. Each UAV has onboard sensors and cameras to collect data from the monitoring area. A UAV's mission is to collect data from IoT devices in the absence of base stations or when a disaster damages the base stations. Therefore, UAV-based data collection and processing is a worldwide topic among researchers. The UAV collects data in air-to-air (A2A) and air-to-ground (A2G) communications. The base stations

are prone to environmental conditions which affect the reliability of A2A and A2G UAV communication [2]. By utilizing flying base stations, the impact of weather and altitude on A2A and A2G communication is amplified, maximizing their energy consumption [3,4]. Less efficient path planning for UAVs leads to serious Quality of Service (QoS) issues, such as packet loss rate and network latency [5]. There is a lack of consideration for both static and moving obstacles and no differentiation between various emergency events, which reduces the performance and effectiveness of UAV communication [6].

The 5G-enabled UAV communication reduces the communication latency and bandwidth issues; however, the conventional problems, such as increased energy consumption, are not yet addressed [7]. Clustering is a promising solution for energy consumption since it increases network scalability, reduces overhead, extends battery life, and boosts the throughput [8]. The optimal cluster head (CH) is selected for managing different user groups; bypassing the information through CH reduces the network delay [9]. However, current clustering schemes are required to construct frequently. This is due to the poor grouping of nodes based on limited parameters. In addition, UAVs are clustered without focusing on the vulnerability of the devices and base stations [10,11]. Data collection from disaster environments is challenging; using multiple UAVs requires proper positioning and efficient path planning [12,13]. However, deploying many UAVs without prior knowledge of traffic demand and event occurrence increases deployment costs. To reduce such drawbacks, relay-based methods and deployment algorithms are used [14,15]. Multiple constraints must be evaluated, including weather impact, traffic demand, coverage ratio, and emergency event counts. Based on these factors, the number of UAVs is considered, and is also helpful in planning an optimum path and effective deployment [16,17].

In a multi-UAV environment, meteorological conditions must be monitored [18,19]; UAV speed, direction, altitude, position, and distance must be adjusted accordingly. On the other hand, dynamic path planning is critical in multi-UAV-served disaster situations to avoid collisions and minimize energy consumption due to random trajectories. The path planning problem is considered an optimization problem [20], and several optimization algorithms are used to determine the optimal path, such as particle swarm optimization (PSO), genetic algorithm (GA), etc. However, there is still a research gap in UAV positioning and path planning.

1.1. Motivation & Objectives

There is a need for an operational communication network whenever a disaster occurs, and a portion of the existing communication network is destroyed. Therefore, network operators must deploy an emergency communication network to provide connectivity to the ground devices. In this regard, using a mobile network through the deployment of UAVs can be viewed as a potential alternative for emergencies. Due to its dynamic nature and three-dimensional (3D) properties, UAV communication faces multiple challenges. Existing research in the multi-UAV environment has not adequately addressed various positioning and path planning problems. While deploying UAVs, limited parameters are considered in the literature, which is insufficient to perform optimal positioning, path planning, and reliable and energy-efficient communication. Different solutions have been used for the positioning and path planning of UAVs. However, a proper joint technique is still needed for positioning, clustering, and path planning, while considering multiple parameters to ensure optimal QoS, reliability, and energy efficiency in disaster and non-disaster scenarios. The challenges listed below inspired us to conduct this work and fill in the gaps in existing studies.

- Lack of Weather Conditions—Wind factors, such as direction, speed, velocity, and turbulent flow significantly impact UAV communication. When determining optimal location and path planning, failing to do so will result in poor QoS performance.
- Higher UAV Energy Consumption—The UAV is comprised of multiple resource-constrained sensors. UAVs consume energy in data gathering, movements, processing,

and transmission. As a result, the issue of energy consumption requires careful consideration to reduce the need for frequent replacement and charging.

- Obstacles in Path Planning—One of the challenges is path replanning is due to stationary and mobile obstacles in the network. Without prior knowledge of obstacles, path planning increases the likelihood of a collision between UAVs. Consideration of obstacles also minimizes packet loss and latency during data transfer.
- Delay in Disaster Situations—To maximize performance, the latency in data transfer from the source to the UAV must be minimized in disaster scenarios, when data collecting is more susceptible to delay.

This research is motivated by the problems mentioned above encountered by state-of-the-art work. The primary goal of this study is to examine the performance of various UAV communications (A2A and A2G) under weather-suffered disaster scenarios. Path planning and positioning are required for a higher QoS, improved network coverage, and connectivity. These are met by the sub-objectives listed below.

- Predicting the absolute weather impacts the selected area of interest based on past weather data, often known as historical weather information.
- To maximize the scalability of the UAVs for a large-scale environment in which deployment of multiple UAVs positioning must be optimum.
- To maximize the energy efficiency of UAVs and minimize the time of data collection without any packet loss.
- To reduce the communication overhead in a multi-UAV environment by optimal path planning and positioning. The diagrammatical representation of motivation and objectives is presented in Figure 1 for a better understanding.

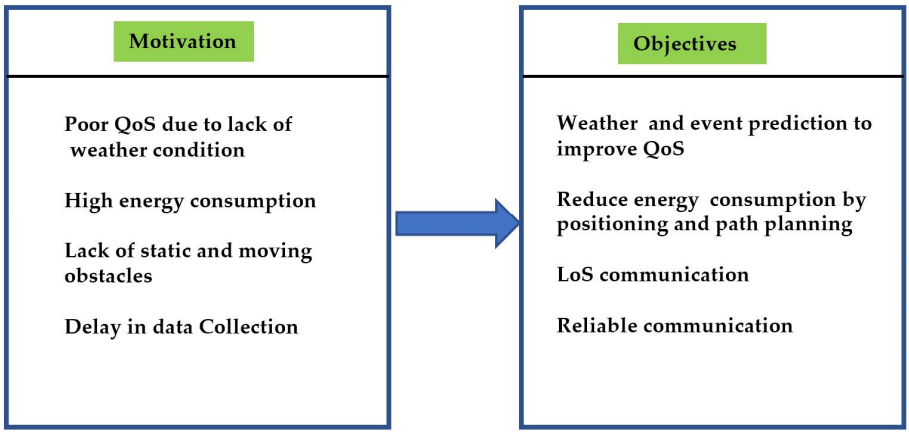

Figure 1. Motivation and objectives.

1.2. Paper Contributions

We propose a dynamic positioning and path planning approach for disaster scenarios in a 5G-assisted muti-UAV environment (Dynamic-UAV), depending on the environmental context. The following are the significant step-by-step contributions of this paper:

- Analyzing the context of the environment, the lightweight gated recurrent unit (LGRU) is applied to predict weather conditions (sunny, rain, lightning, cloudy, windy) and events (disaster/non-disaster). Consideration is given to historical weather information and environmental photographs while deploying UAVs for efficient communication.
- Once the event and weather conditions are predicted, the density-based optics clustering (DBOC) method is used to cluster IoT devices in both disaster and non-disaster zones to increase the communication reliability between the UAV and devices.
- A satellite that uses dynamic positioning-based soft actor-critic (DPSAC) algorithm is considered to estimate the required number of UAVs and dynamically position

the UAVs, thereby reducing communication delay and maximizing the throughput and coverage.

- The shuffled shepherd optimization with dynamic-window method (SSO-DWM) is used to design UAV paths, which takes into account both static and dynamic objects in the environment to avoid collisions and improve energy efficiency. The performance of the proposed method has been validated and determined to be superior compared to other existing approaches.

1.3. Paper Organization

The remainder of this paper is organized as follows: Section 2 outlines the fundamentals and different types of UAV communication. This section also provides a synopsis of the literature and relevant work. Section 3 addresses the problem statement and proposes dynamic UAV positioning and energy-efficient path planning for disaster scenarios in a 5G-assisted multi-UAVs environment. Section 4 includes the simulation setup and a comparative study of numerous metrics with existing works. Section 5 explains the application of the proposed approach, Section 6 provides the summary, and Section 7 provides the conclusion and future direction of the proposed work.

2. Preliminaries and Related Work

The preliminary knowledge of this work is explained in this section to understand our concept better. This section covers the basics of UAV communication, types of UAV communication, and the integration of 5G and UAV. In addition, to analyze the research gap, different state-of-the-art path planning and positioning approaches for the assistance of UAVs is examined in this part.

2.1. UAV Communication

UAV communication refers to the communication initiated by the UAVs to relay or process the data from the ground environment. UAV communication is utilized as an alternate solution for the Ground Base Station (GBS) damaged during a disaster or as an additional technology to improve network performance in a large-scale environment. The UAVs perform spectrum sharing, information sharing, etc., to achieve reliable communication and complete the given task. There are three types of UAV communication present in this work: A2G communication, A2A communication, and satellite to UAV communication (S2A) [2,3]. In A2G communication, the ground IoT devices, such as sensors, actuators, mobiles, etc., communicate with UAVs directly to perform a task. The A2G communication is applied in various applications, such as surveillance, agricultural monitoring, photography, traffic control, package delivery, telecommunications, and search and rescue. In A2A communication, the UAVs communicate with each other regarding spectrum sharing, information about users, etc. A2A communications are used when any UAV is vulnerable to environmental conditions. The information in the vulnerable UAVs is shared among the different UAVs. This helps to achieve reliable communication. In S2A communication, the UAVs act as a relay node controlled by the satellite with global coverage. This type of communication is more suitable for network management during natural disasters. At that time, the satellite communicates with UAVs to monitor the disaster and take corrective actions by the authorities.

2.2. 5G-Assisted UAV Communication

The conventional UAV communication techniques encounter several network challenges, such as increased latency and less availability of bandwidth, which further affects its performance, especially during disaster situations. The emergence of 5G technology provides many opportunities to overcome the existing network challenges and achieve better QoS. The 5G communication is categorized into three types: namely, massive machine type communication (mMTC), extreme mobile broadband (eMBB), and ultra-reliable low-latency communication (URLLC) [7]. The 5G-UAV communication falls under URLLC,

which provides services with low latency. Figure 2 depicts the various applications of 5G-UAV communications, in which the data from a heterogeneous environment are collected and processed.

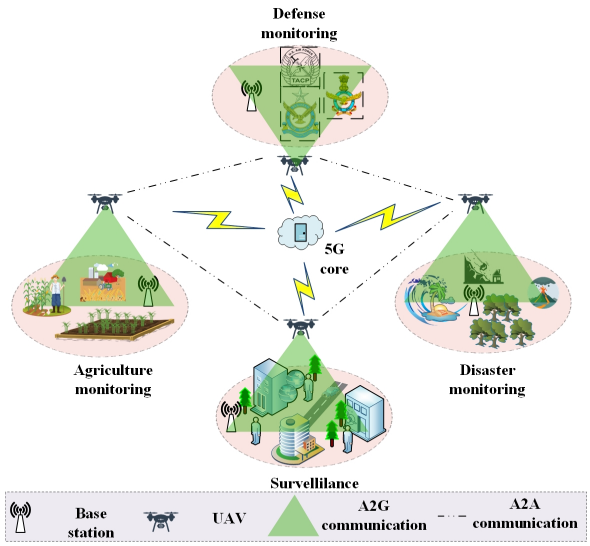

Figure 2. Applications of 5G-UAV communication.

The 5G-assisted UAV communication is hindered by several factors, such as increased interference, inefficient path planning, positioning, and the distance between the UAV and devices. As a result, the placement and path planning of the UAVs in our approach focus on attaining superior performance by considering multiple parameters. We examine the performance of A2A and A2G UAV communications in weather-suffered disaster scenarios where UAVs go to the desired location while considering the weather characteristics, obstacles, user density, coverage area, elevation angle, path loss, LoS, and NLoS components. The number of UAVs is determined by the satellite using S2A communication. Clustering, path planning, and positioning are conducted to enhance QoS, reliability, and energy efficiency.

2.3. UAV Positioning Approaches

Bhandari, S. et al. proposed a stable clustering approach based on mobility and location in UAV networks [21]. UAV is deployed with optimal CH to maximize coverage with minimum transmit power. Distance-based k means a clustering algorithm is proposed for updating the relative location by considering UAV speed and transmission range. The cluster includes several UAVs, and data collected from the CH are forwarded to the sink. The simulation results show that the proposed method achieves better performance in terms of PDR and end-to-end delay compared to the conventional Ad hoc On-Demand Distance Vector (AODV), ant colony pptimization (ACO), and grey wolf optimizer (GWO) schemes. The k-means clustering algorithm performs clustering, but the number of clusters is required prior to this. In a real-time scenario, we cannot predict the number of clusters previously, thus reducing the efficiency of the process.

Positioning UAVs for a highly-functional differentiated metropolitan scenario in an edge-assisted smart IoT environment is proposed by Tan, Z. et al. [22]. The proposed system used a scheduling strategy by deploying UAVs to fill the space between service cycles. The energy efficiency and data collecting method is executed during information updating, which minimizes the transmission delay. First, UAVs collect sensor data from IoT devices during uplink transmission. Then UAVs perform the computing-intensive task of processing sensor data and creating augmented information. First, the augmented information is pressed into mobile devices, and then the augmented reality extracts the visual objects by a camera and a geo-location sensor.

The deployment of a UAV base station for satisfactory communication services is presented by Zhong, X. et al. [23]. All the user equipment (UE) is initially clustered to

be served using multiple UAV-based stations. The aim is to detect optimal locations for placing UAV base stations, which maximize the coverage of the ground users. The optimal UAV placement is conducted by using the genetic algorithm that provides wireless services to the UEs group. The results show that the proposed system performs better in coverage ratio and has a good tolerance for UEs localization error. However, a genetic algorithm is proposed for placing UAVs in the optimal position, which generally takes many iterations to complete the task; hence the proposed system has high latency, thus reducing the overall network performance.

The forest-fire-fighting method using hundreds of UAVs to create a non-stop flow of liquid on the forest fire is proposed by Ausonio et al. [24]. The UAV's battery and liquids are refilled to continue the action. The UAVs takes action for several hours without downtime. The proposed system maintains a support unit that manages the drone swarm to move and position it close to the fire. The forest fire is estimated based on moisture content, wind speed, direction, flame length, and intensity. The simulation results show that water flow is essential to fight low intensity and support current forest-fire-fighting methodologies.

2.4. UAV Path Planning Approaches

Cheng, L. et al. proposed a staged adaptive firefly (SAFA) algorithm for charge planning of UAVs in wireless sensor networks [25]. The proposed SAFA algorithm has a high convergence speed and better quality. Distance and brightness are taken to promote the convergence and diversity of the algorithm. The algorithm performs both global and local optimization, thus increasing the convergence speed. The proposed system was compared and tested with six functions, and the result shows that the proposed scheme achieves high convergence and accuracy.

The path planning-based minimization of completion time for fixed-wing UAV communication is proposed by Wang, H. et al. [26]. The non-convex optimization is converted into an equal form using a S-procedure. The path-planning method is improved by applying the exact penalty method, and a heuristic path-planning algorithm is proposed to reduce the mission accomplishment time. The proposed system divides the flight method into three phases. In the first phase, both the UAVs attempt to reach each other from their starting locations; in the second phase, they move while keeping a certain distance; and in the third phase, both return to their end locations. The simulation result verifies that the proposed system achieves better throughput while keeping the interference lower. Only two UAVs are used for processing; however, they will be suitable only for a small environment as it covers a limited area, thus reducing the system's efficiency.

Li, K. et al. proposed the path planning for multiple UAVs by online changing tasks using a fly optimization algorithm based on the optimal reference point (ORPFOA) to solve the task assignment problem [27]. Initially, the tasks are assigned to UAVs based on their priority, and then an optimal path is generated for changing the tasks. In this work, all the tasks are divided into several task points. An optimal path is developed to ensure that every UAV can fly over all the task points within the required flight time. The result shows that the proposed system achieves higher efficiency than other systems. Here, the ORPFOA algorithm is used for path planning, which provides an optimal path, but this algorithm takes too much running time, thus increasing the process's complexity.

A comprehensive risk assessment method for UAV path planning in the urban environment is proposed by Hu, X. et al. [28]. The proposed system considers three significant risks: people on the ground, human-crewed aircraft, and vehicles. The total cost is evaluated based on the above three risks. This work aims to create a risk cost map for providing cost-effective path planning. A modified A* algorithm is used for detecting optimal paths with low-risk costs. Additionally, a modified ant colony algorithm is used for searching the shortest path.

Tang, J. et al. proposed a joint multi-UAV 3D trajectory planning and resource allocation using a deep reinforcement learning algorithm for minimum throughput maximization [29]. The author considers a wireless-powered communication network in which

multiple UAVs provide services to the ground devices. UAV's path design and time resource assignment are optimized to maximize the throughput. Planning and resource allocation considers UAV flight speed and IoT uplink transmit power, for which they proposed a multi-agent deep Q learning method. Simulated results show that the proposed system achieves high performance in terms of throughput.

The path planning of UAVs using a meta-heuristic algorithm, named the grey wolf optimizer algorithm (GWO), is proposed by Qu, C. et al. [30]. This algorithm is further integrated with the reinforcement learning algorithm to control switch operations dynamically to obtain a feasible route. UAV's path planning is implemented by four operations: exploration, exploitation, geometric adjustment, and optimal adjustment. For smoothening the UAV's path, a cubic B–spline curve is applied. He proposed a reinforcement learning-based GWO algorithm that obtained the effective route in a complex 3D environment.

The path planning of UAVs in three-dimensional space using improved particle swarm optimization (PSO) is proposed by Shao, S. et al. [31]. A chaos-based logistic map theory is applied to improve the distribution of particles. In PSO, velocity and acceleration coefficients are adjusted to obtain better optimization solutions. The proposed path planning algorithm can be implemented and adopted for various path planning constraints, such as terrain, threat, and collision avoidance. Both convergence speed and optimum solution features are adopted in this paper for feasible UAV path generation. However, the lack of consideration of moving obstacles in threat areas causes path loss issues.

Shi, L. et al. addressed the coverage issue of UAVs during path planning in 5G mmWave communications [32]. QoS requirements of the ground users are satisfied for the online sensor data transmission from the UAV to the receiver. The blockage and movement of UAVs under various channel conditions of 5G are focused on path planning. To consider QoS requirements, a speed control algorithm is proposed to adaptively handle the UAV's movement in a disaster area. This paper has obtained a minimum data loss due to UAV's speed control and coverage considerations.

The path planning of UAVs for satisfying QoS constraints in D2D-assisted 5G networks is executed by Shu, L. et al. [33]. For the path planning task, the PSO algorithm was proposed. For local information collection and optimum path planning, PSO is integrated with two other techniques: path encoding and local search. Flight deployment costs are reduced by planning the path for covering the considerable monitoring area. With the modified PSO, the performance of path planning time is reduced since PSO finds the heuristic approach. This approach does not provide a valid path since the velocity and acceleration coefficient parameters are not optimized for different time intervals. The path planning of UAVs in a large-scale environment was proposed by Wu, X. et al. [34]. When the distance is far from the UAV to the obstacle, it is safe; otherwise, UAV is announced to be in an obstruction area, and data collection is not practical. To improve the scalability problem, optimality, and efficiency maximization, this paper proposes a bi-directional adaptive A* algorithm. This algorithm works by multi-directional search theory in which the path is smoothened and guaranteed. The multiple constraints analyzed in this paper are UAV angle, position, and environment modeling.

Path planning based on multiple UAV constraints, such as height, angle, and limited UAV slope is focused on by Yu, X. et al. [35]. When considering path planning in the optimization problem, UAV risk and traveling distance were computed in fitness functions. During the path planning, maximum turning angle and safe distance metrics are considered and applied to the B–spline model. These constraints are applied in the dynamic differential evolution algorithm. Based on the fitness functions, the performance of the UAV path is optimized in disaster cases. Table 1 summarizes the findings of the literature review in a concise manner.

Table 1. Summary of literature survey.

Approaches	Authors	Objective	Algorithm/Model Used	Limitations
UAV Positioning Approaches	Bhandari, S. et al. [21]	Cluster-based positioning of UAVs	K—means clustering algorithm	Initial clusters are unpredictable. Inefficient during a varying number of UAVs in each cluster.
	Tan, Z. et al. [22]	Data collection by UAVs for augmented reality applications	Multi-UAV mechanism	Undetermined distance between UAVs caused overlap.
	Zhong, X. et al. [23]	3D deployment of UAVs to achieve maximized coverage	Genetic algorithm	Iterations increase latency.
	Ausonio. El. et al. [24]	Positioning of UAV to achieve water flow on forest fire	Cellular automata model	Not considering UAV altitude.
UAV Path Planning Approaches	Cheng, L. et al. [25]	Charging planning of UAVs based on speed and distance	Staged adaptive firefly algorithm	gets trapped in local optima, which reduces planning performance.
	Wang, H. et al. [26]	Minimization of completion time through path planning	Heuristic optimization algorithm	Fixed time slot leads to wastage of time resources under certain situations.
	Li, K. et al. [27]	Assignment of tasks and optimal planning of paths	ORPFOA algorithm-based path planning	Increased time complexity affects the performance of this approach.
	Hu, X. et al. [28]	Risk-aware, cost-effective path planning	Modified A* algorithm	Increases latency when the number of iterations is increased.
	Tang, J. et al. [29]	Optimization of trajectory and resource allocation	A reinforcement-based deep Q learning algorithm	Relatively long training time increases latency during motion.
	Qu, C. et al. [30]	Adaptive path planning of UAVs	Reinforcement-based grey wolf optimizer	Lack of consideration of obstacles increases collisions.
	Shao, S. et al. [31]	Collision-aware path planning of UAVs	Improved PSO algorithm	Lack of consideration of moving obstacles leads to replanning.
	Shi, L. et al. [32]	Minimize data loss by controlling UAVs	The adaptive speed control algorithm	Lack of consideration of weather conditions
	Shi, L. et al. [33]	Adaptive planning and communication during flight	Particle swarm optimization	Reduction of convergence rate when iteration increases.
	Wu, X. et al. [34]	Minimization of path cost during flight time	Bi-directional adaptive A*	Lack of consideration of weather conditions.
	Yu, X. et al. [35]	Risk-aware path planning of UAVs in a disaster scenario	Dynamic differential evolution algorithm	Frequent replanning due to lack of consideration of obstacles.
Proposed dynamic UAV positioning and path planning	Objectives		LGRU DBOC DPSAC SSO-DWM	Contributions
	Events/Weather prediction Events-aware clustering Multi-UAV positioning Energy-efficient path planning			Improves QoS Improves scalability Improved Energy efficiency Reduce communication overhead

3. Problem Statement and Proposed Work

The summary presented in Table 1 shows that most existing approaches performed UAV positioning or path planning. However, the lack of consideration of obstacles makes it hard to achieve their objective. Moreover, the weather conditions in which UAVs travel greatly influence their performance. Our approach addresses these factors to achieve maximum throughput and minimum energy consumption in UAV communication. In our system, the environment is classified into disaster and non-disaster regions after predicting it through the LGRU algorithm. The IoT devices in both areas are clustered based on several factors given in Section 3.2. The UAVs are responsible for providing services to IoT devices. Let the number of devices present in the environment are $N = \{1, 2, \ldots, N\}$ and the number of devices in a single k^{th} cluster be denoted as N_k, $k \in K = \{1, 2, \ldots, M\}$. The clusters of devices formed do not overlap with other clusters, which can be formulated as,

$$N_k \cap N_{k'} = \varnothing,\ k \neq k', \tag{1}$$

Let's write the number of UAVs as $B = \{1, 2, \ldots, B\}$. The flight period of the UAVs can be expressed as $f_t \in [0, T]$ which depends on the mission and battery of the UAV. The location of both devices and UAVs can be formulated as,

$$w_N = (x_N, y_N, 0) \tag{2}$$

$$w_B = (x_B(t), y_B(t), h_B(t)) \tag{3}$$

where (x, y) denotes the latitude and longitude of the devices and UAVs. $h_B(t)$ denotes the height of the UAV B at time t. The term $h_B(t)$ influences the coverage of the UAV [36]; as the height of UAVs increase, the coverage also increases until the UAV reach its optimal location. $h_B(t)$ can be determined as:

$$h_B(t) = Cr_B \tan(\theta_{\max}) \tag{4}$$

In Equation (4) Cr_B denote the coverage radius of the UAV B. The existence of objects in the surroundings affects the channel between the ground devices and UAVs. The probability of Line of Sight (LoS) between UAVs and devices is modeled as a function of $\phi_{N,B}$ as [37]:

$$P_{\text{LoS}}(\phi_{N,B}) = \nu_1 \left(\frac{180}{\pi} \phi_{N,B} - \eta \right)^{\nu_2} \tag{5}$$

In Equation (5), ν_1 and ν_2 denote the constant values influencing the environment, η represents the constant representing the relation between environment and antenna. The LoS probability depends on the elevation angle. $\phi_{N,B}$ denotes the angle of elevation between the IoT device and the UAV B, which can be formulated as:

$$\phi_{N,B} = \sin^{-1} \left(\frac{h_B(t)}{Dt_{(N,B)}(t)} \right) \tag{6}$$

where, $Dt_{(N,B)}(t)$ denotes the distance between the IoT device and the UAV. The probability of non-line of sight (NLoS) can be computed as [38]:

$$P_{\text{NLoS}} = 1 - P_{\text{LoS}} \tag{7}$$

The path loss that occurrs in the channel between the device and the UAV can be formulated as [39]:

$$PL_{(N,B)} = \begin{cases} \lambda_1 \left(\frac{4\pi f r_c Dt_{(N,B)}}{c} \right)^{\delta}, & \text{LoS} \\ \lambda_2 \left(\frac{4\pi f r_c Dt_{(N,B)}}{c} \right)^{\delta}, & \text{NLoS} \end{cases} \tag{8}$$

In Equation (8), λ_1, λ_2 denote the coefficient of attenuations of the LoS and NLoS channel link. $\frac{4\pi f r_c}{c}$ is the path loss in free space. $f r_c$, c and δ denote the carrier frequency, light speed, and path loss exponent, respectively. The throughput of the IoT devices can be formulated as [37]:

$$Tr_N = \frac{1}{T}\sum_{i=1}^{I} C_{N,B} G_N \log_2\left(1 + \frac{P_N^U PG_N}{If_N + \mu^2}\right) \tag{9}$$

where, $C_{N,B}$ denotes the connectivity between the device N and UAV B. The value of $C_{N,B}$ equals 1 if the device is under the coverage of UAV; otherwise the $C_{N,B}$ will be equal to 0. The last term in Equation (9) is the signal-to-noise and information ratio where P_N^U denotes the uplink power of the device, PG_N denotes the power gain of the device, If_N denotes the interference between the UAV and neighbor cluster, and μ^2 is a function of power spectral density. The UAV's energy consumption is divided into three categories, including energy consumption during motion and data collection. The entire energy consumption can be expressed in the following way:

$$E_B = t_M \cdot P_M + t_C \cdot P_C \tag{10}$$

In Equation (10), t_M and t_C denote the time involved in motion and data collection, and P_M and P_C denote the power utilized during motion and data collection, respectively. From the above equations, we can formulate the primary problem as follows:

$$\text{Maximize} \leftarrow Tr_N \tag{11}$$

$$\text{Minimize} \leftarrow E_B \tag{12}$$

The positioning of the UAVs in the environment is conducted to enhance the coverage of UAVs to maximize the throughput. The multi-objective utility-based maximization of the total sensing information in wireless sensor networks is proposed [40]. The optimal position is derived by using PSO based on sensing utility, communication path quality utility, and network connectivity utility functions. The positioning of low-altitude UAVs for effective data collection is proposed in [37]. The observed time difference of arrival time (OTDOA) positioning method was used for device location, with the UAV being positioned in a 2D plan. The following are the primary issues that various techniques face:

- The UAV positioning considers only limited parameters, such as location and link quality, which is not enough for optimal positioning. Weather conditions are the essential factors in UAV positioning, which were not considered, thus reducing coverage.
- The UAV was assumed to be at a constant height, which is not the case in reality; the channel has several variations, resulting in a coverage reduction.
- The number of UAVs needed for adequate data gathering was not calculated, affecting the average data collecting throughput.

The optimal path planning of UAVs is performed by grouping the user equipment into clusters [36]. The individual communication between UAVs and UEs was terminated, and a CH-based communication was performed. This way of planning the path of UAVs considerably reduced the energy consumption of the UAVs. Time-sensitive data collection by planning UAV trajectory and resource allocation is executed to maximize the number of served IoT devices [41]. The game theory-based selection of UAVs and the reinforcement-based path planning optimization achieve minimum path loss [42]. The significant problems involved in these approaches are:

- The UAV trajectory is affected by many weather conditions, but they only focus on wind speed, leading to poor trajectory planning, thus increasing path loss [36].
- The planning only considers wind characteristics and the length of the path. However, the performance of this method is affected by the fact that obstacles in the environment. Furthermore, the UAV's energy consumption was not taken into account [42].

- The trajectory planning was conducted only on the basis of distance, which is insufficient for picking an ideal path; the weather is one of the most important aspects impacting UAV trajectory, and it was overlooked, resulting in poor trajectory planning and higher energy consumption [41].

The proposed approach overcomes all the problems mentioned above by performing the following processes; initially, the prediction of weather conditions and recognition of disaster regions are achieved by using the LGRU model. Significant features, such as wind characteristics and temperature parameters, are utilized. The clustering of IoT devices is performed in which the devices in disaster and non-disaster regions are grouped based on density. This eventually optimizes the communication between the devices and UAVs. The satellite is in charge of locating UAVs in 3D space, determining the number of UAVs to be deployed, and positioning them using the DPSAC algorithm. Further, the energy consumption of the UAVs is minimized by planning their path. Considering obstacles in the environment makes it more realistic that our approach would be be adopted. The path loss is also reduced by utilizing the dynamic window model.

The proposed work mainly focuses on performing the dynamic positioning and path planning in a 5G-assisted multi-UAV environment. The proposed Dynamic-UAV approach comprises entities, such as IoT devices, UAVs, 5G GBS, and a satellite. Figure 3 depicts the overall architecture of the proposed approach. The processes involved in the proposed Dynamic-UAV approach are given below.

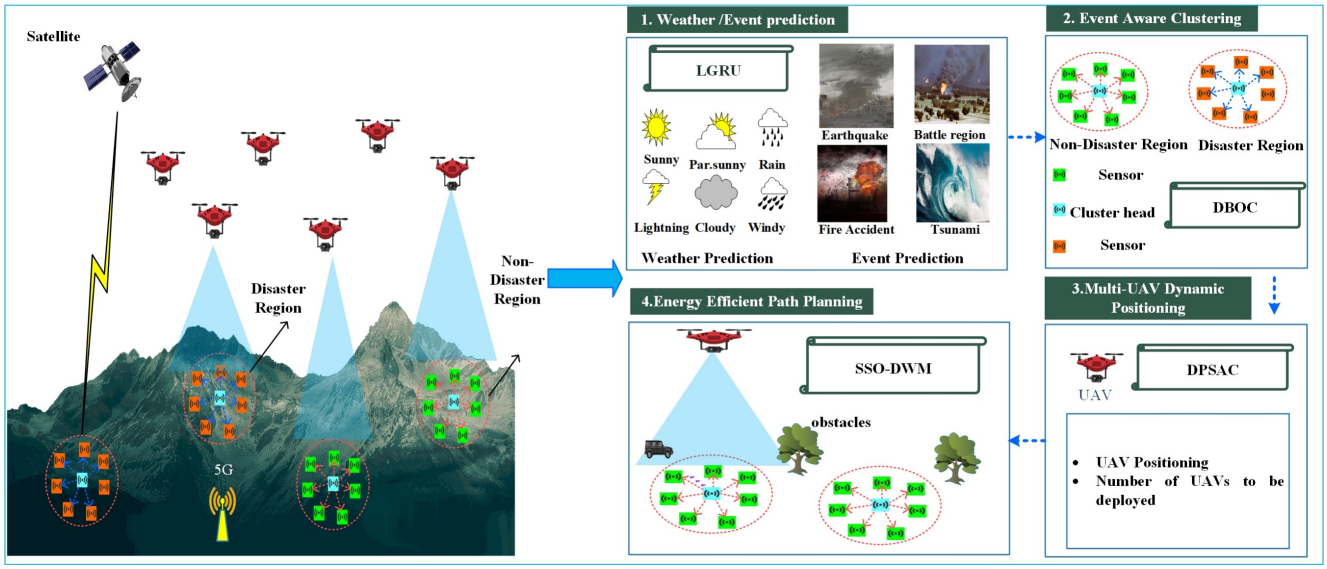

Figure 3. The overall architecture of the dynamic UAV approach.

3.1. Events/Weather Prediction

The weather influences the position and communication channel of UAVs. Mainly the wind characteristics, such as wind direction (wd), speed (s), velocity (ve), and turbulent flow (tf) mostly affect the UAV communication. Lightning and heavy rain are also the factors that limit UAV communication. Hence, we need to predict weather conditions for UAV communication. Let $đ = \{wd, s, ve, tf\}$ where $đ$ represents the wind characteristics. For instance, if there are extreme weather conditions, such as lightning, cyclones, etc., UAV communication may be impossible, or it may cause physical damage to the UAVs, so it must be predicted to achieve better communication and avoid those damages. The events are predicted using historical information, which helps improve UAVs' communication efficiency. Based on the historical data, we predict the disaster regions from the UAV image by using a satellite. For example, if the image consists of collapsed buildings, then the event is known as an earthquake, and if the image has active flames or smoke, it is known as a

fire accident. Prior knowledge of these weather conditions is very important for efficient communication. This historical information is used for predicting the disaster region, thus helping to give priority compared to the other areas. For this reason, we proposed the LGRU algorithm that contains an update gate and a reset gate. The update gate (g_u) controls the iteration range of previous information state to current information state. The reset gate (g_e) controls the overload of information state from the g_u. For weather prediction, the wind characteristics $\underline{đ}$ are used respectively, which are updated periodically to the UAV.

$$g_{uo} = \text{ϰ}(\mathrm{WM}_{g_u}\left[\mathrm{Ph}_{\underline{đ}}, \mathrm{CI}_{\underline{đ}}\right]) \tag{13}$$

$$g_{eo} = \text{ϰ}(\mathrm{WM}_{g_e}\left[\mathrm{Ph}_{\underline{đ}}, \mathrm{CI}_{\underline{đ}}\right]) \tag{14}$$

$$h^c = \text{þ}\left(\mathrm{WM}_h\left[g_{uo} \odot \mathrm{Ph}_{\underline{đ}}, \mathrm{CI}_{\underline{đ}}\right]\right) \tag{15}$$

$$h^s = (1 - g_{eo}) \odot \mathrm{Ph}_{\underline{đ}} + h^c \odot g_{eo} \tag{16}$$

The above equations represent the weather prediction formulas using LGRU. Equation (13) represents the gate update output (g_{uo}) which acquires the current input (CI) as wd, s, ve, tf and previously hidden state information (Ph) as wd, s, ve, tf that forms a weighted matrix function of the gate update (WM_{g_u}) using activation function (ϰ). Equation (14) shows the gate reset output (g_{eo}) which controls the state information from g_{uo} and forms a weighted matrix of gate reset (WM_{g_e}) using ϰ. Equation (15) shows the contestant hidden state, which combines the previous information with current information (h^c) that forms a weighted matrix function of the hidden state (WM_h) using activation function (þ), and finally, all the state information is combined to give a predicted result. Equation (16) shows the hidden state (h^s) which combines the processed results and gives predicted results which can be formulated as:

$$\mathrm{P_{Re}}(\mathrm{wea}) = \{h^s,\ \mathrm{sunny},\ \mathrm{rainy},\ \mathrm{cloudy}, \mathrm{windy}\} \tag{17}$$

Let the past images ($\mathrm{Im} = e, f, t, b$) and (wea) denotes the weather. For event predictions, the past images are required for predicting the accurate event in the present, which can be formulated as:

$$g_{uo} = \text{ϰ}\left(\mathrm{WM}_{g_u}[\mathrm{Ph_{Im}}, \mathrm{CI_{Im}}]\right) \tag{18}$$

$$g_{eo} = \text{ϰ}\left(\mathrm{WM}_{g_e}[\mathrm{Ph_{Im}}, \mathrm{CI_{Im}}]\right) \tag{19}$$

$$h^c = \text{þ}(\mathrm{WM}_h[g_{uo} \odot \mathrm{Ph_{Im}}, \mathrm{CI_{Im}}]) \tag{20}$$

$$h^s = (1 - g_{eo}) \odot \mathrm{Ph_{Im}} + h^c \odot g_{eo} \tag{21}$$

The above equations represent the event prediction using past images (Im) of an earthquake (e), fire (f), tsunami (t), and battle region (b). With these past images, LGRU predicts the accurate event in the present ($\mathrm{P_{Re}}$) which can be formulated as:

$$\mathrm{P_{Re}}(\mathrm{event}) = \{h^s,\ \mathrm{earthquake},\ \mathrm{fire},\ \mathrm{battle}, \mathrm{tsunami}\} \tag{22}$$

Algorithm 1 and Figure 4 represent the working of LGRU in weather and event predictions, respectively. In Algorithm 1 we used the cost function (Fc), which holds the set of all parameters. Fc is updated for every prediction based on the environmental condition. The performance is evaluated using this function. Cost function required constant minimization. The model's performance improves with minimization in the cost function. In the case of accurate prediction, its value becomes zero. By using LGRU, we perform event prediction using images from past events and weather prediction with weather characteristic parameters, such as temperature (Temp), wind speed and direction

(wswd), humidity (H), dew point (DP), pressure (p), time (T), and precipitation time (P_t). The above measurements are considered for effective positioning, optimal path planning, and ensuring the safety of the UAVs. Table 2 represents the weather reports predicted by the proposed LGRU algorithm for 24 h.

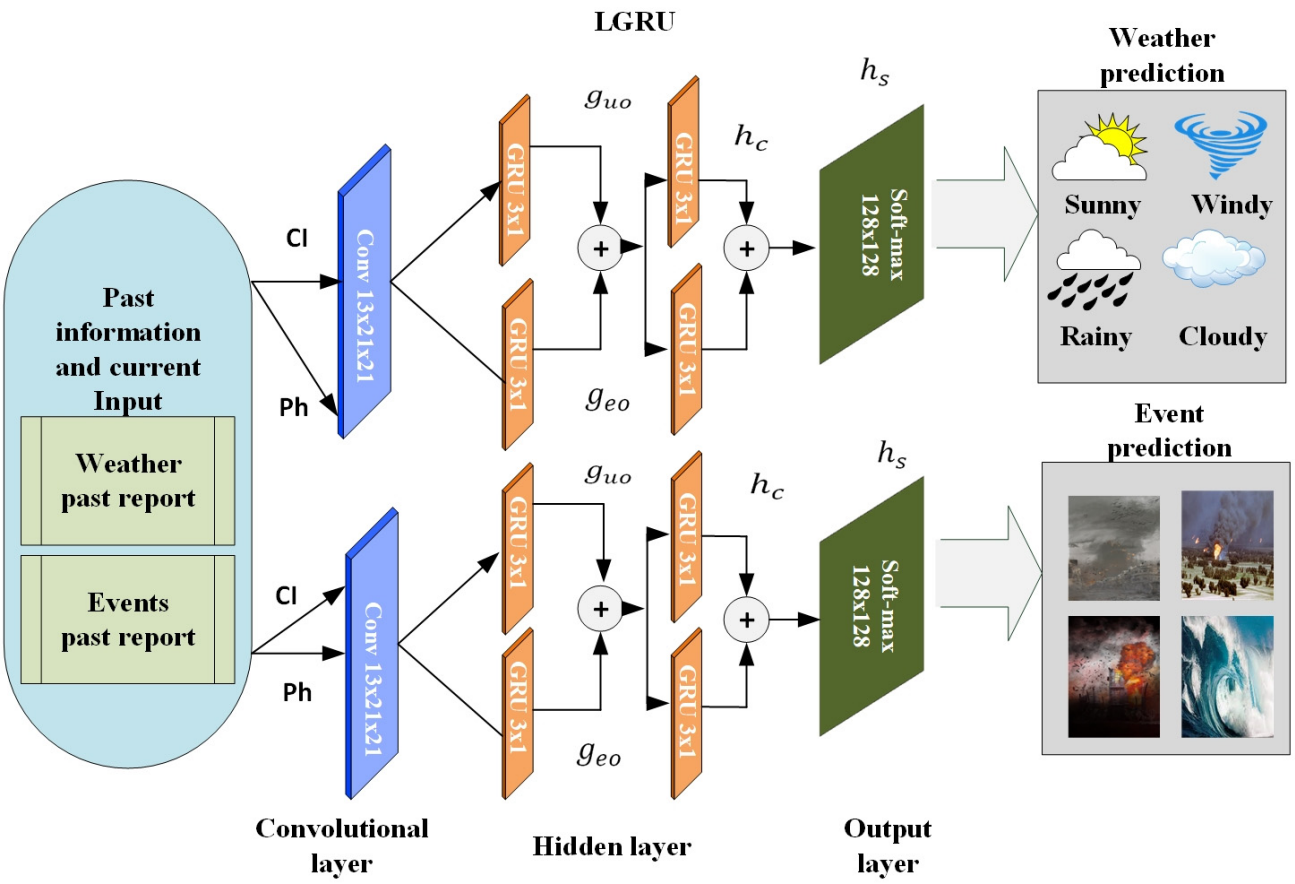

Figure 4. LGRU weather and event prediction.

Table 2. Weather report for 24 h.

Weather	P_t	T	Temp	p	DP	wswd	H
Windy	0.9 mm	22.00	29 °C	1001 hpa	26 °C	10 km/s, NE	85%
Cloudy	0.2 mm	19.00	28 °C	1001 hpa	26 °C	10 km/s, NE	75%
Rainy	1.7 mm	5.00	31 °C	1100 hpa	23 °C	10 km/s, NE	67%
Sunny	2.7 mm	2.50	36 °C	1232 hpa	27 °C	2 km/s, NE	75%
Cloudy	0.6 mm	13.00	29 °C	1028 hpa	21 °C	3 km/s, NE	75%
Sunny	0.5 mm	15.00	21 °C	1001 hpa	26 °C	10 km/s, NE	88%
Windy	0.3 mm	09.00	23 °C	1100 hpa	23 °C	2 km/s, NE	61%
Cloudy	0.1 mm	07.30	26 °C	1006 hpa	22 °C	6 km/s, NE	93%
Rainy	3 mm	23.26	30 °C	1001 hpa	26 °C	7 km/s, NE	88%

Algorithm 1 LGRU-based weather and event prediction.

1. Input $\mathrm{CI}, \mathrm{CI}_{\mathrm{Im}}$
2. Output $\mathrm{P}_{\mathrm{Re}}(\mathrm{wea})$, $\mathrm{P}_{\mathrm{Re}}(\mathrm{event})$
3. Begin
4. **While** $(Fc) \neq 0$**, do**
5. **For** each time slot, do
6. Update Ph, CI// to UAV
7. Compute g_{uo}// using (13)
8. Compute g_{eo}// using (14)
9. Calculate h^c// bitwise multiplication using (15)
10. h^s// bitwise multiplication using (16)
11. $\mathrm{P}_{\mathrm{Re}}(\mathrm{wea})$// using (17)
12. **End**
13. **For** each time slot, do
14. Update $\mathrm{Ph}_{(\mathrm{Im})}, \mathrm{CI}_{\mathrm{Im}}$// to UAV
15. Compute g_{uo}// using (18)
16. Compute g_{eo}// using (19)
17. Calculate h^c// bitwise multiplication using (20)
18. Calculate h^s// bitwise multiplication using (21)
19. Compute $\mathrm{P}_{\mathrm{Re}}(\mathrm{event})$// using (22)
20. **End**
21. **Stop**
22. End

3.2. Event Aware Clustering

After predicting the weather conditions, a clustering of IoT devices is performed to increase communication reliability. Based on the past event information, the environment is clustered in two regions: disaster and non-disaster. The regions are clustered into the disaster region and non-disaster region. Each area has multiple clusters. Each cluster has various IoT devices that send the data to the UAV via the CH. For clustering, we consider the parameters (ɯ) of density (de), distance (di), and the number of users (u). Let us consider, ($\text{ɯ} = \mathrm{de}, \mathrm{di}, u$). The DBOC algorithm performs the clustering process. For example, in case of any natural or manmade disasters, the base stations which sends the information to the authorities are affected; at that time, the IoT devices, such as sensors, actuators, etc., forms a cluster as a disaster and non-disaster region and sends data via the CH. The cluster formation can be formulated as:

$$D_{c(\mathrm{MR,\ MP})} = \begin{cases} \left|\mathrm{UN}_{\mathrm{dis}},\ \mathrm{MP}'(\text{ɯ}) \leq \mathrm{MR}\right| < \mathrm{MP} \\ \left|\mathrm{UN}_{\mathrm{non-dis}}, \mathrm{MP}'(\text{ɯ}) \leq \mathrm{MR}\right| < \mathrm{MP} \\ \mathrm{MP}_{\mathrm{dis,\ non-dis}},\ \text{otherwise} \end{cases} \tag{23}$$

Equation (23) represents the minimum points (MP) that are closely related to IoT devices in disaster and non-disaster regions. The $D_{c(\mathrm{MR,\ MP})}$ represents the MP and maximum radius (MR) for forming clusters between the IoT objects. The DBOC algorithm first calculates the main distance (D_c) of the untreated IoT devices (UN) in the regions. $\mathrm{UN}_{\mathrm{dis}}$, $\mathrm{MP}'(\mathrm{den},\ \mathrm{dis},\ \mathrm{users})$ represents the untreated IoT device in the disaster area, which must be less than or equal to the MR, $\mathrm{UN}_{\mathrm{non-dis}}$, $\mathrm{MP}'(\mathrm{den},\ \mathrm{dis},\ \mathrm{users})$ represents the untreated IoT device in the non-disaster areas, and if all the IoT devices are treated, then the MP are calculated in disaster and non-disaster regions. After calculating the D_c of the IoT devices, the distance reachability (D_r) is calculated for the devices to form clusters which can be formulated as:

$$D_{r(\mathrm{MR,\ MP})} = \begin{cases} \left|\mathrm{UN}_{\mathrm{dis}},\ \mathrm{MP}'(\text{ɯ}) \leq \mathrm{MR}\right| < \mathrm{MP} \\ \mathrm{MR}_{\mathrm{dis,\ non-dis}},\ \text{otherwise} \end{cases} \tag{24}$$

Equation (24) represents the distance reachability ($D_{r(\mathrm{MR,\ MP})}$) for the untreated IoT devices from disaster and non-disaster regions. Afterwards, all the IoT devices compute D_c and D_r, and a list of a clusters is formed as disaster and non-disaster regions. The final clustered output is formulated as:

$$C_o = \{(\mathrm{dis}_{\mathrm{MR,MP}}),\ (\mathrm{non} - \mathrm{dis}_{\mathrm{MR,MP}})\} \tag{25}$$

Equation (25) represents clusters output (C_o) at the disaster (dis) and non-disaster (non–dis) region based on the maximum radius (MR) and minimum points (MP). The clustering method reduces the complexity and energy of UAV communication. As CH sends the data to UAV hence, we need to select optimal CH; for that, we consider energy and centrality that can be formulated as:

$$\mathrm{CH} = \{K_N > \mathrm{energy},\ \mathrm{centrality}\} \tag{26}$$

Equation (26) shows the optimal CH selection from clustered IoT devices (K_N) in C_o for sending data to UAV. Centrality is the frequency of cluster nodes located on the shortest path between other cluster nodes. Energy is the capacity of cluster nodes to withstand other cluster nodes in the surrounding environment. Algorithm 2 and Figure 5 represent the working of DBOC in events-aware clustering.

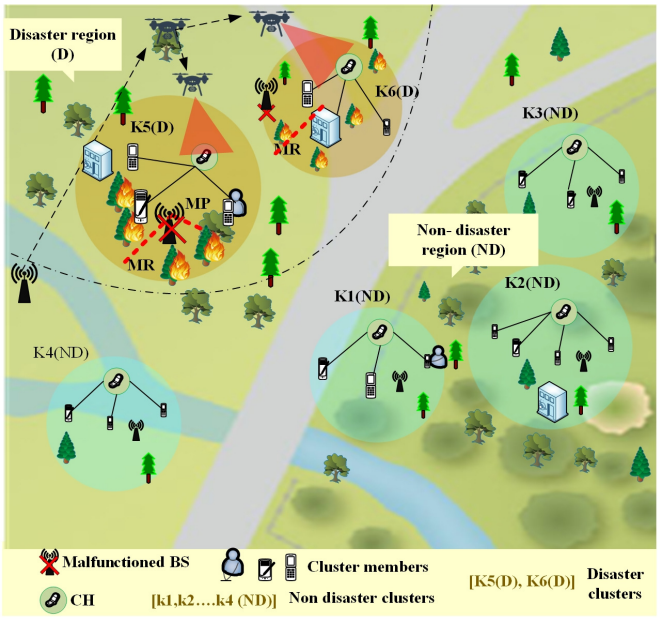

Figure 5. Density-based optics clustering.

Algorithm 2 Events-aware Clustering.

1. Input $\mathrm{UN}_{\mathrm{Ц}}$
2. Output C_o
3. Begin to obtain information form $\mathrm{P}_{\mathrm{Re}}(\mathrm{wea})$, $\mathrm{P}_{\mathrm{Re}}(\mathrm{event})$
4. **For** (cluster formation), do
5. Compute $D_{c(\mathrm{MR,\ MP})}$ // *using (23)*
6. Compute $D_{r(\mathrm{MR,\ MP})}$ // *using (24)*
7. Elect CH // *using (25)*
8. Compute C_o // *using (26)*
9. **End**
10. End

3.3. Multi-UAV Dynamic Positioning

The effective positioning of UAVs is performed after the clusters of IoT devices are generated by DBOC in a disaster region, which improves communication and provides adequate coverage during an emergency. Many variables influence UAV placement, including altitude, weather conditions, speed, and the existence of obstacles that obstruct communication between IoT devices and UAVs. During an emergency, the satellite is responsible for deploying the appropriate number of UAVs depending on traffic demand. In our proposed work, the UAV acts as an edge server that collects the data from the IoT devices and takes action based on that data. In the proposed Dynamic-UAV approach, the DPSAC algorithm is utilized. The goal of the DPSAC algorithm is to identify the optimal policy. The combination of policy and value-based approaches maximizes the long-term reward. The UAV positioning is constructed as a Markov Decision Process (MDP) with state attributes (ς) which are predicted weather conditions, coverage area, user density, delay sensitivity, elevation angle, path loss, and LoS/NLoS characteristics. The reason for adopting MDP is to allow sequential decision-making, and it gives optimal results for partially known environments. An MDP is comprised of state, action, transition probabilities, and reward. The DPSAC algorithm aims to identify the optimal policy and maximize the reward to determine the optimal position and number of UAVs. The combination of policy and value-based approaches maximizes the long-term reward. The position of UAVs in the proposed approach is constructed with state attributes (ς) that are predicted weather conditions, coverage area, path loss, angle of elevation, and LoS/NLoS characteristics. The state parameters for UAV number determination are delay sensitivity and density of users. The action set consists of two major actions: UAV count determination and positioning. Latency increases without determining the number of UAVs, which impacts the throughput. The coverage enhances while increasing the height of the UAVs from the ground. On the other side, path loss also occurs by increasing the height of UAVs, which creates interference, eventually influencing the throughput. Optimal positioning also improves the QoS in UAV communication. There is an impact on throughput by taking actions (position and number of UAVs to be deployed) in the environment, so it must be optimized to maximize the reward. The MDP tuple is given as $[\,Tu, \varsigma_T, \text{Å}, \text{Pro}\,(.\big|\varsigma_T, \text{ac}), \mathbb{R}\,(\varsigma_T, \text{ac}), \Theta\,]$. The state, reward, and transitions are based on real-time interactions with environmental attributes. From the tuple, Tu denotes the epochs, which range from $Tu = 1, \ldots, N$, ς_T denotes the state, and Å denotes the action set consisting of two major actions discussed above. The actions are dynamically executed based on the current situation (disaster or non-disaster). The reward ($\mathbb{R}$) is generated based on the action value function to maximize the throughput. The DPSAC algorithm increases the reward from the agent's interaction with the environment. DPSAC uses soft policy iteration to reach this goal. Soft policy iteration is evaluating the policy and making it optimal to maximize the reward. The Pro denotes the transition probability as $\text{Pro}_{\text{st}}^{\text{ac}} = [\varsigma_{T+1} = \varsigma' \big| \varsigma_t = \text{st}, \text{Å} = \text{ac}]$, and the discount factor is denoted by Θ, and is set between 0 and 1. The discount factor determines the agent's care about the reward in the long term compared to those in the near future. When the discount factor is 0, the agent only cares about the immediate reward. When the discount factor is 1, the agent cares about the future reward, and the rewards can increase based on the interpretation of the discounting factor. For every given state and action, the reward can be provided based on adding immediate and future rewards. DPSAC consists of three networks. The first network represents state value, the second network represents policy function, and the third is the soft Q function derived in this section. The policy and Q-network are updated by collecting data from the policy that is different from the current policy. The transition of data is stored in a replay buffer for each roll-out of actor, which is denoted by (D) in Equation (27). The state value function is denoted as $V_\psi(\varsigma_T)$.

The soft Q function is denoted as $Q_\theta\left(\varsigma_T, \mathring{A}_T\right)$ which is trained as formulated below:

$$H_v(\psi) = E_{\varsigma_T \sim D}\left[\frac{1}{2}\left(V_\psi(\varsigma_T) - E_{\Omega_T \sim \pi_\phi}\left[Q_\theta\left(\varsigma_T, \mathring{A}_T\right) - \log \pi_\phi\left(\mathring{A}_T | \varsigma_T\right)\right]\right)^2\right] \quad (27)$$

A separate approximation function $E_{\varsigma_T \sim D}$ is utilized to minimize the squared residual error. The gradient function is estimated for the parameter updation, which is formulated as:

$$\hat{\nabla}_\psi H_v(\psi) = \nabla_\psi\, V_\psi(\varsigma_T)\left(V_\psi(\varsigma_T) - Q_\theta\left(\varsigma_T, \mathring{A}_T\right) + \log \pi_\phi\left(\mathring{A}_T | \varsigma_T\right)\right) \quad (28)$$

The optimization of the soft Q function is carried out by using the stochastic gradient function, which is computed as:

$$\hat{\nabla}_\theta H_Q(\theta) = \nabla_\theta Q_\theta\left(\mathring{A}_T, \varsigma_T\right)(Q_\theta\left(\varsigma_T, \mathring{A}_T\right) - \mathbb{R}\left(\varsigma_T, \mathring{A}_T\right) - \delta\, V_\psi(\varsigma_{T+1}) \quad (29)$$

The optimal policy of positioning the UAV is achieved by learning the parameter policy, which is computed as:

$$H_\pi(\phi) = E_{\varsigma_T \sim D, \epsilon_T \sim N}\left[\log \pi_\phi(f_\phi(\epsilon_T; \varsigma_T) | \varsigma_T) - Q_\theta(\varsigma_T, f_\phi(\epsilon_T; \varsigma_T))\right] \quad (30)$$

By doing so, the positioning of the UAV is achieved optimally amidst several challenging factors. Figure 6 illustrates the positioning of UAVs. The pseudocode for DPSAC-based optimal positioning of the UAV is given in Algorithm 3.

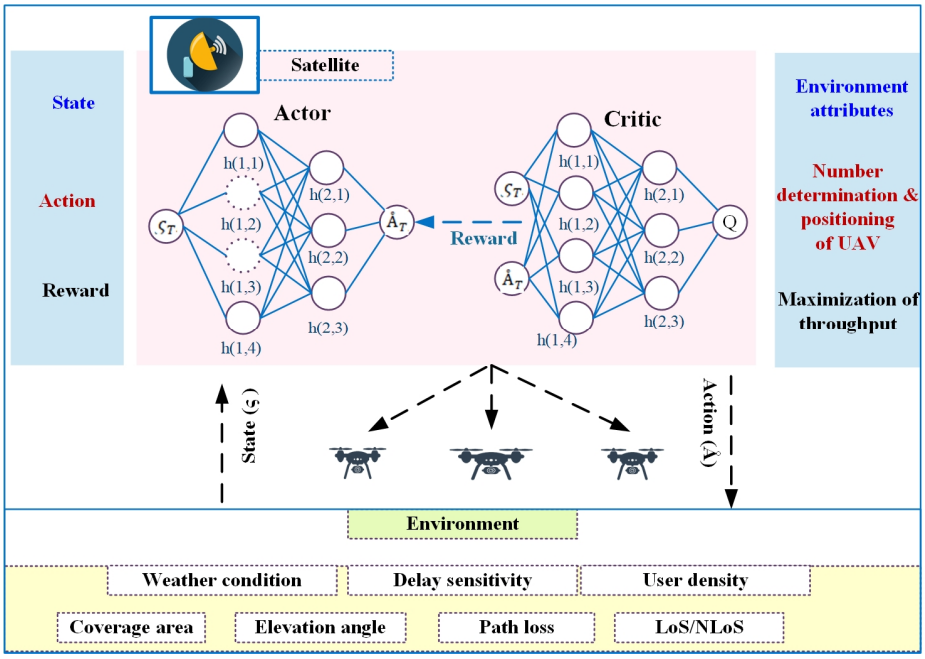

Figure 6. DPSAC-based multi-UAV positioning.

Algorithm 3 DPSAC-based UAV positioning.

1. Input: State attributes (ς)
2. Output: Number determination and positioning of UAVs
3. Begin
4. Parameter initialization $(\theta, \phi, \psi, \dot{\psi})$
5. **For** each episode, **do**
6. Set initial state $\varsigma_0 = 0$
7. **For** each time step, **do**
8. **Perform action** $\mathring{A}_T$ from the policy $\pi_\phi\left(\mathring{A}_T \middle| \varsigma_T\right)$
9. Move to the next state ς_{T+1}
10. Generate reward $\mathbb{R}$ based on $\mathring{A}_T$
11. Store $\left(\varsigma_T, \mathring{A}_T, \mathbb{R}, \varsigma_{T+1}\right)$ in the replay buffer
12. **End for**
13. **For** each gradient step, **do**
14. $\psi \leftarrow \psi - \alpha_v \hat{\nabla}_\psi H_v(\psi)$
15. $\theta_n \leftarrow \theta_n - \alpha_Q \hat{\nabla}_{\theta_n} H_Q(\theta_n)$
16. $\phi \leftarrow \phi - \alpha_\pi \hat{\nabla}_\phi H_\pi(\phi)$
17. $\dot{\psi} \leftarrow \tau\psi + (1-\tau)\dot{\psi}$
18. **End for**
19. **End for**
20. End

3.4. Energy-Efficient Path Planning

Path planning for UAVs is a crucial part of successful communication. After the UAVs have been dynamically positioned, the optimal path is planned in order to reduce their energy consumption. Many elements, such as wind conditions and limited availability of energy, influence UAV path planning. We propose a hybrid algorithm named SSO-DWM for path planning, which learns the obstacles' mobility and dynamically changes the path. This process performs UAV path planning to maximize coverage capacity and reduce path loss. For that, we consider the parameters of wind characteristics (đ), LoS/NLoS, energy (E), static and moving obstacles, distance (D), and optimality (OP). et, $\text{Ω} = \left(\text{đ},\ E,\ D,\ OP\right)$. Initial evaluation of all alternative pathways and trajectories enables the UAV to determine the best path, which can be expressed as:

$$PT_{B(\text{Ω})} = \text{ω} \times RM(OPT_i - OPT_B) + \text{ч} \times RM((OPT_i - OPT_B) \tag{31}$$

Equation (31) represents the evaluation of the UAV path by using path parameters $(PT_{B(\text{Ω})})$. OPT_i denotes the first selected path and OPT_j denotes the second selected path for the UAV to find an optimal path (OPT_B). ω, ч are used for the iteration process, which can be set to zero at the time of the searching process. RM denotes the random number which states the UAV time interval $[f_t = 0,\ f_t \neq 0]$ while $f_t \in [0, T]$. It depends on the UAV battery and mission. The flight time is the time taken by a UAV during motion and communication with IoT devices. The first path selected (OPT_i) is the best path, and no path is more optimal than itself, so $PT_{B(\text{Ω})}$ is '0', and the second path selected (OPT_j) is the worse than any of the paths, so the second path $PT_{B(wc,\ E,D,OP)}$ is also '0'. Therefore, an increase in ω and a decrease in ч improves the manipulation of the algorithm and reduces the investigation, which can be formulated as:

$$\text{ω} = \text{ω}_0 - \frac{\text{ω}_0}{\text{iter max}} \times \text{iter} \tag{32}$$

$$\text{ч} = \text{ч}_0 - \frac{\text{ч}_{\text{maxi}} - \text{ч}_0}{\text{iter max}} \times \text{iter} \tag{33}$$

The above two equations represent the manipulation of the algorithm for finding the optimal path using the SSO optimization algorithm with parameters wc, E, D, OP. Another set of parameters is also considered, such as LoS NLoS and SMO, which are used for detecting the static and moving obstacles which can be formulated as:

$$\begin{aligned} PT_{B(\text{LoS NLoS, SMO})} &= \text{Ю}(W_{\mathfrak{g}} PT_{B(\text{'}\Omega)} \text{head}(\text{LoS NLoS, SMO}) \\ &+ W_{\mathfrak{y}} \text{Sep}(\text{LoS NLoS, SMO}) + W_{\varrho} \text{SV}(\text{LoS NLoS, SMO}) \end{aligned} \tag{34}$$

Equation (34) represents the evaluation of the UAV path by using parameters ($PT_{B(\text{LoS NLoS, SMO})}$). The *head* (LoS NLoS, SMO) is used to calculate the angle between the direction of the current position, speed, and simulated trajectory direction. The angle of deviation must be more significant for a smaller value of *head* (LoS NLoS, SMO). *Sep* (LoS NLoS, SMO) represents the distance between simulated vector velocity (SV (LoS NLoS, SMO)) and trajectory. The overall value of $PT_{B(\text{LoS NLoS, SMO})}$ must be smaller to reduce the collision with obstacles. Ю, $W_{\mathfrak{g}}$, $W_{\mathfrak{y}}$, W_{ϱ} denotes the weighted value coefficient. Using DWM, obstacles in the path are detected, reducing the total energy consumption. The overall optimal path is formulated as:

$$OPTP_{B_{i,\ldots,n}} = PT_{B(\text{'}\Omega)} + PT_{B(\text{LoS NLoS, SMO})} \tag{35}$$

The energy consumption and path loss are reduced by using this approach. The effective path planning approach is depicted in Figure 7, in which the UAV optimally selects paths and detects obstacles using the proposed SSO-DWM. The proposed approach reduces path cost (1–4) and energy consumption compared to traditional UAV path planning. Traditional approaches detect the obstacles but have a high path cost, resulting in higher energy consumption. Algorithm 4 depicts the steps of SSO-DWM for energy-efficient path planning.

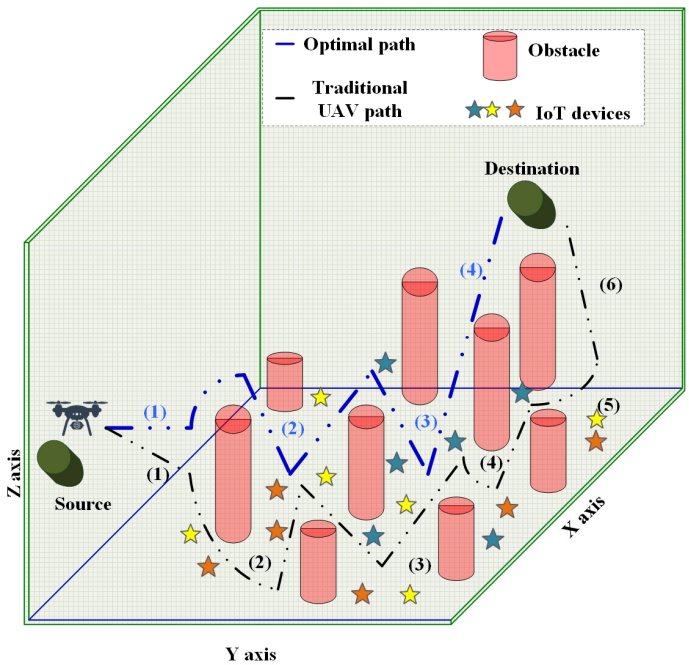

Figure 7. Hybrid SSO-DWM approach for obstacle detection.

Algorithm 4 Energy-efficient path planning.

1. Input $PT_{B('\Omega)}$, $PT_{B(\text{LoS NLoS, SMO})}$
2. Output $OPTP_{B_{i...n}}$
3. Begin to Evaluate the path
4. **while** criteria for stopping not met ($f_t \neq 0$), do
5. **For** each UAV
6. Evaluate path // *using (31)*
7. Manipulate path // *using (32) & (33)*
10. **End**
11. **For** each UAV
12. Evaluate obstacles // *using (34)*
13. **End**
14. **Compute** $OPTP_{B_{i...n}}$ // *using (35)*
15. **End** while
16. End

4. Simulation Setup, Comparative Analysis, and Experimental Results

The Dynamic-UAV technique is simulated using the NS 3.26 simulator [43]. Table 3 shows the hardware and software required to mimic our technique accurately. IoT devices, ground base stations, UAVs, and a satellite are all part of the network model. The prediction of weather conditions is performed first, followed by the prediction of the event. The placement and route planning of the UAVs is then performed to enhance the throughput and energy efficiency. The simulation parameters needed to execute the proposed technique are shown in Table 4.

Table 3. Hardware and software requirements of system.

System Components	Descrition
OS	Ubuntu 14.04 LTS
Network Simulator	NS3.26
RAM	8 GB
Hard Disk	60 GB
Processor	Intel(R) Core (TM) i5-4590S CPU @ 3.00 GHz 3.00 GHz

The Dynamic-UAV technique is experimentally analyzed. QoS, reliability, and energy efficiency are evaluated using the proposed method. This section comprises a simulation setup, comparative analysis, and summary. The proposed Dynamic-UAV approach is validated and compared to that of previously published studies, such as EIC-UAV [36], PSO-UAV [40], and DC-UAV [41], in terms of QoS (throughput (bps/Hz)), PDR, delay (ms)) reliability (coverage probability and the number of collected packets), and energy efficiency (KJ).

Table 4. Simulation Parameters.

	Parameters	Description
Network Parameters	Simulation area	1000 m ×1000 m × 900 m
	Number of IoT devices	100
	Number of UAVs	10
	Number of GBS	1
	Number of Satellite	1
	Transmit power of UEs	13 mW
	UAVs transmit power	4.55 W
	Blade chord	0.2 m
	Number of blades	4
	flying time	4 min
	Packet size	105 Bytes
	Wind speed	5 m/s
	Air density	1.156 kg/m3
	Bandwidth	1 MHz
	Noise power	−160 dBm
	Buffer distance	2 m
	Path loss constant	3
	Path width	12 m
	Carrier frequency constant	12
	Data bit rate	300 kbps
	Wavelength	1.45 m
	Capacity	70.32 kbps
	Cell coverage	0.93
	Path gain	−13.3 dB
	Response time constant	0.987
	QoS	0.92
	Algorithm Parameters	
LGRU	Total epochs	25
	Total learning rate	0.01
	Optimizer	Adam
	Hidden layers	2
	Dropout rate	0.5
DBOC	MR	25
	MP	0.10
DPSAC	Learning rate	0.0001
	Discount factor	0.8
	Hidden layers	3
	Activation function	ReLU
	Replay buffer size	105
	Updating interval	2
SSO-DWM	Iter max	100
	population	100

4.1. QoS Analysis

QoS is the measurement of overall network performance. The analysis of QoS is performed in terms of throughput, PDR, and delay.

4.1.1. Throughput Comparison

The amount of information transferred in a certain period is known as throughput. High throughput is essential for an effective communication system. Figure 8 represents the throughput achieved with an increasing number of UAVs, compared with existing approaches. As the number of UAVs increases, so does throughput, proving that the proposed Dynamic-UAV approach achieves a high throughput rate in comparison to existing works. This is because of weather prediction, multi-UAV placement, and events-aware clustering performed in the proposed Dynamic-UAV approach. The LGRU algorithm separates disaster and non-disaster regions. Then, the DBOC algorithm clusters the IoT devices to reduce complexity and energy consumption during the communication of UAVs with ground devices. DPSAC is used to determine the optimal number of UAVs to be deployed in disaster and non-disaster regions and then provides optimal positioning based on those numbers to increase the reliability of communications. Compared to the proposed Dynamic-UAV approach, the location of the UAV is fixed at a constant altitude in the DC-UAV approach [41], which reduces the throughput and increases communication complexity between UAVs and IoT devices. In PSO-UAV, the impact of weather conditions on UAV positioning is not addressed, which reduces the throughput performance [40]. The EIC-UAV approach only considers windspeed while other parameters considered in our approach are not taken into account; thus, it also increases the data loss, resulting in low throughput performance [36].

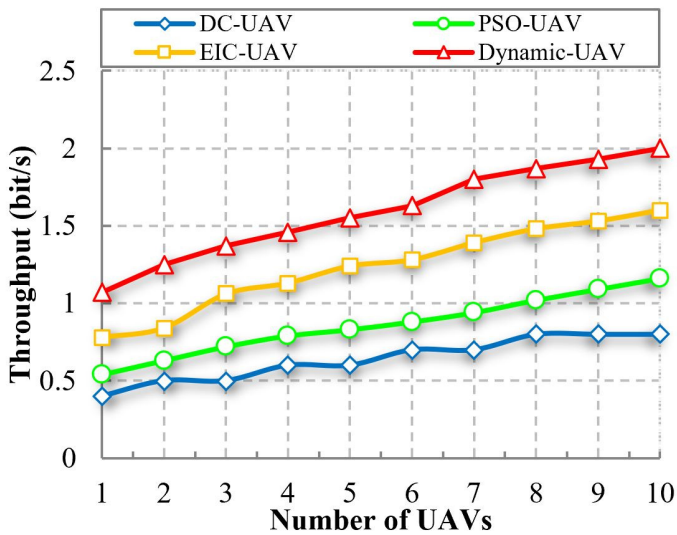

Figure 8. Number of UAVs vs. Throughput.

With 10 UAVs, the proposed Dynamic-UAV approach achieves a throughput of 2 bit/s, while the existing work EIC-UAV, PSO-UAV, and DC-UAV achieve 1.6 bit/s, 1.16 bit/s, and 0.8 bit/s, respectively. Compared to the existing approaches, the proposed work has a throughput rate of 1.593 bit/s on average, where the average throughput rate is 1.233 bit/s in EIC-UAV, 0.86 bit/s in PSO-UAV, and 0.64 bit/s in DC-UAV.

4.1.2. PDR Comparison

PDR is the ratio of packets successfully delivered to the destination compared to the total number of packets transmitted by the sender. Figure 9 compares PDR with the number of UAVs to existing works. The PDR increases with the number of UAVs, as illustrated in Figure 9. The proposed Dynamic-UAV method achieves a high PDR in comparison to

the previous works. Event-aware clustering is utilized to boost the PDR in the proposed Dynamic-UAV approach. In PSO-UAV, the information from all the devices is collected randomly by UAVs, thus increasing communication complexity and decreasing the PDR. The PDR is lower due to the unaddressed impact of weather conditions in the EIC-UAV approach. The DC-UAV approach leads to a lower PDR due to the fixed altitude of the UAV, channel fluctuations, and inability to adjust its position dynamically.

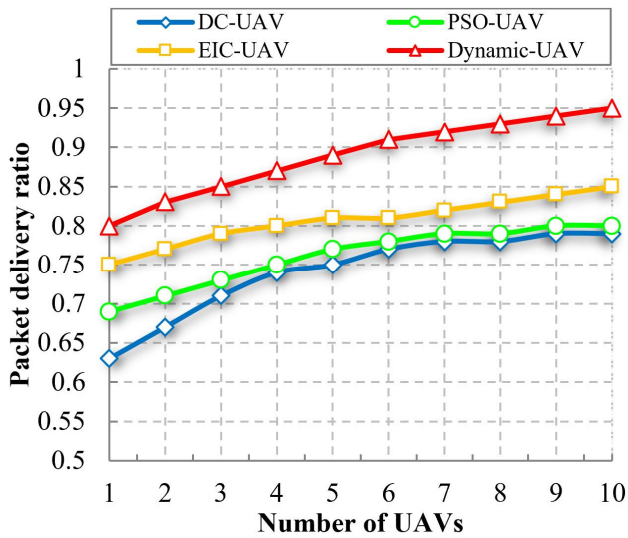

Figure 9. Number of UAVs vs. PDR.

When the number of UAVs increases to 10, the proposed Dynamic-UAV approach achieves a PDR of 0.95. In contrast, the state-of-the-art approaches DC-UAV, PSO-UAV, and EIC-UAV earn PDRs of 0.79, 0.8, and 0.85, respectively. The average PDR of the proposed work is 0.88. In terms of PDR, the numerical results depicted in Figure 9 reflect the effectiveness of the proposed method.

4.1.3. Delay Comparison

Delay is the time taken by a packet from the source IoT device to its destination. It is formulated as follows:

$$\mathfrak{z} = \mathfrak{p} - \mathfrak{t} \tag{36}$$

where $\mathfrak{z}$ represents the delay, $\mathfrak{p}$ denotes the packet transmission time, and $\mathfrak{t}$ shows the actual transmission time. Figure 10 depicts the delay as the number of IoT devices increases. The proposed Dynamic-UAV transmits packets from source to destination with a shorter delay than the existing approaches. It is due to proper clustering using the DBOC algorithm, which clusters the IoT devices in disaster and non-disaster regions and selects the optimal CH based on energy and centrality. The existing EIC-UAV approach used shift algorithm for clustering ground devices in which a detailed explanation of centroid selection is not present. In the PSO-UAV approach, the UAV tries to collect information from all the sensors, which increases the delay when the number of sensors increases. Due to the fixed altitude, the DC-UAV approach encounters path loss; hence, the delay increases when the number of IoT devices increases.

When we increased the number of IoT devices to 100, Dynamic-UAV encountered a 35 ms delay in packet transmission. In contrast, the DC-UAV, PSO-UAV, and EIC-UAV approaches encounter delays of 150 ms, 120 ms, and 130 ms, respectively. The average delay in the proposed work is 18.5 ms for the number of IoT devices, which is less than the existing approaches.

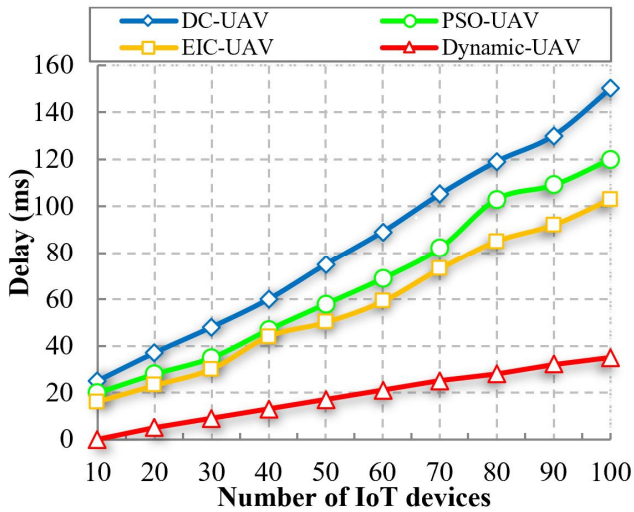

Figure 10. Delay vs. Number of IoT devices.

Figure 11 depicts the delay experienced during packet transmission as the number of UAVs increases. The length of delay increases with the number of UAVs. The proposed approach outperforms the existing schemes due to multi-UAV positioning in terms of delay. UAVs are effectively positioned using the DPSAC algorithm, which optimally determines the number of UAVs required for a specific area while minimizing communication delays between UAVs and IoT devices. The EIC-UAV approach is inefficient when the number of UAVs increases because of the absence of centroid during the clustering of ground devices. In PSO-UAV, the algorithm falls into local minima for an increasing number of UAVs, due to which the delay also increases, whereas the number of UAV increases the DC-UAV encounters high delay because of its fixed altitude.

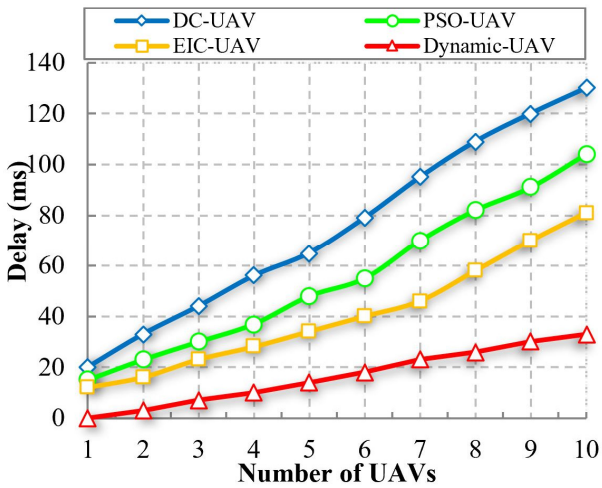

Figure 11. Delay vs. Number of UAVs.

When the number of UAVs is increased to 10, the proposed Dynamic-UAV approach has a delay of 33 ms. On the other hand, DC-UAV, PSO-UAV, and EIC-UAV have delays of 130, 104, and 81 milliseconds, respectively. Our system experiences an average delay of 16.4 ms, validating its effectiveness. The average performance of each QoS metric is displayed in Table 5.

Table 5. QoS analysis.

Approaches	Average Throughput (bit/s)	Average PDR	Average Delay (ms)	
	No. of UAVs	No. of UAVs	No. of Devices	No. of UAVs
DC-UAV	0.64	0.74	83.8	75.1
PSO-UAV	0.86	0.76	67.1	55.5
EIC-UAV	1.23	0.80	57.5	40.8
Dynamic-UAV	1.59	0.88	18.5	16.4

4.2. Reliability Analysis

Reliability is the measure of the successful delivery of data packets without loss. The proposed reliability analysis is compared in terms of coverage probability and a number of collected data packets.

4.2.1. Coverage Probability Comparison

The coverage probability is defined as the distance that UAVs cover as their altitude increases. Figure 12 depicts the coverage probability of the proposed Dynamic-UAV technique relative to the UAV's height, compared to the existing approaches.

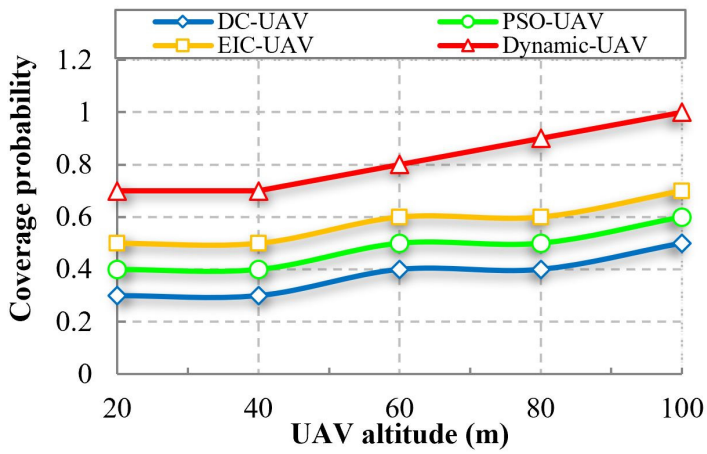

Figure 12. The altitude of UAVs vs. coverage probability.

In Figure 12, it is demonstrated that as the altitude of UAVs increases, so does the likelihood of coverage. Since the DPSAC algorithm considers several different parameters while positioning multi-UAVs, the proposed Dynamic-UAV method achieves a high probability of coverage in comparison to previous techniques as a result.

On the other hand, the most traditional systems use UAVs that are fixed in place, resulting in a limited likelihood of coverage. Only wind speed is not sufficient for positioning of UAV, and that is why coverage probability of the EIC-UAV approach is affected. The coverage probability of PSO-UAV is also affected due to the lack of weather conditions and other parameters. After reaching a maximum height of 100 m, the coverage probability of the proposed approach increases to 1, while that of the existing DC-UAV, PSO-UAV, and EIC-UAV techniques is only 0.5, 0.6, and 0.8, respectively. The proposed Dynamic-UAV approach has an average coverage probability of 0.82, significantly higher than the previous DC-UAV, PSO-UAV, and EIC-UAV techniques.

4.2.2. Number of Collected Packets Comparison

Compared to previous methodologies, Figure 13 shows the number of packets captured as a function of UAV speed. In proportion to the speed of UAVs, the pace of packet collection slows down. The Dynamic-UAV technique has a greater packet-collecting rate than previous approaches.

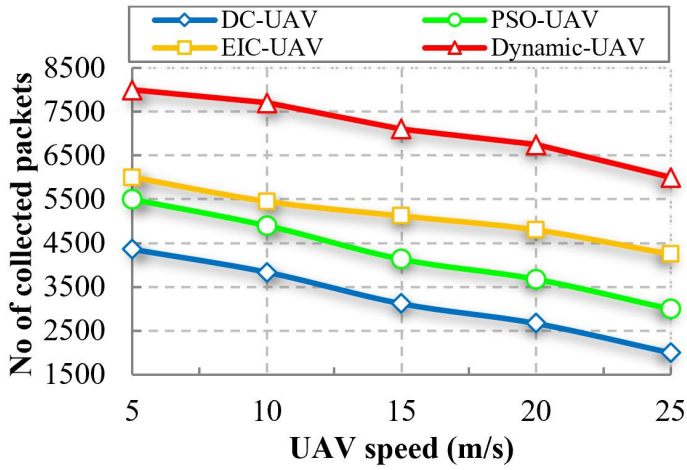

Figure 13. Number of the collected packet compared to UAV speed.

Effective path planning is performed using the hybrid SSO-DWM, which finds an optimal path, detects obstacles during flight, and increases the packet collection rate despite increasing UAV speed. In contrast, the existing DC-UAV, PSO-UAV, and EIC-UAV approaches consider limited path planning parameters, decreasing the packet collection rate. When the speed of the UAV is 25 m/s, the suggested Dynamic-UAV approach collects 6000 packets, while the existing DC-UAV, PSO-UAV, and EIC-UAV systems gather 2000, 3000, and 4250 packets, respectively. The proposed work has an average packet collection rate of 7109, outperforming the existing DC-UAV, PSO-UAV, and EIC-UAV techniques.

Figure 14 depicts the correlation between UAV altitude and the number of collected packets. From Figure 14, it is clear that the packet collection rate grows linearly with the increasing altitude of UAVs up to 80 m. The graph declines after 80 m (the saturation threshold) since the UAV is designed to fly only up to 80 m. Due to event/weather predictions and multi-UAV placement, the Dynamic-UAV technique achieves a large number of collected packets even at that height.

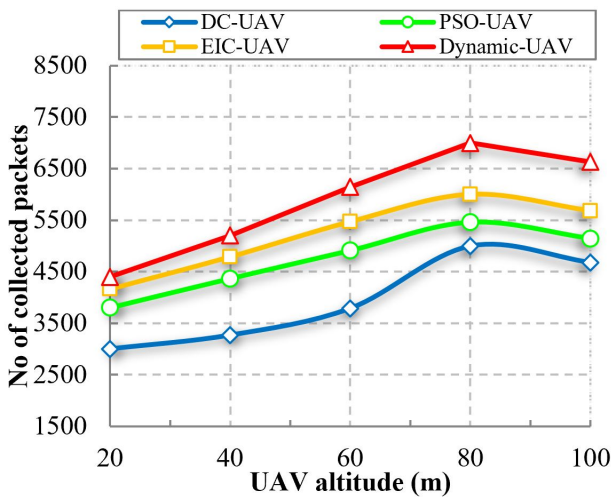

Figure 14. Number of collected packets to UAV altitude.

The LGRU prediction algorithm is used to predict weather and events based on past data, reducing the risk of UAVs suffering from physical damage. In contrast, the DPSAC algorithm is used to optimize UAV placement to provide enough coverage to IoT devices, even when UAVs fly at a high altitude. The average performance of each reliability matric is presented in Table 6.

Table 6. Reliability analysis.

Approaches	Average Coverage Probability	Average No. of Collected Packets	
	UAV Altitude (m)	UAV Speed (ms)	UAV Altitude (m)
DC-UAV	0.38	3197	3947
PSO-UAV	0.48	4243	4736
EIC-UAV	0.59	5124	5221
Dynamic-UAV	0.82	7109	5875

4.3. Energy Consumption and Efficiency Analysis

The amount of energy consumed when the number of IoT devices increases is known as energy consumption (∂). It is measured by taking the difference of total energy (Λ) to the residual energy (β) of the IoT devices, which is formulated as follows.

$$\partial = \Lambda - \beta \tag{37}$$

We computed the total energy consumed by the IoT devices. Figure 15 represents the comparison of energy consumption to the number of IoT devices. Figure 15 demonstrates that, as the number of IoT devices increases, so does their energy consumption. However, the Dynamic-UAV approach reduces energy consumption due to event/weather prediction, event-based clustering, and multi-UAV positioning. Predicting weather/events using the LGRU algorithm and event-aware clustering using the DB-OPTICS method minimizes energy consumption under extreme weather conditions. DPSAC-based multi-UAV positioning finds the suitable altitude for UAVs, decreasing the energy consumption and minimizing the delay significantly.

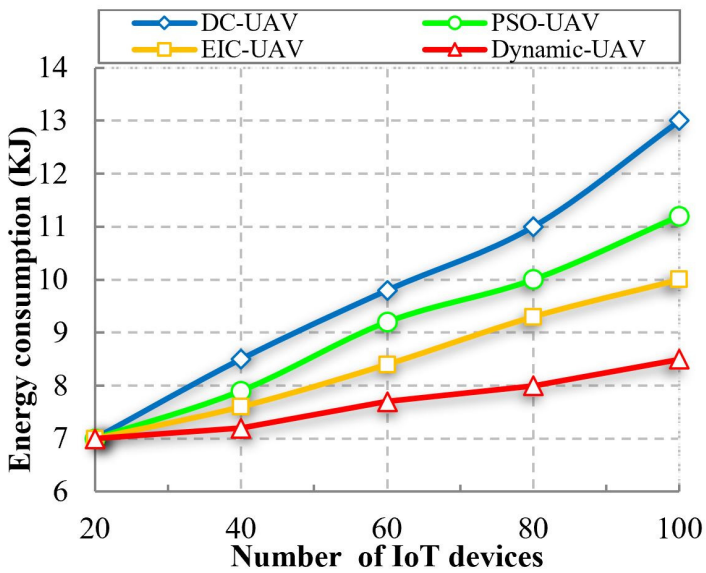

Figure 15. Energy consumption to the Number of IoT devices.

PSO-UAV solely considers wind speed; however, obstacles were not considered, resulting in poor path planning, increased risk of damage, and high energy consumption. The proposed approach consumes 8.5 kilojoules of energy for 100 IoT devices, compared to 13, 11.2, and 10 kilojoules for DC-UAV, PSO-UAV, and EIC-UAV. The proposed work consumes 7.68 kilojoules of energy on average, compared to DC-UAV, PSO-UAV, and EIC-UAV methods.

Energy efficiency is known as the minimum amount of energy consumed when the number of UAV devices increases. A perfect system must have high energy efficiency. More devices with low energy consumption lead to high energy efficiency. The energy efficiency is calculated by:

$$\mathrm{EE} = \frac{\text{Energy consumed}}{\text{Initial Energy}} \tag{38}$$

Figure 16 demonstrates that, as the number of UAVs increases, so does energy efficiency. Our proposed Dynamic-UAV approach provides excellent energy efficiency due to event/weather prediction and energy-efficient path planning. Efficient path planning uses a hybrid approach of the SSO-DWM methods to find the optimal path and detect obstacles, increasing energy efficiency. Collectively, these approaches are implemented to improve the overall system performance in an orderly manner.

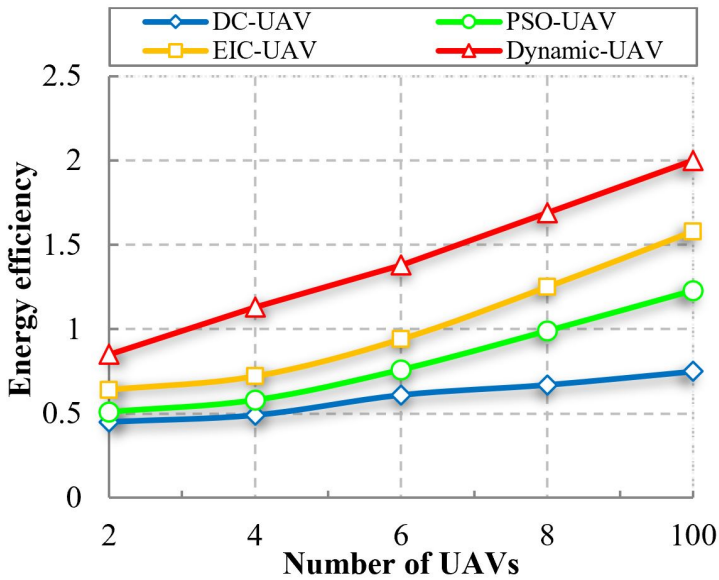

Figure 16. Energy efficiency to Number of UAVs.

Using 100 UAVs, the proposed Dynamic-UAV technique has an energy efficiency of 2, whereas the existing DC-UAV, PSO-UAV, and EIC-UAV are 0.75, 1.23, and 1.58, respectively. The proposed work has an average energy efficiency of 1.41 compared to the existing ones. A lack of weather conditions, lack of consideration of static and moving obstacles, and a lack of dynamic positioning reduces the performance of EIC-UAV, PSO-UAV, and DC-UAV, which results in higher energy consumption and lower energy efficiency. The amount of average energy consumption and average energy efficiency is presented in Table 7.

Table 7. Average energy consumption and energy efficiency analysis.

Approaches	Average Energy Consumption (KJ)	Average Energy Efficiency
DC-UAV	9.86	0.594
PSO-UAV	9.05	0.656
EIC-UAV	8.46	1.026
Dynamic-UAV	7.68	1.544

5. Application of Dynamic-UAV Approach

It is essential to establish reliable communication during a disaster. The proposed work can be applied to relay the information when the existing ground network is no longer functional. The conventional communication network is not functional during floods, fires, or earthquakes. In such a case, a UAV with a long endurance time can be used to enable the network and restore the information exchange. The proposed work can be applied in the real-time vehicular ad hoc network (VANET) environment. The UAV-based monitoring system is widely adopted in-vehicle road safety. The VANET environment is highly vulnerable to manmade disasters (i.e., accidents). Hence, a monitoring and early detection system should be deployed to mitigate and rescue the losses caused by these disasters.

6. Summary

This section summarizes the proposed Dynamic-UAV approach presented in this paper. The numerical analysis of the performance of our approach, along with the existing approaches presented in Tables 5–7 proves its efficacy in terms of QoS, reliability, and energy efficiency. The proposed Dynamic-UAV approach achieves linear performance when the number of UAVs and IoT devices increases because of the linear capacity constraints of each UAV and IoT device, respectively. The proposed methods and algorithms support the linearity of the proposed work. The analysis of the context of the environment periodically helps the approach to differentiate disaster regions from non-disaster regions and maintain the system's performance in any situation. The communication reliability between the devices and UAVs is enhanced by clustering the devices at the ground level. Further, the proposed approach takes advantage of 5G communication to eradicate bandwidth and latency issues. The dynamic determination of the required number of UAVs and the ideal location of the UAVs helps to improve the coverage and total throughput. Considering both static and dynamic obstacles in the environment eliminates the chances of collisions and improves the coordination between UAVs. This helps to obtain the optimal path and improves the system's energy efficiency. The highlights mentioned above of the Dynamic-UAV approach confirm its optimal performance. The individual LGRU, DBOC, DPSAC, and SSO-DWM techniques jointly improve the overall system performance. Table 8 shows the temporal complexity involved in executing the proposed method.

Table 8. Time complexity analysis.

Schemes	Complexity	Symbols Description
Weather or event prediction	$O\left(f_t h^{s2} + f_t h^s \mathrm{CI}\right)$	f_t is the flight time, h^s represents hidden state, and CI is the current input
Events-aware clustering	$O(n \ \log n)$	n is the iterations number
Multi-UAV positioning	$O\left(K\left\|\text{Å}\right\|\right)$	K is the number of iterations
Energy-efficient path planning	$O(\text{Iter max} \times V \times W \times X)$	Iter max is maximum iteration, V is maximum search iterations, W is the size of the population, and X is fitness time.

7. Conclusions

This study addresses the major obstacles in 5G-assisted UAV communications, such as high dynamicity and weather-related disturbances. Based on historical weather conditions and visuals of the environment, a dynamic-UAV method is proposed that performs weather prediction and event monitoring utilizing the LGRU algorithm to understand the environmental context. The DBOC algorithm is used to cluster IoT devices in disaster and non-disaster areas to improve communication reliability between the devices and UAVs. The DPSAC method is used to determine the required number of UAVs. The DPSAC algorithm also performed dynamic positioning of UAVs by considering predicted weather conditions and other important elements to enhance coverage probability and throughput. Obstacle-aware path planning is achieved using the SSO-DWM algorithm, which considers static and dynamic obstacles to identify the ideal path, conserve energy, and improve LoS communication. The proposed approach is evaluated by comparing it to existing techniques in terms of throughput, PDR, delay, coverage probability, number of collected packets, energy consumption, and energy efficiency. The effectiveness of our approach is assessed using numerical analysis, which demonstrates that our method surpasses all existing methods across all metrics. The future development of the proposed work will focus on enhancing the security of UAVs to ensure uninterrupted services.

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