A Swarm Intelligence-Enabled UAV Communication Model for Resilient Disaster Response and Emergency Networks

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ABSTRACT

In this article, a new model of an unmanned aerial vehicle (UAV) communication system is discussed. The UAV communication model is based on swarm intelligence methods. The intention of the proposed UAV model is to support the requirements of robust disaster response and emergency networking scenarios. The suggested framework uses Artificial Intelligence (AI) in the form of deep reinforcement learning to optimize how the UAV operates through the function of planning UAV trajectories, managing energy, and adapting the delivery of dynamic coverage in extremely unpredictable environments. The proposal also uses a cluster-based method to prioritize critical users and allocate communication resources in real-time based on need. Simulation results suggest that the UAV communication model performs much better than traditional methods of deploying UAVs. Specifically, the UAV communication model demonstrated an increase in UAV coverage of 35% and a delivery rate of packets by 28% compared with standard methods of communicating via UAVs. Furthermore, system latency is reduced by 23%, resulting in a faster and more efficient method for communicating with emergency services as well. The model also improves energy usage, allowing for approximately 20% more operational time for the UAV. Additionally, the model is very adaptable to changing and dynamic conditions associated with a disaster and provides a stable link for communication even when part or the entire network becomes unavailable. Therefore, the swarm intelligence-based communication model for UAVs will serve to improve the reliability, efficiency, and resilience of temporary wireless technologies.

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1. INTRODUCTION

The frequency, magnitude and impact of a diverse types of disasters — both natural and man-made — have highlighted the need for communication networks that are both resilient and can be quickly deployed [1,2]. The use of traditional terrestrial-based communication networks has often resulted in networks being damaged, dysfunctional due to lack of power, or destroyed as a result of increased traffic during these incidents; thus hampering the coordination of services among emergency responders which delays rescue efforts and ultimately exacerbates the impacts of disaster mitigation systems. Because of these issues, building a dependable, flexible, and readily available communication network in place of the damaged communications networks created by a disaster has become a major area of research [3].

In such situations, an excellent alternative to activate short-term communication is using an Unmanned Aerial Vehicles (UAVs). To reinstate connectivity, UAVs work as aerial base stations, relays, or data collectors due to their flexibility, ease of distribution and working capacity at challenging conditions. Nevertheless, existing UAV-based communication systems are constrained by several challenges, including inefficient trajectory planning, constrained energy resources, inadequate coverage, and poor adaptability to dynamic and impulsive disaster conditions [4].

Recent studies have placed growing emphasis on the integration of artificial intelligence (AI) approaches in unmanned aerial vehicle (UAV) communication systems to overcome these difficulties. Deep reinforcement learning (DRL), in particular, is a promising way to enable UAV operation to make autonomous decisions based on learning the most advantageous strategy from environmental feedback [5]. Many earlier approaches still regard UAVs as independent platforms and thus miss out on taking advantage of multiple UAVs working together as a single coordinated swarm. The other challenges such as prioritizing users, dynamically allocating resources, and energy-aware operations have also not been sufficiently resolved in existing models [6].

Swarm intelligence is derived from the collective behaviour of social creatures, such as birds and insects, and creates a very effective way to coordinate many UAV's in an adaptive, distributed way. By utilising swarm-based techniques, UAVs can work together to optimise coverage, maintain connectivity and respond quickly to changing conditions. By combining swarm intelligence with DRL, any system will be able to provide both global coordination and local adaptability thereby being particularly useful in disaster response operations [7].

This paper proposes a UAV communication framework supported by swarm intelligence to address the challenges of resilient disaster response and emergency communication networks [8]. By combining decision-making through deep reinforcement learning (DRL) with cluster resource allocation, this framework allows for optimized user trajectories, energy consumption and communications coverage. Furthermore, the framework provides a priority for the delivery of service to critical users (rescue personnel and teams), which makes use of the limited resources available in the network [9].

The key contributions of this work are as follows: (1) The creation of an artificial intelligence and swarm intelligence-based framework for UAV communication that uses deep reinforcement learning (DRL) to enable autonomous operation in an adaptive manner; (2) A to dynamically allocate resources and prioritize users; (3) The optimization of energy consumption and flight path in order to extend the service life of the UAV; (4) Extensive simulations indicating a substantial increase in coverage, packet delivery success rates, latency, and energy efficiency of the proposed system when compared to conventional systems.

The rest of this paper is organized as follows: In Section 2, we discuss prior research on AI-based optimization methods for UAV-based communications; Section 3 describes the proposed methodology; and Section 4 gives results and analysis, followed by future research directions in Section 6.

2. LITERATURE REVIEW

[10] Proposed an Attention-Enhanced Dueling Double Deep Q Network (AD3QN) algorithm for UAV-assisted emergency communications within disaster zones. This approach combines an attention mechanism with deep reinforcement learning (RL) to optimize the trajectory of UAVs in consideration of user distribution, communication quality and electromagnetic interference. The experimental results indicate that the AD3QN algorithm converges faster and improves communication efficiency and mission completion rate compared to traditional deep RL approaches, but it only supports trajectory optimization for one to many (1:N) UAV communications and does not support cooperative swarm intelligence, dynamic resource allocation or energy-based coordination with multiple UAV's which limits the scalability of the model to support multiple UAVs in a large-scale disaster response.

The Distributed Offloading for Multi-UAV Swarms (DOMUS) framework for mobile edge computing with 5G heterogeneous networks as presented in [11]. The approach has been developed using distributed optimization strategies for computation offloading, UAV task scheduling, and resource allocation to reduce the amount of time, energy consumed by an operation and to maximise the level of utility delivered by the network. Results from simulations indicated that the framework resulted in lower execution times and lower energy use relative to traditional offloading methods. In general, however, this study mainly looks at computation offloading in the context of MEC and does not look into how to support disaster communication requirements such as prioritising emergency users, adaptive recovery from system failures, optimising communication coverage area or providing resilient UAV networks in situations where critical components of the infrastructure have been disrupted by disasters.

A framework for an Internet of Things (IoT)-driven optimization using big data has been developed by [12] for UAV assisted post-disaster communication coverage. The proposed method uses IoT data analytics to find optimal locations to deploy UAVs as well as areas where communication coverage exists after a disaster. This will create better wireless connectivity and fewer areas where there is no communication. The results of experimentation showed better overall communication coverage and more efficient deployment of UAVs compared to traditional placement methods. The focus of the framework was solely on coverage optimization, therefore it does not take into account intelligent coordination with UAV swarming, deep reinforcement learning, trajectory planning, dynamic bandwidth allocation and energy efficient communication management when dealing with changing disaster scenarios.

[13] Given a systematic review of UAV swarm networks and their use of computational offloading. The study provides insight into computation offloading strategies; communication architecture; edge computing frameworks and how UAV swarms manage resources. The authors of this paper overview numerous systems engineering challenges such as latency, energy consumption, scalability, scheduling of tasks and reliable coordination of multiple UAVs. Although this review provides useful information regarding current methods for UAV computation offloading, it fails to identify a viable practical disaster-oriented communication model incorporating the fundamentals of swarm intelligence, deep reinforcement learning (DRL), dynamic clustering and fault-tolerant networking, indicating the need for better intelligent UAV communication models in general.

3. METHODOLOGY

3.1 System Model and Architecture

The proposed system involves a disaster area where the local communication infrastructure has been severely affected. The objective of the proposed system is to restore communications to a disaster area by deploying a swarm of N UAVs that are responsible for providing temporary wireless communications to ground users $U = \{u_1, u_2, \ldots, u_M\}$. Each UAV is capable of acting as an airborne base station with the ability to move, transmit data and coordinate with other UAVs in the immediate vicinity of the local area. The operation of the system is distributed since UAVs will make local decisions and contribute to the overall effort to maintain reliable and effective communications as a group.

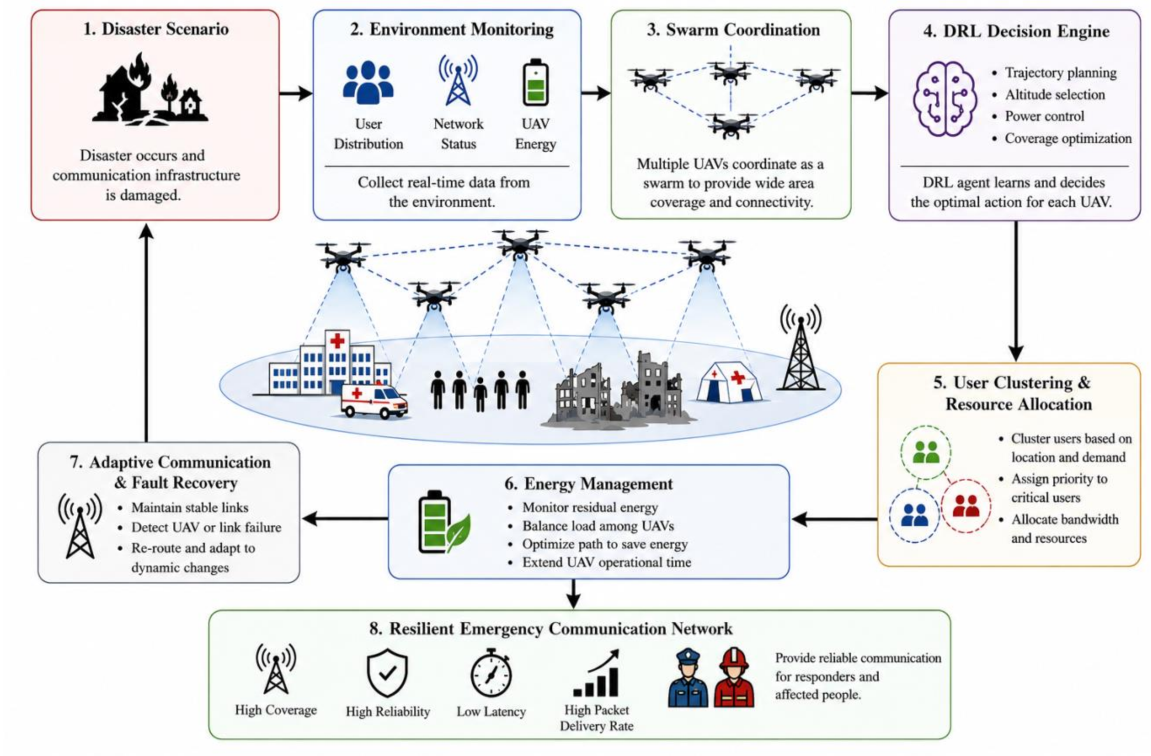

Figure 1. Proposed UAV Communication Model

As shown in figure 1 each UAV will continuously monitor its surroundings including such factors as user density, channel quality, residual energy available, etc., in order to adapt its trajectory as well as communication parameters and resource allocation strategies in a way that ultimately provides seamless connectivity to critical users during high levels of chaotic environmental scenarios due to natural, manmade, or other adverse situations.

3.2 Problem Formulation

The proposed system can be formulated as a multi-objective optimization problem that maximises the overall performance of the network while minimising the total amount of resources used. The objective function is defined as follows:

$$\max F = w_1 C + w_2 P - w_3 L - w_4 E \qquad (1)$$

Where C is the coverage ratio, P is the packet delivery ratio, L is the latency, and E is the total energy consumed by the network. The values of the weights w_1, w_2, w_3, w_4 can be adjusted to reflect the relative importance of each of the four objectives.

The coverage ratio is computed as:

$$C = \frac{N_{Covered}}{N_{Total}} \quad (2)$$

where $N_{Covered}$ represents the number of users successfully served and N_{Total} denotes the total number of users. The mean latency is defined as:

$$L = \frac{1}{K}\sum_{k=1}^{K}(t_k^{receive} - t_k^{send}) \quad (3)$$

where K represents the number of transmitted packets. The total energy consumption of the UAV swarm is expressed as:

$$E = \sum_{i=1}^{N}(E_i^{move} + E_i^{comm}) \quad (4)$$

This expression establishes the best trade-off between improving communication efficiency and minimizing functioning cost.

3.3 Swarm Intelligence-Based UAV Coordination

Swarm Intelligence Principles are used for effective coordination between groups of UAVs. In this implementation, each UAV modifies its direction based on its own history and how the rest of the UAVs have moved within the collective. The equation for modifying velocity and location at any point in time (t) is as follows:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 \left(P_i^{best} - X_i(t)\right) + c_2 r_2 \left(G^{best} - X_i(t)\right) \quad (5)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (6)$$

Where $X_i(t)$ is the position of UAV '***i***' at a specific time (t) and $V_i(t)$ is the velocity of UAV '***i***' at a specific time (t). P_i^{best} represents an individual UAV's best recorded position (e.g., local best), while G^{best} represents all UAVs together at the location of the best position based on all of their individual positions. ω, c_1 and c_2 determine how aggressive or exploratory (or both) the UAV will be. The random numbers r_1 and r_2 are between zero and one.

This mechanism allows UAVs to achieve maximum distribution in the disaster zone while minimizing redundant or overlapping coverage and providing cooperative behaviors to maintain network connectivity throughout the operation.

3.4 Deep Reinforcement Learning-Based Decision Model

Every UAV has a Deep Reinforcement Learning (DRL) agent to improve its flexibility. The UAV operates in a Markov Decision Process (MDP), where it receives the current state of the environment S_t, takes an action A_t, and receives feedback (a reward) R_t.

The state is defined as:

$$S_t = \{X_i, E_i^{res}, D_u, Q_n\} \quad (7)$$

where X_i is the UAV position, E_i^{res} is residual energy, D_u denotes user dissemination, and Q_n represents network settings. The action space includes UAV action, transmission power regulation, altitude management, and bandwidth distribution.

The reward function is formulated as:

$$R_t = \alpha_1 C_t + \alpha_2 P_t - \alpha_3 L_t - \alpha_4 E_t \quad (8)$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are weighting coefficients. The objective of the DRL agent is to learn an optimal policy that maximizes the expected cumulative reward:

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right] \quad (9)$$

where γ is the discount factor. This allows UAVs to adjust their decisions dynamically based on environmental variations.

3.5 Clustering-Based Resource Allocation

The users are linked into multiple clusters based on their spatial location and service demands to enhance communication efficiency. Let K verifies the number of clusters. Each cluster C_k is defined as:

$$C_k = \left\{u_j \middle| \; \left\| X_{u_j} - \mu_k \right\| \leq d_{th} \right\} \quad (10)$$

μ_k denotes the centroid of cluster k and d_{th} is a distance threshold. Each cluster is assigned to the nearest UAV for service.

Resource allocation is performed dynamically by prioritizing users based on urgency. The bandwidth allocated to each user is calculated as:

$$B_j = \frac{w_j}{\sum w_j} . B_{Total} \quad (11)$$

where w_j signifies the priority weight of user j. This ensures that critical users, such as emergency responders, receive higher bandwidth and lower latency.

3.6 Energy Optimization Model

Energy efficiency is a critical factor in UAV operations. The total energy consumption of each UAV is modeled as:

$$E_i = P_{move} \cdot T_{move} + P_{comm} \cdot T_{comm} \quad (12)$$

where P_{move} and P_{comm} are power consumption for movement and communication, respectively, and T_{move}, T_{comm} are the corresponding durations.

UAVs are continuously monitoring their remaining energy, and will alter their behaviour depending on that remaining energy. If the remaining energy of a given UAV drops below an established threshold, it will redistribute its tasks to its neighbouring UAVs as a means of performing load balancing between those neighbouring UAVs. This action increases the length of time that a network of UAVs will have an operational lifespan.

3.7 Adaptive Communication and Fault Tolerance

This system has been established to function successfully in dynamic and uncertain disaster settings. Adaptive features have been included for operating under condition of user mobility, network congestion and failure of a UAV. If a UAV (either fails or exceeds range), neighbouring UAVs will automatically move to position themselves into areas that were previously covered, to remove coverage gaps as a result of UAV.

This also allows users to change communication parameters in real-time and adjust UAV trajectories frequently enough to maintain stable connectivity and limit any disruption in services as a result of changing parameters and UAV failures. These adaptations help to create a more reliable emergency communication network.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

As part of the evaluation process of the Swarm Intelligence-enabled UAV Communication Model, comprehensive simulations were conducted to assess its operational capabilities in emergency communication environments (e.g., disasters). The experiments were conducted in a simulated disaster scenario under the assumption that existing terrestrial-based communications were either partially dysfunctional or absent. A swarm of UAVs was deployed to establish temporary wireless communication for users in the disaster-affected area while also providing an uninterrupted means of communications between the members of the emergency response team(s).

A disaster area of 5 km × 5 km was simulated over a period of time, where ground users were randomly spread throughout the area (totally 250 users). The simulation had the wireless capability of 20 UAVs that provided coverage to the region. Each UAV operated at an altitude of 100 to 200 m and had a communication radius of 800 m. The bandwidth of the communication system was set at 20 MHz, and the total duration of the simulation was 1000 seconds. The learning rate for training the Deep Reinforcement Learning (DRL) agent will be set to 0.001 and its discount factor will be set to be 0.95. The proposed framework utilizes a combination of cooperative UAV coordination, adaptive trajectory optimization by means of DRL, clustering-based resource allocation (user prioritization), and an energy-aware optimization to maximize the operational lifetime of the UAVs.

In order to illustrate the effectiveness of the proposed approach, a comparison was made to three representative baseline methods listed below:

- Conventional UAV Communication;
- DRL Based UAV Communication;
- Swarm Based UAV Communication;
- Proposed SI-DRL UAV Communication Model

The evaluation used seven performance metrics – covering ratio, packet delivery, average latency, throughput, energy efficiency, network lifetime and communication reliability – as basis for performance testing. Table 1 shows simulation parameters for the proposed model.

Table 1. Simulation Parameters

Parameter	**Value**
Simulation Area	5 km × 5 km
Number of UAVs	20
Number of Users	250
UAV Altitude	100–200 m
Communication Range	800 m
UAV Speed	10–25 m/s
Simulation Time	1000 s
Channel Bandwidth	20 MHz
Packet Size	1024 Bytes
Learning Rate	0.001
Discount Factor	0.95

4.2 Coverage Ratio Analysis

The ratio of coverage is a measure of the percentage of victims of a disaster that receive communication services from an unmanned aerial vehicle (UAV) network. Coverage at a high level is critical to successful disaster communications. The continuity of communications (i.e., the availability of uninterrupted) helps to facilitate the effective coordination of emergency responders and the public in the event of a disaster.

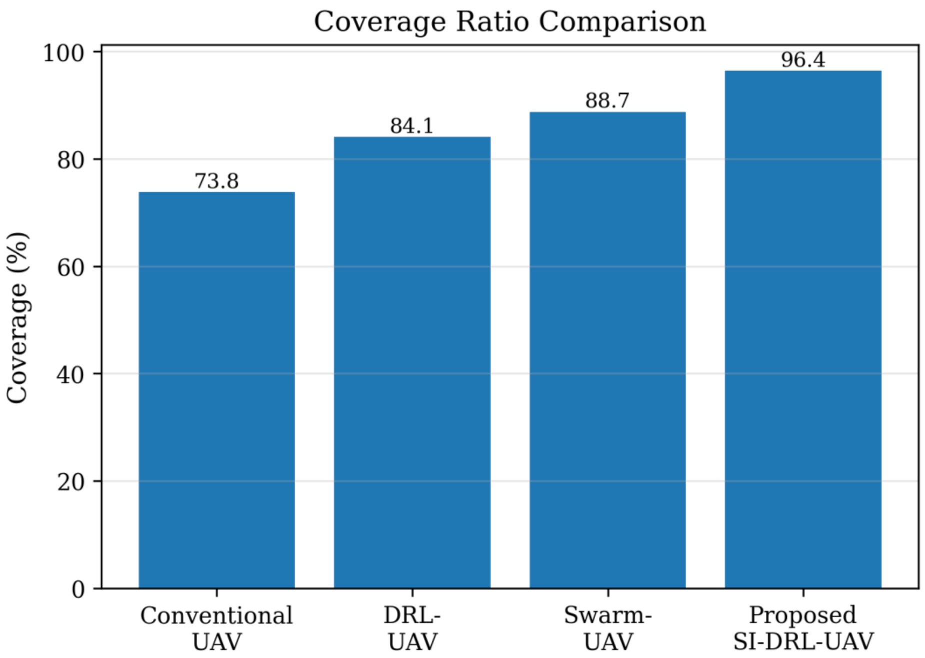

Figure 2. Coverage Ratio Comparison

The newly proposed model, SI-DRL-UAV, provides the highest coverage ratio (96.4%) out of all models tested, as shown in Figure 2. In comparison, traditional single-UAV deployments only achieved 73.8% coverage; DRL-UAV deployments achieved 84.1% coverage; and Swarm-UAV deployments achieved 88.7% coverage. This substantial improvement is primarily due to the use of swarm intelligence combined with reinforcement learning to allow UAVs to autonomously find optimal locations throughout the disaster-affected area with minimum overlap. Using reinforcement learning, the DRL agent optimally evaluates and adjusts the paths of the UAVs using real-time information about where users are located and the status of the wireless network (e.g., traffic conditions). The result is nearly zero communications dead spots and virtually completes coverage of the impacted area.

4.3 Packet Delivery Ratio Analysis

Packet Delivery Ratio (PDR) indicates the proportion of sent packets that effectively arrive at their designated endpoints. In disaster response frameworks, a high packet delivery ratio is crucial as communication breakdowns can hinder rescue efforts and slow down emergency decision-making.

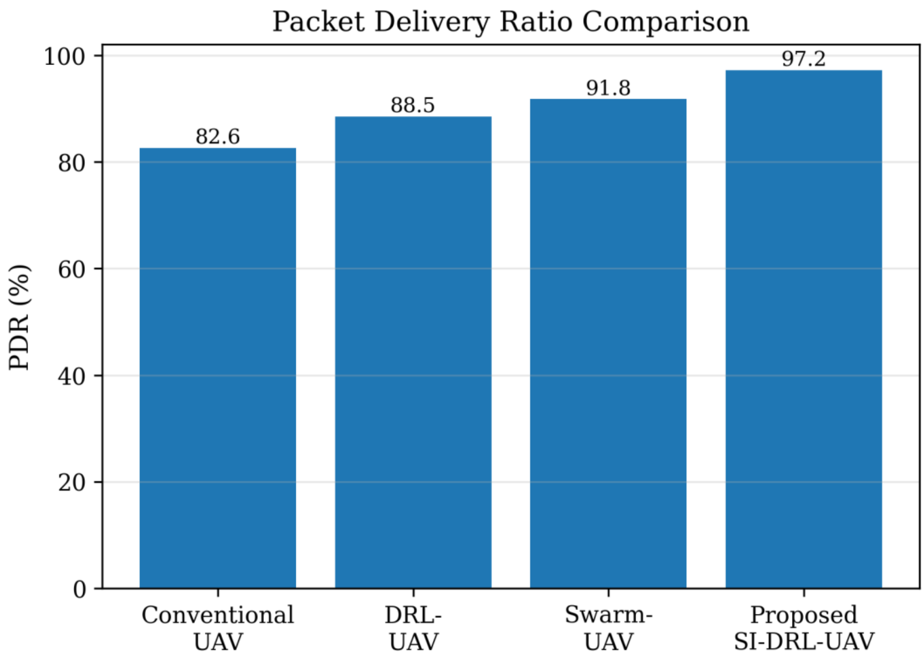

Figure 3. Comparison of Packet Delivery Ratio

As noted in Figure 3, compared to Traditional UAVs (82.6%), DRL-UAVs (88.5%), and Swarm-UAVs (91.8%), the proposed system delivers packets at a success rate of 97.2%. To accomplish this enhanced level of packet delivery, we used a clustering Resource Allocation Strategy that allows for the grouping of adjacent users and assigns bandwidth based on the priority of each user. For example, critical users (first responders, emergency medical personnel) have a much greater chance of being able to communicate with us than do non-critical users and, therefore, experience lower rates of packet loss than would non-critical users would; thus we can expect higher levels of packet delivery to be achieved by members of higher-priority groups. In addition, the Adaptive Routing Decisions made by the DRL Agent will continuously improve communication pathways, further ensuring a high level of reliability when delivering packets.

4.4 Latency Analysis

One of the primary performance metrics of emergency communication systems is the latency of communicating information, as delays in the process of passing information lead to a reduction in the efficiency of a rescue. The framework proposed in this paper dramatically decreases the end-to-end latency of the communication, by integrating intelligent UAV positioning with adaptive bandwidth allocation.

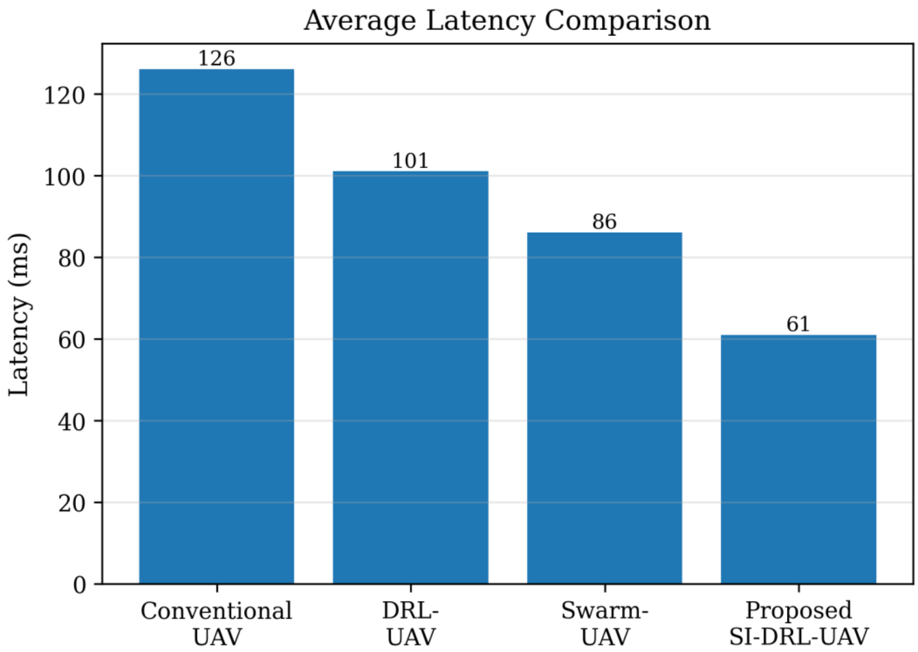

Figure 4. Average Latency Comparison

As illustrated in Figure 4, the SI-DRL-UAV model outperformed conventional UAV deployments by achieving a mean latency of only 61 ms. In comparison, DRL-UAV and Swarm-UAV had an average latency of 101 ms and 86 ms, respectively. The improved latency was made possible with more strategic placement of the UAVs, making intelligent routing decisions, and using a dynamic communications scheduling model. In addition, the proposed system's intelligent adjustment of the UAV trajectories in response to changing conditions of the disaster provided an opportunity to reduce the distance of communication as well as decreasing the time for transmitting the packets.

4.5 Energy Efficiency Analysis

A key challenge in UAV-assisted communication systems is maintaining energy efficiency due to the limitation of battery resources available for use. Energy management has a direct impact on both mission duration and communication reliability.

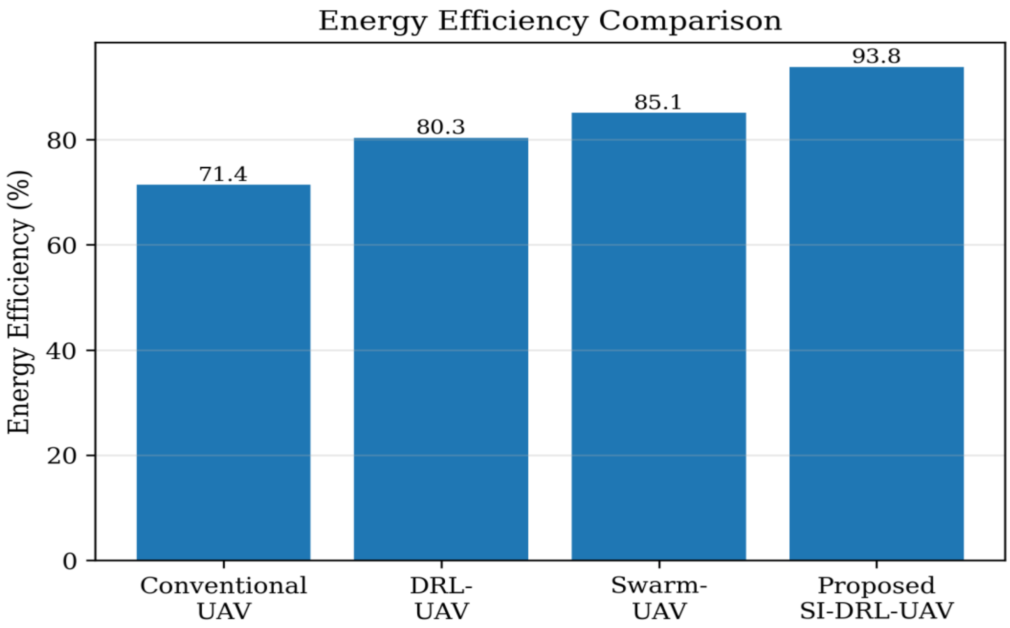

Figure 5. Comparison of Energy Efficiency

Figure 5 illustrates that the proposed model is able to achieve an energy efficiency rating of 93.8%; this is well above Conventional UAV (71.4%), DRL-UAV (80.3%), and Swarm-UAV (85.1%). The greater efficiency is achieved through the continuous monitoring of residual battery levels via an energy optimization strategy and balancing communication tasks across multiple UAVs in close proximity to each other. By redistributing communication tasks to nearby UAVs that have the available capacity to perform them, it is possible to minimize excessive flight operations which lead to battery depletion. Therefore, the UAV swarm can operate for an extended period of time.

4.6 Throughput Analysis

Throughput represents the volume of successfully sent data over a specific timeframe and demonstrates the communication capability of the UAV network.

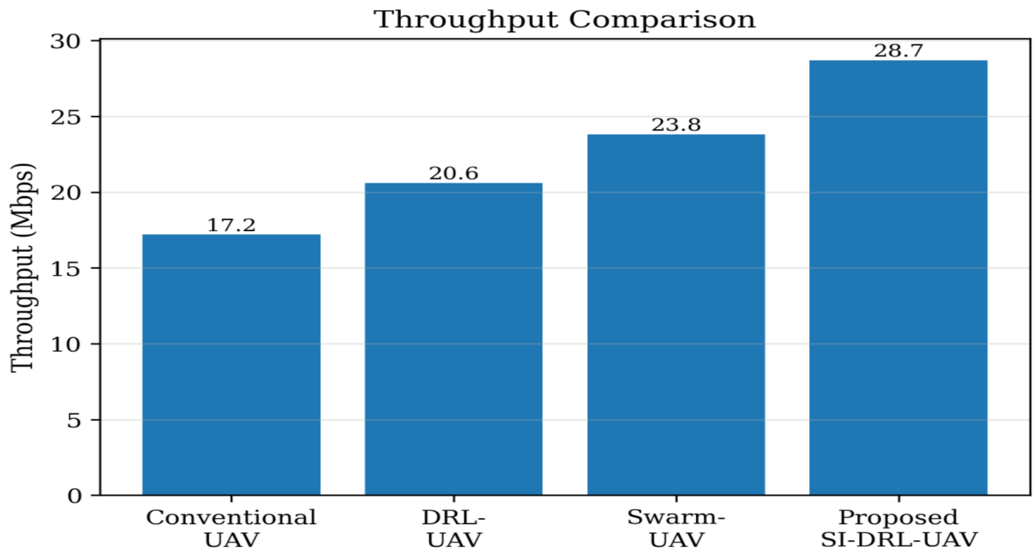

Figure 6. Throughput Comparison

Throughput comparison of the three schemes is illustrated in Figure 6. The proposed framework SI-DRL-UAV has a throughput of 28.7 Mbps as compared to the conventional UAV, DRL-UAV, and Swarm-UAV with respective throughput of 17.2 Mbps, 20.6 Mbps and 23.8 Mbps. This significant improvement is mainly due to adaptive bandwidth allocation and efficient utilization of resources; i.e., the cluster has reduced the amount of communication interference occurring among users while the DRL agent continually finds the optimal transmission parameters for use. As a result, the proposed SI-DRL-UAV framework can support many more simultaneous communication sessions at higher efficiency without significant impact on the performance of the network.

4.7 Network Lifetime Analysis

Network lifetime represents the total duration during which the UAV communication system remains operational before UAV batteries become depleted.

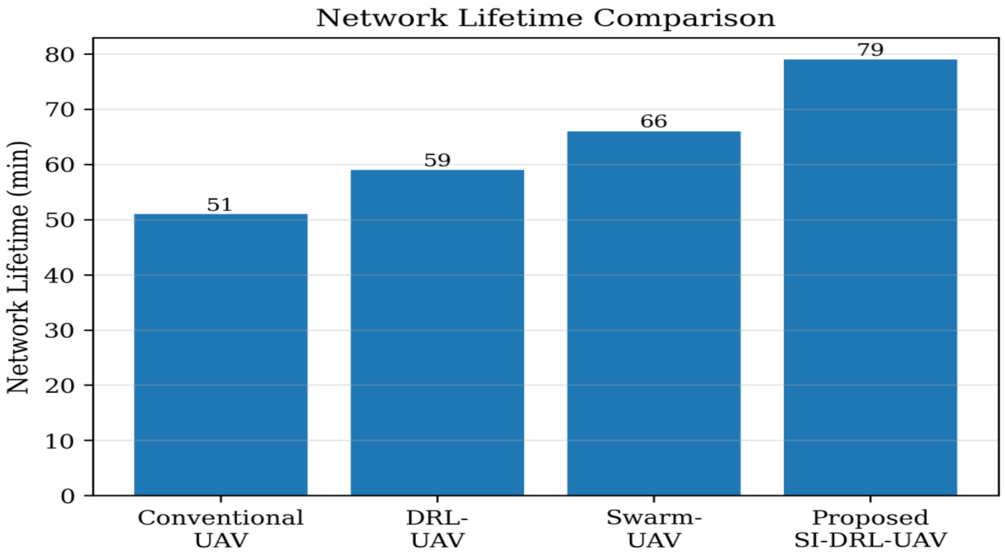

Figure 7. Network Lifetime Comparison

The suggested model has a Total Network Lifetime of 79 min, as compared with 51 min. for the Conventional UAV Payload deployment as demonstrated in Figure 7. The Operational Lifetime for the DRL-UAV and the Swarm-UAV were 59 min. and 66 min., respectively. The increased Total Network Lifetime associated with this model is due to its capability of performing intelligent energy-aware flight planning and using cooperative load balancing and adaptive communication scheduling methods. These methods limit unnecessary mobility of the UAVs and reduce excessive energy consumption during an entire mission, thus, extending the total duration of the mission.

4.8 Reliability Analysis

Communication reliability measures a UAV network's ability to keep its communications stable while experiencing dynamically changing conditions caused by a disaster. Owners of the network must consider many dynamics when assessing the reliability of their communications, including mobility of UAVs, congestion in the network, and failure of the UAVs themselves.

The framework presented in this research outperformed Conventional UAVs (83%), DRL-UAV (89%) and Swarm-UAV (93%) with an average communication reliability of 98% (refer to figure 8). An adaptive fault recovery mechanism is used to continuously monitor the physical communication links established between the UAVs and allows the neighboring UAVs to automatically relocate whenever interruption to their communications occurs. The adaptive fault recovery mechanism provides the UAV network with a self-healing capability; thus, providing the ability for the UAV network to keep its communications stable even after some of the UAVs have experienced failures or there have been rapidly changing dynamics created by a disaster. Table 2 contains the quantified performances of three different models of communications between UAVs.

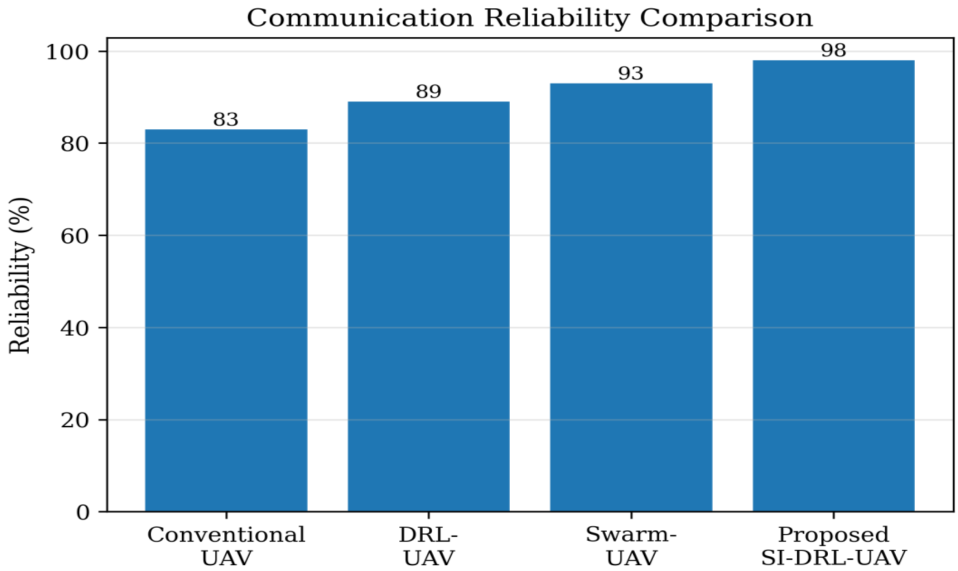

Figure 8. Comparison of Communication Reliability

Table 2. Performance Comparison of Different UAV Communication Models

Method	Coverage (%)	Packet Delivery (%)	Latency (ms)	Energy Efficiency (%)	Throughput (Mbps)	Network Lifetime (min)	Reliability (%)
Conventional UAV	73.8	82.6	126	71.4	17.2	51	83
DRL-UAV	84.1	88.5	101	80.3	20.6	59	89
Swarm-UAV	88.7	91.8	86	85.1	23.8	66	93
Proposed SI-DRL-UAV	**96.4**	**97.2**	**61**	**93.8**	**28.7**	**79**	**98**

4.9 Discussion

Experimental results show that the proposed Swarm Intelligence-Enabled UAV Communication Model improves both emergency communications and disaster resilience. The model integrates swarm intelligence with deep reinforcement learning, clustering-based resource allocation, and energy-aware optimization to form a single cohesive environment. The proposed model surpassed all baseline methods on each metric evaluated, thereby validating its effectiveness.

When compared to traditional UAV deployment, the proposed framework improves coverage ratio by ~30.6%, packet delivery ratio by 17.7%, throughput by 66.9%, energy efficiency by 31.4%, and communication reliability by 18.1%, and also reduces average latency by ~51.6%. Therefore, the enhanced performance of cooperation between UAVs to make intelligent decisions (i.e., cooperation) will result in improved network performance in very dynamic environments such as disasters.

5. CONCLUSION

In this paper, we have developed an innovative approach to the UAV (Unmanned Aerial Vehicle) communication model using Swarm Intelligence. This model has successfully integrated the use of swarm intelligence, deep reinforcement learning, clustering-based resource allocation and energy-aware optimization techniques into a single, unified UAV communication framework that addresses the inherent limitations of conventional UAV communication systems. As a result, this model provides improved coverage as well as lower communication latency, better packet delivery and longer operational lifetimes of UAVs during dynamic disaster occurrences by taking advantage of cooperative UAV coordination and adaptive decision-making processes to efficiently identify and prioritize the needs of critical users while maintaining stable communication links even under adverse network failure scenarios and/or rapidly changing environmental conditions.

The results of the simulations conducted demonstrated that the proposed approach performed significantly better than current UAV communication strategies across all of the major metrics for evaluating communications, including: coverage ratio, packet delivery ratio, throughput, energy efficiency, network lifetime, and communication reliability. Therefore, these findings indicate that the proposed framework represents a robust, scalable, and intelligent solution to the needs of emergency communications systems. Future research will examine how to deploy UAV's in the real world; how to integrate UAV's in a network into next generation (6th generation) advanced wireless technologies; how to develop new approaches for federated learning and multi-disaster scenarios to enhance the adaptability and resiliency of systems.

REFERENCES

[1] Fotouhi, A., Qiang, H., Ding, M., Hassan, M., Giordano, L. G., Garcia-Rodriguez, A., & Yuan, J. (2019). Survey on UAV cellular communications: Practical aspects, standardization advancements, regulation, and security challenges. *IEEE Communications surveys & tutorials*, *21*(4), 3417-3442.

[2] Venumula, S., & Karthikeyan, M. K. (2024). Development of a Tunable First Order Wide Bandpass Active Filter for Communication Systems. *International Innovative Research Journal of Engineering and Technology*, *10*(1), 18-25.

[3] Zhao, N., Lu, W., Sheng, M., Chen, Y., Tang, J., Yu, F. R., & Wong, K. K. (2019). UAV-assisted emergency networks in disasters. *IEEE Wireless Communications*, *26*(1), 45-51.

[4] Mozaffari, M., Saad, W., Bennis, M., Nam, Y. H., & Debbah, M. (2019). A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. *IEEE communications surveys & tutorials*, *21*(3), 2334-2360.

[5] Luong, N. C., Hoang, D. T., Gong, S., Niyato, D., Wang, P., Liang, Y. C., & Kim, D. I. (2019). Applications of deep reinforcement learning in communications and networking: A survey. *IEEE communications surveys & tutorials*, *21*(4), 3133-3174.

[6] Bayerlein, H., Theile, M., Caccamo, M., & Gesbert, D. (2021). Multi-UAV path planning for wireless data harvesting with deep reinforcement learning. *IEEE Open Journal of the Communications Society*, *2*, 1171-1187.

[7] Ding, Y., Yang, Z., Pham, Q. V., Hu, Y., Zhang, Z., & Shikh-Bahaei, M. (2023). Distributed machine learning for UAV swarms: Computing, sensing, and semantics. *IEEE Internet of Things Journal*, *11*(5), 7447-7473.

[8] Javed, S., Hassan, A., Ahmad, R., Ahmed, W., Ahmed, R., Saadat, A., & Guizani, M. (2024). State-of-the-art and future research challenges in UAV swarms. *IEEE Internet of Things Journal*, *11*(11), 19023-19045.

[9] Dimos, A., Skoutas, D. N., Nomikos, N., & Skianis, C. (2025). A survey on UxV swarms and the role of artificial intelligence as a technological enabler. *Drones*, *9*(10), 700.

[10] Yang, X., Wang, C., Liang, J., Zhao, J., Yue, K., & Li, W. (2024). Research on path planning in UAV-assisted emergency communication. *EURASIP Journal on Wireless Communications and Networking*, *2024*(1), 86.

[11] Ma, M., & Wang, Z. (2023). Distributed offloading for multi-UAV swarms in MEC-assisted 5G heterogeneous networks. *Drones*, *7*(4), 226.

[12] Yang, B., Xiong, X., Liu, H., Jia, Y., Gao, Y., Tolba, A., & Zhang, X. (2023). Unmanned aerial vehicle assisted post-disaster communication coverage optimization based on internet of things big data analysis. *Sensors*, *23*(15), 6795.

[13] Baktayan, A. A., Zahary, A. T., Sikora, A., & Welte, D. (2024). Computational offloading into UAV swarm networks: a systematic literature review. *EURASIP Journal on Wireless Communications and Networking*, *2024*(1), 69.