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Secure and Self-healing Drone Network using Quantum Key Distribution, Federated Meta-reinforcement Learning, and AI-driven Digital Twin Systems

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***Abstract*—Rapid response and reliable operation are crucial for saving lives through timely access to affected areas. A secure and adaptive drone network integrates Quantum Key Distribution (QKD) for ultra-secure communication, AI-driven adaptive learning for optimizing missions autonomously, and Digital Twin simulations for real-time health monitoring and predictive maintenance. These drones can autonomously address issues like imbalance or component failures, detect hazards, and locate individuals using onboard sensors and radar, ensuring uninterrupted operation even in tough conditions. The system employs intelligent path-planning and navigation to determine the quickest and safest routes for rescue missions, dynamically adjusting to environmental changes and obstacles. Collaborative intelligence enables drones to share data and coordinate tasks effectively while maintaining local data privacy. The framework supports scalable deployment, allowing multiple drones to operate together across large disaster zones. By combining resilient communication, self-healing capabilities, adaptive intelligence, and real-time situational awareness.**

Keywords—Quantum Key Distribution (QKD), Digital Twin, Self-Healing Systems, Disaster Management, Adaptive Learning, Hazard Detection, Autonomous Navigation, Rescue Optimization, Real-Time Monitoring.

I. INTRODUCTION

In recent years, both natural and human-made disasters such as earthquakes, floods, hurricanes, wildfires, industrial accidents, and terrorist attacks—have become more frequent and severe, leading to widespread destruction, loss of life, and major disruptions to essential services. Effective disaster response in these high-stakes scenarios demands fast, secure, and reliable information gathering, along with robust operational systems that can perform under extreme conditions. Traditional methods, like ground-based surveys and manned aerial vehicles, often fall short due to delays in deployment, limited coverage, communication failures, and the high risk posed to human responders. These challenges highlight the critical need for advanced autonomous technologies capable of independent operation, secure communication, and real-time intelligence delivery in volatile and unpredictable environments. Unmanned Aerial Vehicles (UAVs) offer a powerful solution, with their ability to navigate autonomously, access hard-to-reach areas, and rapidly provide situational awareness—ultimately enhancing the effectiveness of disaster management efforts.

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become vital assets in contemporary emergency response and disaster management. Their ability to access hard-to-reach or hazardous areas, capture detailed imagery, and transmit real-time data makes them highly effective for evaluating disaster scenarios, locating survivors, assessing infrastructure damage, and delivering critical supplies. Their adaptability, cost-efficiency, and autonomous flight capabilities make them particularly well-suited for rapidly changing and unpredictable situations. Nevertheless, UAV-based systems still encounter several significant challenges. These include insecure communication links that risk data breaches, difficulties navigating through cluttered or unstable environments, limitations in onboard sensors and hardware, and the complexities of coordinating multiple drones while ensuring data accuracy, situational awareness, and the overall success of the mission.

To tackle these challenges, this research introduces a **Secure and Self-Healing Drone Network,** a unified framework that integrates secure communication, adaptive intelligence, and real-time system diagnostics. The framework leverages **Quantum Key Distribution (QKD)** to create unbreakable communication channels, safeguarding the confidentiality and integrity of critical mission data while blocking interception and unauthorized access. Additionally, it incorporates **Federated Meta-Reinforcement Learning (FMRL)**, allowing individual UAVs to locally refine their mission strategies—such as navigation, hazard detection, and victim identification—without compromising privacy, as only encrypted model updates are shared instead of raw sensor data. To further enhance system resilience, the network employs **AI-powered Digital Twin technology**, assigning each UAV a virtual replica for continuous health tracking, predictive maintenance, and performance analysis. This allows for early fault detection and rapid response to

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environmental or technical disruptions. By merging these advanced technologies, the proposed network delivers a secure, intelligent, and robust infrastructure tailored for efficient disaster-response missions in complex and rapidly changing conditions.

A core strength of the proposed system lies in its self-healing capabilities, driven by Graph Neural Networks (GNNs) that enable adaptive reconfiguration of the drone network. This functionality allows UAVs to dynamically adjust communication routes and reassign mission tasks in response to failures, malfunctions, or disruptions, ensuring continuous and reliable operation. By representing the network as a graph, GNNs empower drones to intelligently assess inter-node relationships, detect vulnerabilities, and implement optimal recovery strategies in real time. As a result, the system remains resilient and functional even when specific nodes or connections fail. In conjunction with onboard sensors and radar, drones can identify survivors, autonomously revise mission objectives, and determine the most effective rescue paths in fast-changing disaster scenarios.

The suggested framework combines these elements into a single, well-designed architecture for disaster management, as opposed to traditional UAV systems that handle issues like security, adaptability, or fault tolerance separately. The system makes use of Graph Neural Networks (GNNs) for robust self-healing capabilities, AI-driven digital twins for predictive diagnoses, privacy-preserving adaptive learning for mission optimization, and Quantum Key Distribution (QKD) for secure communication. By enhancing situational awareness, facilitating proactive fault management, and guaranteeing dependable operations even in the face of failures or disruptions, this multi-layered, intelligent architecture improves UAV performance in volatile environments. The framework is an all-inclusive solution that facilitates quick deployment, safe and flexible operation, and strong resilience, which makes it especially useful for disaster response situations in intricate, high-risk settings.

II. LITERATURE SURVEY

Recent developments in UAV-based disaster management have highlighted the pivotal role of unmanned aerial vehicles in improving situational awareness. As noted in [1], UAVs can quickly access remote or hazardous locations, delivering real-time intelligence to emergency teams. Similarly, [2] underscores their value in locating survivors through high-resolution imaging and thermal sensors. The work in [3] further demonstrates UAVs' effectiveness in infrastructure monitoring, damage assessment, and directing rescue operations. Research in [4] emphasizes that autonomous navigation enables UAVs to operate independently in unpredictable and hazardous environments.

However, securing communication within UAV networks remains a critical challenge. According to [5], Quantum Key Distribution (QKD) offers a means to establish unbreakable communication channels. The integration of QKD with mobile UAV platforms, as explored in [6], helps safeguard mission-critical data from interception. Additionally, [7] shows that combining QKD with AI-driven error correction significantly improves reliability in dynamic environments. Work in [8] stresses that secure and stable communication is essential for real-time coordination among multiple UAVs.

Autonomous UAV operations also depend heavily on adaptive learning. As highlighted in [9], Federated Learning enables UAVs to collaboratively refine mission strategies while preserving sensitive data. According to [10], Meta-Reinforcement Learning (Meta-RL) equips UAVs with the ability to quickly adapt to novel disaster scenarios. Building on this, [11] introduces Federated Meta-Reinforcement Learning (FMRL), which strikes a balance between adaptability and privacy-preserving collaboration. Further studies in [12] show that such techniques enhance multi-UAV coordination and improve hazard avoidance in uncertain conditions.

Digital Twin technology offers continuous oversight and predictive maintenance for UAV networks. Research in [13] presents how virtual UAV models can forecast potential hardware failures. In [14], digital twins are used to optimize operational performance by simulating real-time environmental dynamics. AI-enhanced digital twins, as discussed in [15], can recommend corrective actions to ensure mission continuity. According to [16], integrating real-time data with digital twin models enables proactive interventions and reduces operational downtime.

To support resilient operations, self-healing UAV networks leveraging Graph Neural Networks (GNNs) have been developed. As shown in [17], GNN-based architectures enable UAVs to dynamically reconfigure communication links in response to system failures. In [18], such networks maintain functionality even during partial disruptions. Research in [19] highlights that task redistribution using GNNs enhances swarm efficiency and reliability. According to [20], embedding GNNs into UAV swarms improves fault tolerance and operational resilience during disaster response missions.

Extensive research has explored integrated, multi-layered frameworks that merge secure communication, adaptive learning, digital twins, and self-healing capabilities. As noted in [21], the fusion of these technologies greatly improves situational awareness and operational reliability in UAV networks. Study [22] shows that such integrated systems enhance dynamic path planning and resource efficiency, particularly in disaster response scenarios. According to [23], combining adaptive learning with resilience features significantly boosts the effectiveness of multi-agent UAV collaboration. Research in [24] and [25] underscores the importance of scalable architectures and privacy-preserving communication protocols in large-scale UAV operations. Blockchain-based security solutions, as proposed in [26], further enhance trust and coordination among UAV agents. Hybrid AI-edge computing systems, discussed in [27], enable real-time responsiveness and maintain performance in dynamic environments. Cross-domain learning, highlighted in [28], supports UAV adaptability across various disaster contexts. Additionally, [29] shows that continuous monitoring and predictive analytics aid in early fault detection and support proactive decision-making. Finally, [30] confirms that integrating these components into a unified framework results in a secure, adaptive, and self-healing UAV network optimized for reliable and effective disaster response.

In summary, while existing research provides valuable insights into individual aspects such as secure communication, adaptive learning, digital twins, and self-healing via GNNs, few studies address a fully integrated approach. This research builds on prior work by proposing a comprehensive UAV network that is secure, resilient, and capable of autonomous disaster management operations.

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III. PROPOSED METHODOLOGY

The proposed approach combines cutting-edge technologies such as Quantum Key Distribution (BB84), Meta-Reinforcement Learning, Federated Learning, Digital Twins, Swarm Intelligence, Self-Healing Hardware, and Neuro-Symbolic AI within a unified UAV-based disaster management system. Each technology targets specific challenges across a multi-layered architecture, addressing needs such as secure communication, adaptive decision-making, real-time situational awareness, and fault resilience. These interconnected layers form a robust and cohesive network. The methodology also includes operational strategies and mathematical models for each component, illustrating how they collectively enhance the system's efficiency and reliability in disaster response scenarios.

A. Quantum Key Distribution (BB84)

In UAV-based disaster management, it is crucial to ensure the secure transmission of vital data. The BB84 quantum key distribution protocol provides information-theoretic security by encoding each bit into quantum states, choosing between rectilinear or diagonal bases at random. Photons are transmitted and measured with independently selected bases, and when measurements align, a sifted key is generated. The effectiveness of the transmission is assessed using the Quantum Bit Error Rate (QBER), which is calculated as:

$$QBER = \left(\frac{N_{\text{error}}}{N_{\text{total}}}\right) \times 100\%$$

Keys with a QBER under 5% are then utilized in AES-256 encryption, ensuring secure UAV communication that is resistant to eavesdropping and capable of detecting interception attempts in real time.

B. Federated Meta-Reinforcement Learning (FMRL)

In UAV-based disaster response, the ability to quickly adapt to changing environments is essential. Federated Meta-Reinforcement Learning (FMRL) combines Federated Learning (FL) with Meta-Reinforcement Learning (Meta-RL) to facilitate distributed, privacy-preserving, and adaptive policy learning. Each UAV, denoted as u_i, develops a local policy $\pi_{\theta_i}(a \mid s)$ aimed at maximizing the expected cumulative reward:

$$J(\theta_i) = E_{\pi_{\theta_i}}\left[\sum_{t=0}^{T} \gamma^t r_t\right]$$

Local gradients $\nabla_{\theta_i} J(\theta_i)$are computed by each UAV and then aggregated at a central server:

$$\theta_{\text{global}} = \sum_{i=1}^{N} \frac{n_{\text{total}}}{n_i} \theta_i$$

Meta-learning is applied to refine θ_{global}, allowing the UAVs to quickly adapt to new disaster scenarios. This approach ensures data privacy for each UAV while also supporting the scalability of swarm intelligence.

C. Digital Twin (DT) for Real-Time Monitoring

The Digital Twin framework generates a virtual representation of each UAV, which is constantly refreshed with real-time sensor data, facilitating predictive maintenance and enhancing operational efficiency. This digital version offers a detailed overview of the UAV's status, enabling continuous tracking of essential parameters like altitude, battery level, temperature, GPS position, and rotor performance. The UAV's operational state is captured as a vector:

$$X(t) = [x_1(t), x_2(t), \dots, x_n(t)]$$

where $x_i(t)$includes parameters such as altitude, battery voltage, temperature, GPS location, and rotor status. Future states are predicted using the equation:

$$X^{(t+\Delta t)} = f\left(X^{(t)}, U(t), E(t)\right)$$

with $U(t)$ as control inputs and $E(t)$ as environmental factors like wind or obstacles. Prediction errors are calculated as:

$$\epsilon(t) = |X(t) - \hat{X}(t)|$$

If $\epsilon(t) > \tau$, alerts for faults or preventive maintenance are triggered. This framework ensures reliable missions, optimizes flight routes, and supports dynamic task allocation. Digital Twins also enable AI-driven decision-making for autonomous mission adjustments and provide insights for post-mission analysis. By combining predictive monitoring with real-time telemetry, UAVs maintain high operational readiness and enhance swarm-based disaster response efficiency.

D. Swarm Intelligence for Collective Coordination

In disaster management, effective UAV collaboration is often essential. Swarm Intelligence (SI) allows for decentralized, adaptive coordination, drawing inspiration from natural systems. Each UAV adjusts its velocity and position using Particle Swarm Optimization (PSO) as follows:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(p_i - x_i(t)\right) + c_2 r_2 \left(g - x_i(t)\right)$$
$$x_i(t+1) = x_i(t) + v_i(t+1)$$

Where p_i and g represent the local and global best positions, ω is the inertia weight, and c_1 and c_2 are the cognitive and social coefficients. Random factors r_1 and r_2 promote exploration. This approach enables UAVs to adaptively cover areas, avoid collisions, maintain dynamic formations, and reassign tasks in large, complex disaster environments, all without relying on centralized control.

E. Self-Healing Networks

UAVs are designed with self-healing capabilities to ensure network connectivity and operational continuity in case of failures. The UAV mesh network is represented as a graph $G = (V, E)$, where V consists of UAV nodes and E represents communication links. When a node fails, the system applies shortest-path restoration:

$$d'(u,v) = \min_{(i,j)\in p} \sum_{p \in P(u,v)} w(i,j)$$

where $w(i,j)$represents the communication cost between nodes. UAV health is continuously tracked using metrics $H_i(t)$, with self-healing mechanisms activated if $H_i(t) < \delta$. If a UAV encounters a failure, it either modifies its operational parameters or offloads tasks to nearby UAVs, ensuring the network's resilience to environmental challenges and maintaining uninterrupted mission execution. This system enhances UAV swarm coordination, allowing for quick adaptations and robust operations in dynamic and unpredictable disaster environments.

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F. Neuro-Symbolic Artificial Intelligence (NSAI)

NSAI combines neural perception with symbolic reasoning to facilitate context-aware decision-making. Sensory data:

$$S = \{s_1, s_2, \dots, s_n\}$$

are transformed into high-level features:

$$F = f_\theta(S)$$

and processed using logical inference rules:

$$D = \text{Reason}(F, R)$$

For instance, the detection of a heat signature s_{heat} and an acoustic anomaly s_{sound} would trigger the logical rule:

$$(\text{sheat} \wedge \text{ssound}) \Rightarrow \text{Possible Human Detected}$$

NSAI guarantees that decisions are explainable and ethical, enabling UAVs to prioritize critical tasks, such as rescuing humans, over less urgent ones like environmental mapping. This enhances the effectiveness of UAV operations in disaster response, especially when resources are limited and multiple objectives are competing.

IV. System Design and Workflow Diagrams

The proposed UAV-based disaster management system is envisioned as a decentralized, intelligent, and resilient multi-agent framework capable of autonomous functioning in unpredictable and dynamic disaster environments. It incorporates several key components, such as Quantum Key Distribution for secure communication, Federated Meta-Reinforcement Learning for flexible decision-making, Digital Twin technology for real-time monitoring, Swarm Intelligence for coordinated collaboration, and Neuro-Symbolic AI for cognitive reasoning. This section outlines the system's overall design, workflow architecture, and coordination logic, which together ensure secure, adaptive, and fault-tolerant UAV operations, thereby improving mission effectiveness and situational awareness in complex disaster response situations.

A. System Architecture Overview

The architecture of the proposed UAV-based disaster management system adopts a layered modular design, ensuring scalability, flexibility, and fault tolerance. A fleet of UAVs operates autonomously within disaster-affected areas, communicating both among themselves and with a central Ground Control Station (GCS). The architecture consists of six key subsystems:

1. Secure Communication Layer:

This layer secures all communications between UAVs and between UAVs and the Ground Control Station (GCS) by utilizing the BB84 Quantum Key Distribution (QKD) protocol in combination with AES-256 encryption. QKD enables theoretically unbreakable key exchange by leveraging quantum mechanics, while AES-256 provides robust data encryption. Together, they ensure end-to-end data confidentiality and integrity, even under adversarial conditions. Additionally, the integration of quantum-secured encryption significantly mitigates the risk of cyberattacks and eavesdropping during critical missions.

2. Adaptive Intelligence Layer:

Powered by Federated Meta-Reinforcement Learning (FMRL), this layer enables decentralized decision-making across UAVs. Each UAV independently learns about its local environment and shares model updates (not raw data) with the GCS. The global model is periodically refined using meta-learning, allowing the system to rapidly adapt to new challenges such as weather changes, obstacles, or terrain shifts.

3. Coordination and Navigation Layer:

The coordination of the UAV swarm relies on Particle Swarm Optimization (PSO) to manage spatial distribution, avoid overlaps, and optimize area coverage. Simultaneously, A* path planning is utilized for obstacle avoidance, ensuring each UAV follows the most efficient and collision-free path. The combination of PSO and A* minimizes computational demands while enhancing operational efficiency.

4. Predictive Monitoring Layer:

The Digital Twin (DT) module continuously mirrors the UAV's physical state and the surrounding environment in a virtual model. It tracks parameters like motor performance, battery levels, wind resistance, and payload weight. Predictive analytics detect potential malfunctions early, enabling proactive maintenance and minimizing downtime during missions.

5. Cognitive Reasoning Layer:

This layer leverages Neuro-Symbolic AI (NSAI) to merge neural learning (for pattern recognition) with symbolic logic (for reasoning). The integration of these approaches allows for transparent, interpretable decision-making. NSAI enables UAVs to make mission-critical decisions such as prioritizing search tasks or starting rescue operations based on learned representations and explainable rules.

6. Resilience Layer:

The resilience layer includes self-healing network mechanisms, which autonomously reroute communication in case of failures. If a UAV experiences a malfunction or loses signal, standby drones are deployed to ensure continuous operations. This self-healing capability ensures higher mission reliability with minimal need for human intervention.

B. Integrated Operational Workflow

The operational workflow of the UAV-based disaster management system, illustrated in Fig. 1, outlines a systematic yet adaptable sequence from mission launch to conclusion. Designed to support ongoing learning, dynamic decision-making, and autonomous recovery, the system facilitates real-time data acquisition, processing, and action in response to evolving disaster conditions. Through iterative feedback mechanisms, UAVs continuously update their strategies and improve task efficiency. This intelligent and responsive workflow enables autonomous, high-performance mission execution, significantly boosting the effectiveness

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and resilience of disaster response operations in complex and uncertain environments.

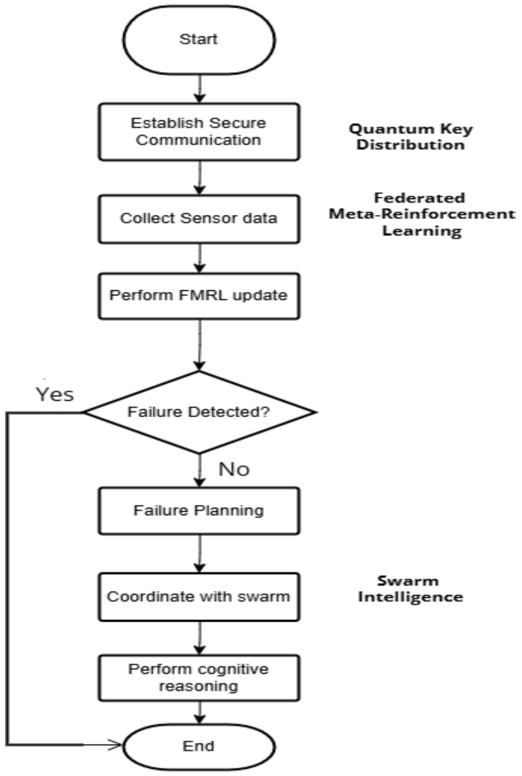

Fig. 1, System Architecture

1. Initialization and Secure Communication:

The process begins with establishing secure communication channels. UAVs utilize the BB84 Quantum Key Distribution (QKD) protocol to exchange quantum keys, which are then used to set up AES-256 encrypted links. This dual-encryption strategy ensures that all communications such as control signals, telemetry, and sensor data remain secure, confidential, and resistant to tampering.

2. Real-Time Data Collection and Learning:

As the UAVs carry out their mission, they gather various types of real-time data, including visual, thermal, and environmental inputs. Each UAV processes this data locally to update its learning model. Using Federated Meta-Reinforcement Learning (FMRL), model updates are shared—rather than raw data—contributing to a centralized meta-model. This global policy is periodically synchronized across the fleet, enabling collective adaptation to dynamic conditions like shifting terrain, weather changes, or new obstacles.

3. Fault Detection and Recovery:

A Digital Twin module continuously monitors the UAV's predicted performance against real-world telemetry. If significant deviations are detected, indicating a potential issue, the system triggers Self-Healing mechanisms. These may involve rerouting communication pathways or deploying backup UAVs to ensure uninterrupted mission execution.

- **If a failure is detected**: The system dynamically initiates corrective actions, such as reassigning roles or launching reserve UAVs.
- **If no failure is detected**: Operations continue as normal, with UAVs optimizing their tasks.

4. Swarm Coordination and High-Level Reasoning:

With the fleet stabilized, UAVs engage in coordinated operations using Particle Swarm Optimization (PSO) for efficient coverage and A* algorithms for obstacle avoidance. Each UAV follows a dynamically adjusted path, balancing wide-area exploration with focused investigation. Simultaneously, the Neuro-Symbolic AI module enables higher-order reasoning. It interprets sensory input—such as combining thermal and acoustic signals—and draws logical inferences, like identifying potential human presence. UAVs are then reprioritized to investigate these critical zones.

5. Mission Finalization:

This iterative process continues until mission goals—such as full area surveillance or victim identification—are achieved. Once completed, all UAVs securely relay mission data and learning outcomes back to the Ground Control Station (GCS) for further analysis. This marks the conclusion of the mission, transitioning the system to its final "End" state.

Overall, the workflow ensures that UAV operations remain intelligent, secure, resilient, and continuously improving throughout the course of a disaster response mission.

C. Trajectory Generation and Swarm Coordination Illustration

The effectiveness of the system's swarm coordination and navigation strategy is illustrated through the visualization of multi-UAV trajectories, generated using a combined A* and PSO approach within a simulated disaster scenario. In this visualization, each colored path corresponds to a UAV's movement, while grey markers denote static obstacles. The A* algorithm determines the shortest viable paths around these obstacles, promoting safe and energy-efficient travel. Simultaneously, the PSO component enhances path smoothness and optimizes the collective behavior of the swarm to achieve mission objectives.

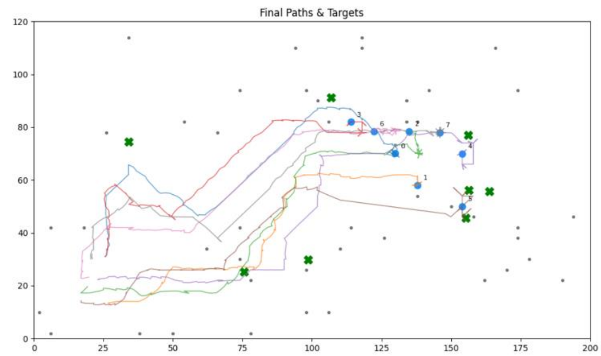

Fig. 2 Final Paths & Targets

As depicted in Fig. 2 (Final Paths & Targets), UAV trajectories converge toward green 'X' markers, which signify identified target locations. This coordinated

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movement reflects the success of FMRL-driven task allocation. The final positions of the UAVs, represented by blue and orange circles, denote effective task execution zones. Overall, the visualization demonstrates that the integrated PSO–A* framework achieves a balanced trade-off among area coverage, obstacle avoidance, and collaborative targeting of critical locations.

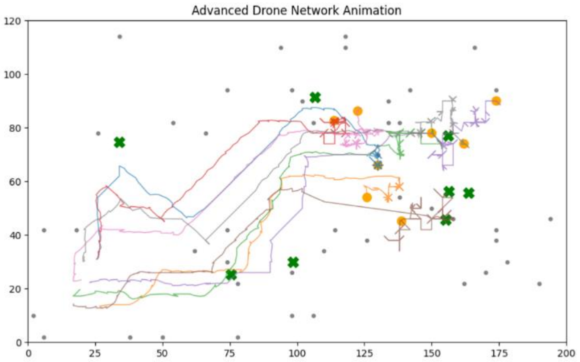

Fig. 3 Advanced Drone Network Animation

Swarm dynamics facilitate real-time coordination and adaptive formation control among UAVs. As illustrated in Fig. 3, the PSO-based interaction model demonstrates emergent collective behavior characterized by dynamic clustering and global synchronization. Individual UAVs adhere to local control rules while actively avoiding collisions, resulting in stable and coherent formations. The velocity updates derived from the PSO algorithm effectively translate FMRL-generated decisions into synchronized movement across the swarm. In the presence of obstacles or unexpected disruptions, the UAVs autonomously reconfigure to preserve coverage and maintain consistent search density. This self-organizing capability highlights enhanced adaptability, formation stability, and overall mission cohesion achieved through PSO integration, enabling efficient and collision-free coordination in complex and dynamic environments.

D. System Performance Metrics

The effectiveness of the proposed system is evaluated through a set of performance metrics that capture its efficiency, adaptability, and robustness. Among these, the primary metric is the number of victims detected over time, which serves as a direct measure of operational success.

Fig. 4, *Victims Found Over Time*

Fig. 4, titled *Victims Found Over Time*, illustrates a time-series plot of cumulative victim detections throughout the simulation. The graph exhibits a sharp initial rise, indicating rapid victim identification during the early exploration phase. As the mission advances, the detection rate stabilizes, signifying concentrated search efforts around previously identified areas of interest.

This performance trend highlights the adaptive learning capability of the FMRL module, and the effective spatial coordination achieved through PSO. Higher detection rates and reduced convergence times demonstrate the swarm's ability to dynamically reallocate tasks and adjust trajectories in response to real-time environmental feedback.

In addition to this primary metric, secondary performance indicators include network recovery time, communication delay, and energy consumption. Together, these metrics provide a comprehensive assessment of the system's responsiveness, accuracy, and fault tolerance.

TABLE I. UAV SYSTEM PERFORMANCE METRICS

Metric	*UAV / Pair*	*Value / Output*	*Status*
BB84 & AES Communication	UAV1 ↔ Base	QBER = 0.98%	Secure
FMRL Reward Aggregation	UAV2	Local Reward = 85, Contribution = 0.18	OK
Digital Twin Prediction Error	UAV2	E(T) = 0.021	ALERT
Victim Detection Rate (VDR)	All UAVs	95%	OK
Overall System Accuracy	All UAVs	93.33%	Secure

The proposed UAV-based disaster response system was evaluated using key performance indicators including communication security, learning efficiency, prediction accuracy, and mission success. According to Table I, secure communication between UAV1 and the base station implemented using BB84 quantum key distribution and AES-256 encryption achieved a Quantum Bit Error Rate (QBER) of just 0.98%, indicating strong encryption integrity. UAV2's Federated Meta-Reinforcement Learning (FMRL) demonstrated effective adaptive learning, with a local reward score of 85 and a global policy contribution of 0.18. State prediction powered by a Digital Twin model for UAV2 recorded a low deviation error of 0.021, which was sufficient to trigger anomaly detection mechanisms. The UAV swarm achieved a 95% Victim Detection Rate (VDR), and the system delivered an overall accuracy of 93.33%. These outcomes confirm the system's robustness, real-time responsiveness, and secure coordination capabilities for disaster response in rapidly changing environments

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V. RESULT AND DISCUSSION

The performance of the integrated UAV swarm system was assessed over 250 simulation steps, with a focus on search efficiency, coverage optimization, and resource utilization. The primary indicator of mission success was the cumulative detection rate. The system achieved full detection accuracy—successfully locating all 8 targets—by around step 190. The steep rise in detection between steps 60 and 190 demonstrates rapid convergence, confirming the effectiveness of the Federated Meta-Reinforcement Learning (FMRL) module in adapting the global search policy. This reflects a strategic shift from broad exploration to focused target localization once initial discoveries were made.

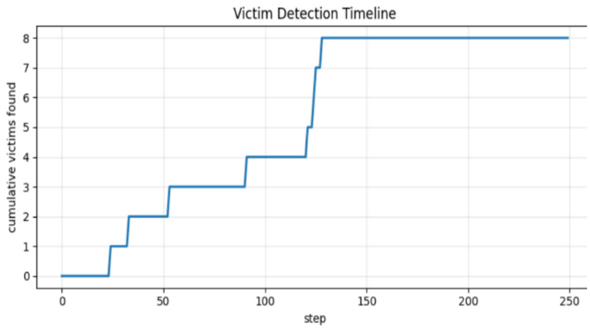

Fig. 5, *Victims Detection Timeline*

The Victim Detection Timeline (Fig. 2) highlights the swift responsiveness of the adaptive UAV swarm. The graph clearly traces the sequential detection of targets throughout the simulation, demonstrating that the FMRL-driven adaptive policy successfully guided the swarm toward areas with a high likelihood of target presence. The rapid pace of detections reflects both the precision and efficiency of the search process, emphasizing the system's ability to quickly shift from broad exploration to focused exploitation of known information. Additionally, the plot shows that the swarm effectively reduced redundant coverage by concentrating efforts in target-rich zones. This behavior confirms the strength of integrating FMRL with PSO for intelligent, adaptive mission coordination.

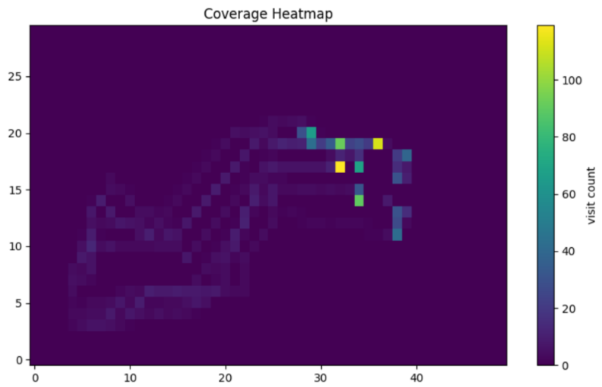

Fig. 6, *Coverage Heatmap*

The Coverage Heatmap (Fig. 3) illustrates how the search effort was distributed across the environment, revealing a distinctly non-uniform pattern with the highest concentration of visits in the right-center region (grid cells x∈ [30,40]). This pattern indicates that the FMRL and PSO coordination mechanisms effectively directed the swarm toward areas with a higher likelihood of target presence, thereby minimizing the overall search area and duration. The adaptive policy also helped conserve energy by avoiding unnecessary uniform scanning, improving both operational efficiency and mission effectiveness. Moreover, the heatmap demonstrates the swarm's ability to dynamically focus on high-priority zones while still maintaining sufficient coverage in surrounding areas. This strategic balance ensures that critical regions are thoroughly examined without neglecting broader mission requirements.

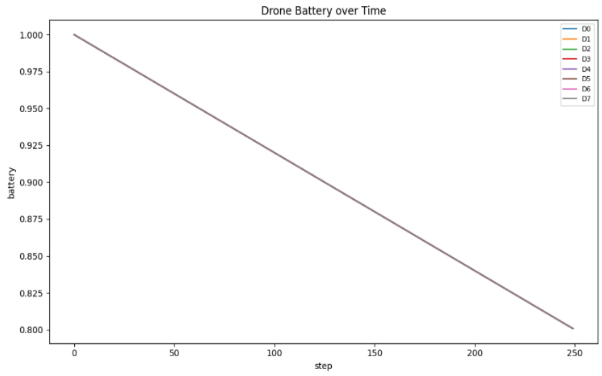

Fig. 7, *Drone Battery Over Time*

Resource utilization was assessed using the Drone Battery over Time plot (Fig. 5), which showed a nearly linear and uniform depletion of battery levels across all eight UAVs (D0–D7). By the conclusion of the simulation at t = 250, each drone maintained over 80% of its original battery capacity. This consistent usage pattern confirms that the FMRL-based task distribution and PSO-driven coordination effectively balanced the workload among all agents. The lack of abrupt drops or irregular consumption signals a healthy system state and strong operational reliability, significantly lowering the risk of mission failure due to power loss.

Additionally, the steady energy consumption reflects efficient path planning and task allocation, ensuring no individual UAV was overburdened. This balanced approach not only extends mission endurance but also reduces the need for frequent recharging or UAV replacements. The uniform battery usage also suggests strong scalability, indicating that similar energy efficiency could be maintained even with an expanded swarm. Altogether, the results highlight the robustness and sustainability of the proposed UAV coordination framework.

The simulation results highlight the effectiveness, adaptability, and robustness of the integrated UAV swarm system in disaster response scenarios. The fast target detection and focused search efforts demonstrate that the Federated Meta-Reinforcement Learning (FMRL) module successfully developed adaptive search strategies, outperforming conventional random or fixed methods. Balanced energy usage among UAVs showcases the efficiency of the load-balancing mechanism, enhancing system reliability and reducing the risk of failure from any single drone. The system's ability to achieve full target detection well before the simulation time limit indicates strong performance in terms of both speed and resource use. By integrating secure quantum communication, adaptive reinforcement learning, and intelligent swarm coordination, the UAV swarm offers a dependable, self-directed, and scalable solution suited for challenging and unpredictable operational environments.

VI. *CONCLUSION*

This study introduces a robust UAV-based disaster management framework that seamlessly integrates secure communications, adaptive intelligence, predictive analytics, swarm coordination, resilience through self-healing, and cognitive reasoning. The system uses the BB84 Quantum Key Distribution (QKD) protocol alongside AES-256 encryption to maintain secure communication between UAVs and ground control. Federated Meta-Reinforcement Learning (FMRL) supports decentralized policy learning, enabling each UAV to refine its strategies locally while contributing to a shared global model, preserving data privacy and enhancing efficiency. Particle Swarm Optimization (PSO) enables real-time coordination, optimizing flight paths and search patterns. Additionally, Digital Twin technology offers predictive monitoring and fault detection, ensuring operational continuity. Neuro-Symbolic AI (NSAI) enhances decision-making by fusing perceptual learning with interpretable symbolic logic.

Simulation outcomes confirm the system's effectiveness: the UAV swarm successfully detected all targets well before mission completion, showing fast convergence and intelligent adaptation. Coverage heatmaps indicate focused search behavior in high-likelihood zones, improving efficiency and reducing redundancy. Energy usage was evenly distributed, reflecting strong load balancing and system stability. Swarm behavior remained self-organizing and collision-free, even under challenging conditions.

In summary, the proposed system offers marked improvements over traditional UAV solutions in adaptability, resilience, and operational performance. Its integration of secure communication, distributed intelligence, coordinated movement, and predictive fault tolerance makes it a highly capable and autonomous disaster response solution, well-suited for complex and unpredictable real-world environments.

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