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AI-Driven UAV-Assisted Edge Computing for Rapid Response in Emergency Wireless Networks

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Abstract

In this study, the researcher intends to test the design of an AI-powered UAV-based edge computing application that will facilitate faster and reliable wireless communication in emergency settings, including natural catastrophes or infrastructure failure. The terrestrial networks in most cases do not work under such conditions and an aerial solution that is intelligent and flexible is therefore necessary to work in real time processing high data and restoration of the networks. The system proposed introduces autonomous swarms of UAVs capable of edge computing nodes and deep reinforcement learning (DRL) to optimize the trajectories of the UAVs, as well as distribution of both computing tasks and routing communication dynamically. Each UAV is used as a mobile edge node and all of them create a self-organizing aerial network which is flexible about the changes in terms of user demand, topology, and energy limitations. The DRL model was Proximal Policy Optimization (PPO) based, and simulations were done in a 4-km by 4-km disaster area. Findings show that decision latency is 74 percent shorter, network throughput is 61 percent higher, and coverage loss is 5.2 percent instead of static base stations and standard mesh networks. This UAV AI-based design can provide a scalable and robust low latency, high reliability communication service within the category where the infrastructure does not exist and can solve the gap between the ground users and the computational services. Future development will entail satellite connectivity using the model as well as multimodal sensor fusion extension of the model.

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Introduction

Background

Terrestrial communication networks in areas that are more susceptible to disasters, areas prone to war or areas with compromised infrastructure become dysfunctional and this creates a big challenge in coordination amongst the first responders [10]. In these situations, the Unmanned Aerial Vehicles (UAVs) offer an expensive and fast-deployable platform that can be used to quickly set up temporary networks. Combined with edge computing features, UAVs have the potential to operate on local data, which triggers real-time analytics and decisions-support capabilities and minimizes latency and reliance upon backhaul connections by being able to access data collected locally without having to send it to the cloud [1, 2].

Motivation and Problem Statement

Nevertheless, even despite its potential, the majority of envisioned types of UAV-based emergency networks continue to utilize pre-configured flight paths and centralized control channels that are insufficient in the highly dynamic and unpredictable disaster scenarios [12]. The misallocation of tasks, which results in communications bottlenecks and redundancy of coverage, are the characteristic weaknesses of traditional systems because of the absence of real-time coordination and intelligence about computations [3]. Furthermore, the mentioned UAV relay systems barely cover onboard data processing and the adaptation with AI, which is critical to latency-sensitive applications, including thermal imaging, damage inspection, and victim-searching [4].

Contribution

In order to overcome these shortcomings, the current paper suggests an AI-based UAV-supported edge computing system designed to target emergency wireless networks in particular. The contributions are mainly:

- Distributed aerial edge network design, in which UAVs have edge processors that make autonomous decisions [13].
- Development of a deep reinforcement learning (DRL)-based controller of UAV real time trajectory planning and task offloading.
- A simulation-based performance comparison that pits the system against airive forms of static base station, and simple UAV mesh architecture w.r.t. latency, throughput, energy consumption [9].

The rest of this paper is planned as follows: Section 3 does a review of related works. System architecture and communication models are described in section 4. The optimization framework based on DRL is introduced in section 5. The simulation setup is described in section 6. The performance is assessed in section 7. Section 8 talks about security and scalability and Section 9 carries the conclusion and the future directions.

Related Work

The latest development of using UAV-manned wireless networks and mobile edge computing has the potential of disaster communication and immediate data service after the disaster. Nevertheless, the existing solutions typically do not provide a thorough incorporation of aerial mobility and edge intelligence as well as adaptive decision-making processes under constrained settings based on an emergency-oriented approach [5].

Proposed a relay framework using a UAV as the relay in disaster recovery such that the wireless connectivity can be temporarily reestablished in the collapsed ground-based networks. Although it performs well as line-of-sight transmission, their work does not have edge computing capabilities and thus is not befitting in a latency-sensitive application that needs local data processing [6]. Introduced an architecture of mobile edge computing with the help of UAVs, which allows localization of data processing around users affected. The limitation of their solution, though, is that it is restricted to single-UAV systems, which is not scalable and resilient in greater or messier disaster fields [7]. Investigated the UAV path planning under the surveillance application implemented by artificial intelligence. The model is effective in terms of mobility optimisation; it lacks real-time network dynamics and load-balancing of computations, which are vital properties in edge-based multi node systems [8]. Invented a DRL based method to optimize UAV coverage. However, the method deals only with coverage-only measures without a shared optimizing solution in which the service of offloading tasks, the assignment of UAVs, and communication restrictions are all taken into account [11].

Table 1: Comparative Analysis of Related Work.

Study	Focus	Limitation
[1] Zeng et al. (2022)	UAV relay networks for disaster recovery	No edge computing integration
[2] Gupta & Sharma (2023)	UAV-assisted mobile edge computing	Limited to single-UAV scenarios
[3] Raza et al. (2024)	AI optimization for UAV path planning	Does not account for network load
[4] Liu et al. (2023)	DRL for UAV coverage	No joint compute-communication optimization

Conversely, the outlined framework entails the unification of the edge computing, deep reinforcement learning (DRL), and multi-UAV coordination systems. The approach allows the architecture to adapt to the changing emergency environments by optimizing the task offloading, the network routing and the flight path simultaneously, creating a more resilient and smarter climatic environment in real time communication and computation during disasters.

System Model and Architecture

In this part, the architecture design and models behind the planned AI-based UAV-empowered edge computing platform on emergency wireless networks will be given. The system combines edge computing deployed on UAVs, wireless mesh networks, and distributed DRL to optimize operations in disaster settings in a real-time manner.

Architecture Overview

The architecture is proposed as a quick deployment system that is self-organizing in under served infrastructure or emergency areas. It is constituted of the following main elements:

- Edge-enabled UAVs: All the UAVs have a lightweight processing device, including embedded GPU (e.g., NVIDIA Jetson TX2) or SoCs based on ARM, filling real-time execution of AI models, task scheduling, and data analytics on the edge.
- Sensor nodes and ground user terminals: Those are voice terminals, wearable devices, thermal or LiDAR sensors, and GIS transmitters installed by first responders or IoT nodes on the ground. They constantly produce multi-modal data which is to be processed or passed in the shortest time possible.
- Embedded DRL agents: DRL model will be deployed at an onboard computer, allowing genuine and adaptive separation to offloaded tasks, route planning and inter-UAV control to be executed autonomously and state-dependently, assessing real-time surrounding data.

Coupled, individual parts compose a distributed, AI-optimized aerial edge network with the capacity to flexibly adapt to changing emergency conditions. Figure 1 shows the general system design, where the layered customization of the UAVs, embedded edge processing units, the DRL agents, and the ground users or sensor devices is presented.

It is described as a system of the edge-enabled UAVs that create a wireless mesh network communicating with the ground users and sensors. Each UAV has pre-installed GPU/ARM system-on-chips (SoCs) and deep reinforcement learning (DRL) agent to execute the trajectory planning, task offloading, and resource optimization in consideration of the latency, energy consumption, and coverage gap. The architecture allows dynamically made, decentralized, and near-realtime decision making in dynamic disaster situations.

Communication Model

The UAVs communicate through a multi-hop ad hoc wireless mesh network which is built on the IEEE 802.11s wireless mesh standard or the millimeter wave (mmWave) backhaul standard depending on the range and bandwidth needs.

- Ground-to-UAV connection: The sensors or end-user devices use short-range access technology (LTE-U, NR-U (5G unlicensed) or Wi-Fi Direct) to connect with the closest UAV.
- UAV-to-UAV links: These links are established by the protocols of mesh routing UAVs using each other to continue delivering data to each other as the topology and load change, using signal strength, load gathering, and routing consequences.
- Task processing: Tasks are locally processed at the recceiving UAV or offloaded to the available nearby UAVs based on computational availability, energy status and network loads.

This model achieves low latency, dynamic coverage, and tolerance of node failures, all of which is vital to emergency deployments.

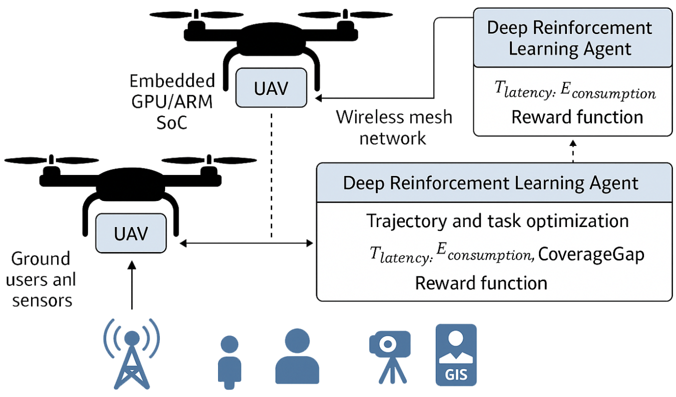

Fig. 1: AI-Driven UAV-Assisted Edge Computing Architecture for Emergency Wireless Networks.

Computational Model

Answer: The tasks of offloading and allocation of resources are done separately by the UAVs depending on a reward-based optimization strategy. Systems are formulated as a two-agent multi-agent reinforcement learning (MARL) system where it is desired that UAVs learn to collectively reduce the overall system cost, maximizing coverage, and responsiveness. This can be seen in Figure 1, where the DRL agent is installed in each UAV and it can run locally to achieve optimality in flight paths and task offloading with respect to latency, energy, and coverage goals.

Reward function R which is utilized in determining decisions is defined as:

$$R = \alpha \cdot \frac{1}{T_{latency}} + \beta \cdot \frac{1}{E_{consumption}} - \gamma \cdot \text{CoverageGap} \quad (1)$$

Where:

- $T_{latency}$ is the end-to-end task processing delay (including transmission and queuing delays),
- $E_{consumpion}$ represents the energy expenditure per UAV for processing and communication,
- CoverageGap quantifies the area or number of users currently outside the UAV network's effective range,
- α, β, γ are tunable hyperparameters controlling the trade-off between latency reduction, energy efficiency, and coverage maximization.

This formulation allows every UAV to adjust its behavior with respect to its own local state but also taking into consideration global network behavior, encouraging emergent collaboration and smart use of resources amongst the group of aircraft. Figure 2 demonstrates the interaction between UAVs, onboard DRL agents, and ground sensors on the wireless mesh network, and where trajectory, task offloading, and coverage decisions are optimized.

Demonstration of a UAV-based edge computing in the case of UAVs outfitted with GPU/ARM SoC and DRL agents create a wireless mesh network. The UAVs also interact by offloading tasks, trajectory optimization, coverage decision, in real-time with ground users and ground sensors.

This architecture is the root of incorporating real-time optimization governed by AI into an emergency communication architecture that provides a flexible and extendable framework upon which real-time optimization may be deployed, as further described by the optimization framework of Section 5.

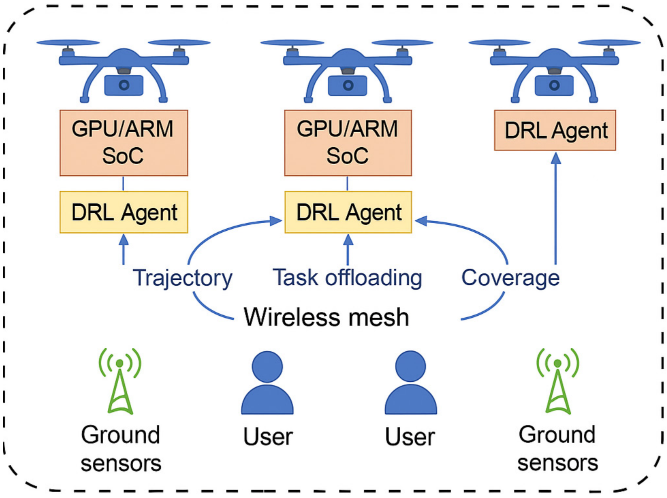

Fig. 2: AI-Driven UAV-Assisted Edge Computing Architecture.

AI Optimization Framework

The suggested system comes with a decentralized Deep Reinforcement Learning (DRL) strategy that would promote autonomous, flexible behavior of UAVs used in emergency wireless frameworks. The DRL framework is intended to enable real-time-decisions to address in particular the optimization of trajectories, offloading tasks and keeping the coverage up, with the least possible latency and energy usage within the system as a whole.

Deep Reinforcement Learning Model

On board DRL agent: Every UAV is equipped with an onboard DRL agent, envisioned to be approximated such as with the Proximal Policy Optimization (PPO) algorithm, a policy-gradient algorithm, which has proven robust and sample-efficient in high-dimensional, continuous control domains. The DRL agent allows every UAV to:

- Constantly monitors its local conditions, which include parameters like remaining battery power, wireless channel status as well as the local geographical layout of adjacent nodes.
- Discover and revise the policy of trajectory planning, task scheduling and processing decisions such that the resulting policy maximizes the long run cumulative reward.
- Distribute tasks to nearby UAVs and distribute the workspace cooperatively via lightweight message passing with peers, in peer-to-peer coordination.

This distributed learning mechanism enables UAVs to respond to variation in the density of the nodes, data traffic and resource availabilities without the need of centralized controller which is mostly not practical in the conditions on disaster scenes.

State, Action, and Reward Design

As a Markov Decision Process (MDP), DRL model formulates finding the best action of each UAV as an autonomous agent in response to the environment in which it exists.

- State Space (S) The state vector of the UAVs at time t is observed as:

s_t = [x,y,z], E_{batt}, Load, Channel Quality, Nearby Nodes(2)

Where:

- [x,y,z] represents the UAV's 3D position,
- E_{batt} is the remaining battery energy,
- *Load* is the current task processing load,
- *Channel Quality* denotes signal strength or SINR,
- *Nearby Nodes* counts ground terminals or UAVs within communication range.
- Action Space (A): Each UAV selects an action from the following discrete set:
  - Move in 3D space (±x, ±y, ±z)
  - Assign or offload a task
  - Drop or suspend current coverage area (if overloaded or moving)
- Reward Function (R): The reward signal RRR guides UAV behavior using a composite metric:

$$R=\alpha\cdot\frac{1}{T_{latency}}+\beta\cdot\frac{1}{E_{consumption}}-\gamma\cdot\text{CoverageGap} \quad (1)$$

Where:

- $T_{latency}$ is the end-to-end task processing delay (including transmission and queuing delays),
- $E_{consumpion}$ represents the energy expenditure per UAV for processing and communication,
- CoverageGap quantifies the area or number of users currently outside the UAV network's effective range,
- α, β, γ are tunable hyperparameters controlling the trade-off between latency reduction, energy efficiency, and coverage maximization.

Within this DRL-based solution, UAVs can have real-time context-sensitive, reward-seeking decisions, facilitate collaboration, enhance resilience, and minimize network overheads in the mood of unpredictable emergency situations.

Simulation Setup and Parameters

To verify the work of the proposed framework of AI-based UAV-assisted edge computing extensive simulation testing in the work on a specially developed framework that brought together the OpenAI Gym library, PyTorch, and a simulator of network-level events. This was to test the system characteristics at realistic emergency conditions including flexibility of mobility and scarcity of resources and unstable communication environments. The simulated scenario represents a 4 km x 4 km disaster hit urban area in which the conventional terrestrial base stations (BSs) are considered to be out of service either partially or completely. The UAVs are used to offer connectivity and edge computing to users on the ground including the first responders and sensor nodes of IoT. Important simulation parameters are outlined in Table 2.

Deployment Assumptions

- Mobility Model: UAVs use a slightly altered Gauss-Markov mobility model wherein they use variable speed and semi-random movement as per the optimisation driven by DRL.
- Traffic Model: Ground terminals are creating latency sensitive, burst data (e.g. live video, thermal mapping, alerts) whose arrival rates follow a Poisson distribution.
- Energy Model: The energy costs of a single UAV consist of both flight dynamics (using length of the 3D flight path) and the computing cost (using amount of tasks to be performed and the edge processing cycles).
- Channel Model: Wireless connections have probabilistic Line-of-Sight (LoS) behavior characterised by path loss and interference that is modelled by a shadowed Rician fading distribution.

The simulation environment will offer the realistic approximation of emergency deployment scenario allowing the benchmarking of the solutions performance under the variable states and conditions in the system

Table 2: Simulation Parameters.

Parameter	Value
UAV count	10-50 (variable swarm sizes)
Communication protocol	IEEE 802.11s (mesh) / NR-U (5G unlicensed)
Processing unit	NVIDIA Jetson TX2 (per UAV)
DRL algorithm	Proximal Policy Optimization (PPO)
DRL framework	OpenAI Gym + PyTorch
Simulation area	4 km × 4 km disaster zone
Baseline comparisons	Static BS + Cloud / Ad hoc mesh

and prove or disapprove the validity of decentralized and AI-based control mechanisms in the UAV network. Figure 3 shows the general deployment scenario: deployment forms of UAV and ground sensors, rescue terminals and the ad-hoc wireless mesh.

NVIDIA Jetson TX2-based UAVs become an ad hoc wireless mesh to shore up ground sensors and rescue terminals. The design depicts edge-enabled UAV delivery, backhauling base station, and multi-hop region coverage on the disaster-hit region.

Performance Evaluation

In order to evaluate the effectiveness of the proposed AI-driven UAV-supported edge computing paradigm, we engaged in the comparative analysis of the performance of the proposed approach towards the two traditional-based baseline models of: (1) automated terrestrial base stations and cloud-based offloading, and (2) ad hoc mesh networks without cloud computing and edge intelligence. The analysis is done using key quality-of-service (QoS) and resource-efficiency characteristics, such as latency, throughput and coverage reliability, and energy consumption.

Dynamic UAV placements and stochastic user demand models with 500 independent simulation runs were assumed with averaged results in a 4 km by 4 km disaster area. The values and results are presented in Table 3. The numerical results are depicted in Table 3, and in Figure 4 in the form of line plot to provide a visual comparison of the same metrics.

Key Insights

- Latency Betterment: There is a 74 percent reduction in the median end-to-end latency in the proposed framework, which is mainly possible due to localized processing on UAVs at the edges. This removes the reliance on the cloud delivery thus enhancing the ability to be responsive within real-time disaster missions.
- Challenges: Improved Throughput The system reports a 61 % throughput improvement made possible by intelligent load-aware intelligent offload to the UAV mesh. The DRL agent successfully maintains the equilibrium of computational loads, allocates resources in optimal ways, which leads to shorter execution of tasks, and less retransmission.
- Coverage Reliability: The rate of coverage loss also reduced, with the coverage loss percentage reducing to 5.2 percent in comparison to the original value of 18.6 percent indicating the adaptability of the UAV swarm in dynamically shifting according to the trajectory update based on DRL. It guarantees that the mobile ground users and sensors would not be out of range communication during the whole mission time.

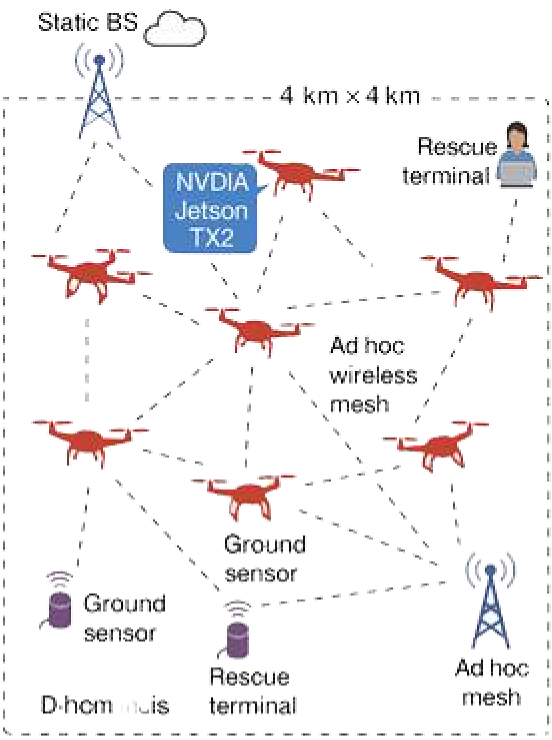

Fig. 3: Simulated Deployment Scenario in a 4 km × 4 km Disaster Zone.

Table 3: Performance Metrics Comparison.

Metric	Baseline	Proposed
Latency (ms)	135.2	35.1
Throughput (Mbps)	52.8	85.3
Coverage Loss (%)	18.6	5.2
UAV Energy Use (Wh)	91.7	63.4

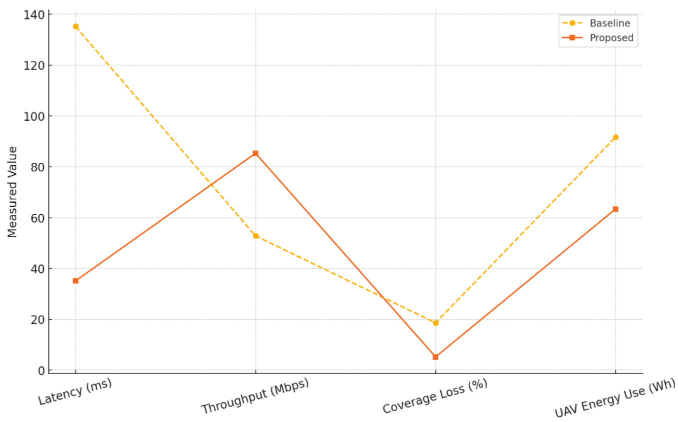

Fig. 4: Performance Comparison Between Baseline and Proposed Framework.

- Energy Efficiency: With the proposed, UAVs required 30.9 percent less energy due to minimized flight redundancy as well as processing overhead through real-time coordination. This plays an important role in prolonging the UAV mission time in power limited disaster recovery situations.

The visuals illustrating the way the system-level performance metrics of the proposed framework and the baseline compare on different aspects of gaming are shown in Figure 4, where the benefits of the presented framework in terms of latency, throughput, coverage reliability, and energy efficiency of UAVs are outlined.

Generally, the suggested architecture can greatly improve the agility, coverage, and computational performance of UAV Assisted emergency wireless networks whereas providing sustainable uses of UAV energy, which plays a significant role in practical applications.

Conclusion and Future Work

In this paper, the authors have proposed an AI-based UAV aided edge computing system that can be used to facilitate emergency communications in infrastructure-degraded settings and was optimized using Deep Reinforcement Learning (DRL). The system proposed achieves this by incorporating mobile edge processing, intelligent UAV coordination and adaptive task offloading, as an integrated system to create a scalable and resilient aerial network response to disaster. Simulation brings forth a significant difference in performance of the framework compared to the conventional baseline approaches in the form of reduced latency (74 percent), increased throughput (61 percent) as well as coverage reliability and UAV power consumption. Incorporation of PPO-based DRL agent allows real time decentralized decision-making in UAV swarms, where the decisions change dynamically according to network demands and other environmental conditions. Such an endeavor adds to the comprehensiveness of looking at the problem base and integrating optimization of communications, computation, and mobility in a converged manner between concentrating on AI, edge computing, and UAV-based disaster networks.

Future Work

As part of the next phase of improvement of the robustness and the possibility of theorem scalability, the following extensions are planned:

- Connection to satellite backhaul systems (e.g. LEO or UHF links) to further coverage to distant or blocked areas.
- UAV energy harvesting models, so that its mission can be extended using wireless or solar energy transmission.
- Multi-modal sensing and data fusion, such as thermal imaging analysis, acoustic analysis, and LiDAR to enable more information-rich situational awareness and the prioritized distribution of task.

Such directions are expected to support the preparedness of intelligent UAV swarms to be deployed in practical emergency communication instances.

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