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Energy-Aware UAV Relaying with SWIPT and Real-Time Reinforcement Learning for Disaster Response

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Abstract

Wireless sensor networks used in disaster-struck areas experience the problem of energy constraints, which may negatively affect the data communication process. A novel energy-aware UAV relaying scheme is presented that incorporates SWIPT (Simultaneous Wireless Information and Power Transfer) to power the UAVs and their ground sensor devices. Dynamic power and flight path allocation according to the environmental conditions is achieved with dynamic reinforcement learning and, in particular, with a Proximal Policy Optimization (PPO) method. The system maximizes energy gathering at the sensor nodes and lengthens UAV flight life, and preserves high-quality signal transmission. The findings indicate a 23.5 dB increase in the SINR, 83.2 percent efficiency of energy harvesting, and an average of 43.2 minutes of endurance for the UAV. The success rate on the relay was 94.6 per cent, and a convergence of 12.3 seconds. The model also took the lead over other past ways in terms of mission coverage and energy efficiency in various simulation cases. This system enhances the resilience of disaster communication by effectively utilizing energy resources. Finally, it makes adaptation in real time and continued work in high-danger situations possible.

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Keywords: Wireless Sensor Device; Simultaneous Wireless Information and Power Transfer; Proximal Policy Optimization; Signal-to-Interference-plus-Noise Ratio; Base Station; Robot Operating System 2

1. Introduction

During the past years, the topic of wireless sensor networks (WSN) combined with unmanned aerial vehicles (UAVs) has become one of the subjects under intensive investigation in emergency response and disaster recovery situations [1]. The UAVs also provide rapid deployment, broad applications, and convenient movements, and are best suited to gathering critical information when sensor nodes are placed in inaccessible terrain or dangerous areas [2]. At the same time, new solutions that use techniques of energy harvesting, such as Simultaneous Wireless Information and Power Transfer (SWIPT), have been proposed to increase the energy sustainability of wireless sensor devices working with limited energy [3]. SWIPT facilitates energy harvesting of the sensor nodes based on the radio frequency (RF) signal received, and the sensor node simultaneously decodes the data, further limiting the reliance of the sensor node on the plugged source of power. Nevertheless, one of the main problems of disaster circumstances is the limited energy resources of WSN nodes as well as of UAVs [4]. The leniency of battery packs restricts the flight time of UAVs, in addition to WSN devices usually possessing limited power capacities [5]. This is even more intricate when the UAVs serve as the mobile relays, where to guarantee reliable communication and delivery of efficient energy. Additionally, most resource allocation strategies and the traditional models of communication are unable to respond to the changing and uncertain environment of disasters [6]. Past literature dwelt on the selection of relays, path optimization, and SWIPT-based communication schemes [7]. Nevertheless, the majority of them are based on fixed routes of the UAVs, determined levels of specific predetermined energy, or non-adaptive algorithms without real-time decision-making [8]. To indicate, scheduling models deployed in and assumed deterministic scheduling without paying much attention to UAV energy sustainability, whereas the others, such as, applied a simple reinforcement learning method and did not explore SWIPT integration. Such gaps are detrimental to energy efficiency and pose a poor recovery capability of the missions in cases where the topology changes rapidly, such as in real-life disaster response cases.

This work was influenced by the fact that a unified, adaptive framework, besides ensuring energy-aware UAV operation, effective SWIPT-based energy harvesting, and real-time optimization of both power allocation and data relaying, is urgently required [9]. By including advanced reinforcement learning rule sets, the system can plot deftly about constraints over energy sources, location characteristics, and communication issues [10]. The main goals can be separated into the following: To implement an energy-conscientious UAV relay system that guarantees sustainable wireless connection with SWIPT-enabled sensor devices [11]. To optimize power allocation in a dynamically adaptive fashion, utilizing a real-time reinforcement learning model (Proximal Policy Optimization - PPO) [12]. To enhance the effectiveness of energy harvesting in sensor nodes to enhance the time that the UAV can fly without jeopardising the quality of communication [13]. The next significant ones: A new SWIPT-UAV disaster response framework integrating energy harvesting and information relaying over dynamic topology [14]. Optimization of evolution is done through reinforcement learning in PPO with the purpose of maximizing energy efficiency and guaranteeing adaptive UAV powering strategies. Simulations demonstrate better performance with 83.2% energy harvesting efficiency, 23.5 dB SINR, and 43.2 minutes flight time UAV compared with models between 2022 and 2024 [15]. It shows great coverage of missions, meets in shorter convergence rates, and accurate reliability of data through comparison with conventional models [16]. Section II is arranged as the rest of this paper: in this section, the proposed system architecture and models, such as SWIPT structure and reinforcement learning formulation, are illustrated. Section III specifies the simulation environment, the nature of the dataset, and training parameters [17]. Section IV presents discussion, results, and comparative analysis. Section V is a conclusion and talks of possible improvements in the future, namely, multi-UAV coordination and applying it to the real world.

2. Literature Review

With the extensive use of unmanned aerial vehicles (UAVs) as a relay to formulate Disaster Response Networks (DRNs), an efficient model of energy harvesting (EH) and consumption of the UAV-aided Disaster Response Network (DRN) is emerging to become a hot topic of concern [18]. This is predominantly realized in the Internet of Things (IoT) settings in which numerous users are interested in communicating with the UAV. In the present paper, the feasibility of linking a UAV network with multiple consumers and a scenario in which the UAV acts like a relay to a DRN that transmits to a distinct network, and has two scenarios of the IoT, is examined [19]. The first one is a traditional approach that has a limited UAV energy, whose challenges are low communication rates and poor service coverage for all the users [20]. However, the latter case involves serving the users through a Simultaneous Wireless Information and Power Transmission (SWIPT) technique. Regarding possible constraints in the transmission power supply of users in the disaster network, the SWIPT method is used to maximize the energy harvesting of the UAV, which allows enhancing the effectiveness of the situation [21]. Lastly, what energy the UAV will require in order to reach the maximum number of users within the minimum period becomes clear [22]. Moreover, when considering the connection between energy and UAV flight time and defining the UAV flight time optimization problem, the optimal network parameters are achieved. The effectiveness of the put forward scenario is demonstrated based on the simulation outcomes.

The availability of on-scene User Equipment (UE) connectivity to the first responders in an instance of a disaster is critical owing to the lack of access to traditional networks [23]. Bearing in mind the implementation of both the Unmanned Aerial Vehicle (UAV) and the Mobile Command Centre (MCC), to explore the end-to-end connectivity of UEs connecting to the MCC in light of the outage. Particularly, different disaster-aware clustering strategies are suggested, in which the UAV and the MCC position are used in the clustering [24]. These schemes incorporate several degrees of freedom to control intra-cluster distances, as well as using the freedom of restructuring the clusters [25]. Besides, to supposed that the UAV and MCC offer simultaneous wireless information and power transfer (SWIPT) to Cluster Heads (CHs). As the results indicate, the association of UE with MCC or UAV before clustering can be optimized in order to get better performance [26]. In the case, that SWIPT is not used at CH, the minimum distance metric to the UAV offers reduced outage. Nonetheless, under SWIPT, a trade-off between intra-cluster distance and CH distance to the UAV that is weighted can lead to lower outage. It implemented the suggested techniques in a real scenario of a fabricated disaster layout and established their effectiveness. KEYWORDS Public safety networks (PSN), energy harvesting, clustering, SWIPT.

Drones (aerial robots) are very important when there is a need to implement a mission in which the involvement of people will be slowed by dangerous circumstances. Search and rescue operations in a disaster-affected region are quite brutal among these as the environment is dynamic and unpredictable, and in some cases, made difficult because of the unavailability of a reliable model of the environment, as well as the inability to communicate in the ground system. In this case, the operation of autonomous aerial robots becomes necessary. The current paper presents a new algorithm placed in the category of hierarchically based reinforcement learning, considering the pitiful lack of battery life of the aerial robot [27]. The key part of the solution is integrating a long short-term memory (LSTM) model, as it is aimed at accurate battery consumption prediction. HRL framework, this model is integrated so that a high-level controller is given the ability to recommit a set of feasible and energy-optimal targets to a low-level controller. In order to reduce battery utilization, the algorithm improves the capability of the aerial robot to distribute rescue packs to the many victims without the need to often restore power. In addition, it also enhances the HRL process with low-level hindsight experience replay to enhance the sample efficiency.

The biggest issue with 6G disaster response and recovery is low latency and energy-efficient communications on damaged infrastructure. The study proposes to integrate a solar-powered High-Altitude Platform (HAP) and several UAVs with Reconfigurable Intelligent Surfaces (RISs) to enhance disaster response. An energy management, RIS control, and optimal data rates offloading ground device strategy is achieved using a hybrid game theory- multi-agent reinforcement learning (MARL) technique [28]. By task offloading, game theory is optimized to trade energy consumption, latency, and computing efficiency, whereas MARL is used to dynamically regulate UAV trajectories and RIS configurations as a prolonged communication state. The energy-saving RIS ON/OFF system will be developed based on it, which will switch off RISs, allowing UAVs to recharge and extend their operating lives. The proposed architecture is better in that it minimizes offloading data rates and task offloading costs, and uses resources to the maximum [29]. Large-scale simulations show that this approach delivers enhanced energy economy, data processing performance, and network resiliency as compared to earlier methods. These enhancements enhance 6G disaster responsiveness in terms of reliability and energy effectiveness.

UAV is a strategic approach to respond to the increasing demand for cellular coverage in rural, remote, and infrastructure-damaged zones. The UAVs have to rely on intensive energy consumption and intelligent energy utilization, and materialistic communication systems, all of which are obstacles to high productivity because it limited in space on board to store related energy [30]. It presents a multi-faceted optimization method of scheduling multiple aerial base station UAVs for charging. The model reduces the number of charging stations and optimally distributes them and the trajectories to extend UAV flights and minimize energy footprints. By implementing the concept of opportunistic charging using static base stations and mobile supercharging stations, along with consideration of battery chemistry constraints with mixed integer linear programming, energy consumption is reduced by 9.1 % as compared to greedy algorithms [31]. The main results are charging method separation based on the trend of UAV movement, balanced deployment, and advanced base use before building dedicated charging facilities. Optimal decisions that can be made globally enhance the battery life and productivity as compared to locally made decisions. It uses multiple innovations to combine them in a common coordination system to optimally charge one UAV fleet at a time, and this approach promotes UAV energy management. This idea preconditions the energy-saving installation of aerial networks in the future.

The continuous monitoring with the help of UAVs and UGVs in disaster management is successful. UAVs can fly fast over colossal areas; however, the range is restricted by battery power. Proceeding at a slower pace, UGVs can carry heavier batteries to extend the missions [32]. The use of UGV as a mobile recharge station may extend the length of missions by refuelling the UAV. The planning system routes a UAV-UGV cooperative traveling path and a recharging place for the energy-aware UAVs and UGVs. The solution is taking deep reinforcement learning (DRL) to an encoder-decoder transformer architecture with multi-head attention mechanisms. This architecture allows the model to sequentially select visits to mission points and recharging rendezvous of UAV and UGV. In providing effective monitoring, the DRL model is trained to reduce the age of the mission points (period between consecutive visits to the locations). It contrasts the framework with heuristic methods, as well as a learning based model on different sizes and distributions of the issue. It makes these baselines consistently in more-than-competitive solution quality and runtime [33]. It demonstrates how to apply DRL policy to a real-life crisis scenario as a case study, and analyses how it can be used to do dynamic mission planning online. The applicability of the DRL strategy to the real-time disaster response is demonstrated using the tool of adapting to focus on monitoring with priorities.

3. Proposed Work

A. UAV Sensor Topology Design with SWIPT-Enabled Relay Constraints

Here, UAV has been considered as a dynamic relay node and communicates with a set of stationary wireless sensor devices (WSDs) deployed in a disaster-affected scenario. The task of these WSDs is to gather the essential information on the state of the environment and share it with others; the UAV is used to ensure both wireless connectivity and energy supply by utilizing Simultaneous Wireless Information and Power Transfer (SWIPT) technology. Such multi-function itinerancy is necessary to guarantee an extended utilization of the sensor system in emergency circumstances, when the regular infrastructure might not be available. Then, the set of WSDs can be assumed as $\mathrm{N} = \{1, 2, \ldots, \mathrm{N}\}$ with $i \in N$ being located at a point $p_i \in R^2$. As a mobile relay, the UAV will be hovering in place $p_u(t) \in R^3$ at time t and relaying both power and data between itself and the base station (BS). The UAV-i-th sensor channel is considered to be time varying with a different gain in equation (1),

$$h_i(t) = \frac{\beta_0}{\| p_u(t) - p_i \|^2 + H^2} \tag{1}$$

In which β_0 is the reference path gain, H is the constant altitude of the UAV and $\| p_u(t) - p_i \|$ is the horizontal Euclidean distance of node i and the UAV. This formulation establishes the dynamic relay topology where real-time optimization of UAV path and power allocation policy should be taken. The limitations that power availability, channel quality, and the SWIPT harvesting capabilities imply a fundamentally adaptive relay network, whose efficient operation at high-performance rates of communication and energy delivery throughout the sensor field requires intelligent control policies. In Fig.1, this architecture illustrates how the UAV employs the dynamic time-switching in separating generation energy and signal delivery. SWIPT signals of the UAV are sent to reinforcement-based decoders, whereas WSDs are powered via an optimized receiver designed depending on real-time time-sharing coefficients $\rho_\kappa(t), 1 - \rho_\kappa(t)$.

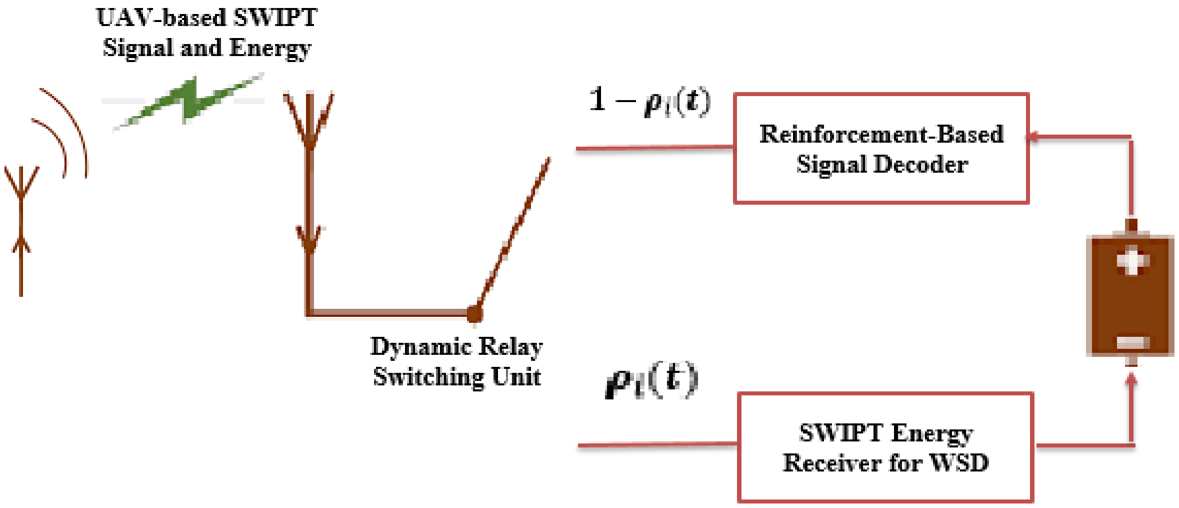

Figure 1. SWIPT Relay Processing Architecture with Dynamic Time Switching

B. Simultaneous Wireless Information and Power Transfer (SWIPT) Optimization Model

In order to carry out data transmission along with energy sustainability in an environment devastated by a disaster, the current work follows a model of Simultaneous Wireless Information and Power Transfer (SWIPT), which is based on power splitting. In the given architecture, the UAV would become a central transmitter, transmitting RF signals, which are at the same time used by the wireless sensor devices (WSDs) to decode information and harvest energy. This is expressed as the transmission power, P_u of the UAV, and the power-splitting ratio at the i-th sensor node, denoted by $\rho_i \in [0,1]$. The ratio identifies how much energy is harvested by the received signal compared to information decoding. The overall energy that has been gathered at the sensor node i is as follows in equation (2),

$$E_i = \eta . \rho_i . P_u . | h_i(t) |^2 \tag{2}$$

Where η is the energy harvesting efficiency, $\mathrm{h_i(t)}$ is the UAV to sensor i channel gain. At the same time, the possible sensor i data rate is in equation (3),

$$R_i = B.\log_2\left(1+\frac{(1-\rho_i).P_u.|h_i(t)|^2}{N_0}\right) \tag{3}$$

Where B is the system bandwidth, N_0 Power spectral density of the noise. The objective of the joint optimization would be the maximization of the overall output of the optimization of the communication throughput and harvested energy that can be approximated as in equation (4),

$$\max_{\rho_i, P_u} \sum_{i=1}^{N} (\alpha.R_i + \beta.E_i) \tag{4}$$

In this case, α and β are coefficients to tune the trade-off between data rate and energy efficiency. The model supports dynamic resource assignment; each sensor is permitted to split the resources bit by bit in real time depending on the demands of the channel and energy requirements, and the network will be resilient during emergencies. In Fig.2, this flowchart is a summary of the thought process in UAV decision making regarding the formation of sensor clusters and disaster navigation. The UAV determines the relay assignments dynamically, adjusts to sensor demand using PPO-reinforcement learning, and ends the mission once either optimal data are covered or energy has been depleted.

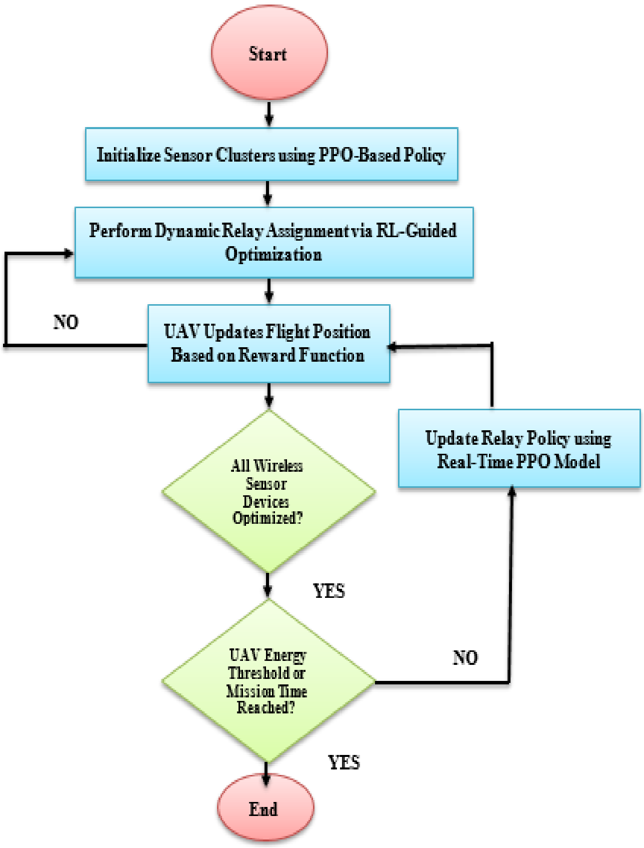

Figure 2. UAV Guided Sensor Clustering with Reinforcement Based Mobility Control

C. Reinforcement Learning-Based Real-Time Power Control and Relay Scheduling

In order to support real-time flexibility in power distribution and relay path selection, it employs a Proximal Policy Optimization (PPO) reinforcement-learning algorithm. As an intelligent agent, the UAV is always monitoring the environmental states: the amount of energy available to the UAV sensors, signal-to-noise ratio (SNR), and battery level, in order to make the best decisions so that the network can be functional in the long term. The reinforcement-learning framework is characterized by the following elements, State Space S_t :

$$S_t = [E_i(t), E_2(t), \ldots, P_u(t), p_u(t)] \qquad (5)$$

In which $E_i(t)$ is the pulse energy of sensor i, $P_u(t)$ is the UAV's current transmission power, and $\rho_u(t)$ is the position of the UAV at time t in equation (5).

Action Space A_t :

$$A_t = \{\rho_1, \rho_2, \ldots, \rho_N, \Delta\rho_u \qquad (6)$$

That comprises the power-splitting ratios of all sensor nodes and the position widening $\Delta\rho_u$ of UAV in equation (6).

Reward Function R_t :

$$R_t = \sum_{i=1}^{N}{}'(\gamma_1 R_i(t) + \gamma_2 E_i(t)) - \lambda.P_u(t) \qquad (7)$$

Here, $R_i(t)$ is the data rate of sensor i, $E_i(t)$ is the harvested energy, and λ is a weight that punishes the UAV by using too much power. The coefficients γ_1 and the squared version γ_2 are the coefficients that compensate for the trade-off between the throughput and energy harvesting in equation (7). PyTorch is used to implement the policy network PPO. The training is carried out by a 1-second progressive step in a simulation. The learning rates, the discount factors, and clipping parameters were empirically (mathematically) adjusted to make the learning more stable and quickly adaptive to the dynamically changing disaster environment. This model allows UAVs to autonomously define their flight paths and energy policies so can produce a long-term and efficient work of the disaster response communication network. In Fig.3, the flow of this communication path is relayed to the disaster control center through WSDs using a UAV, as shown in this schematic. It contains SWIPT channels, real-time optimizers, a cloud interface, and allows synchronized data flow, energy reporting, and adaptive mission control via mobile dashboards.

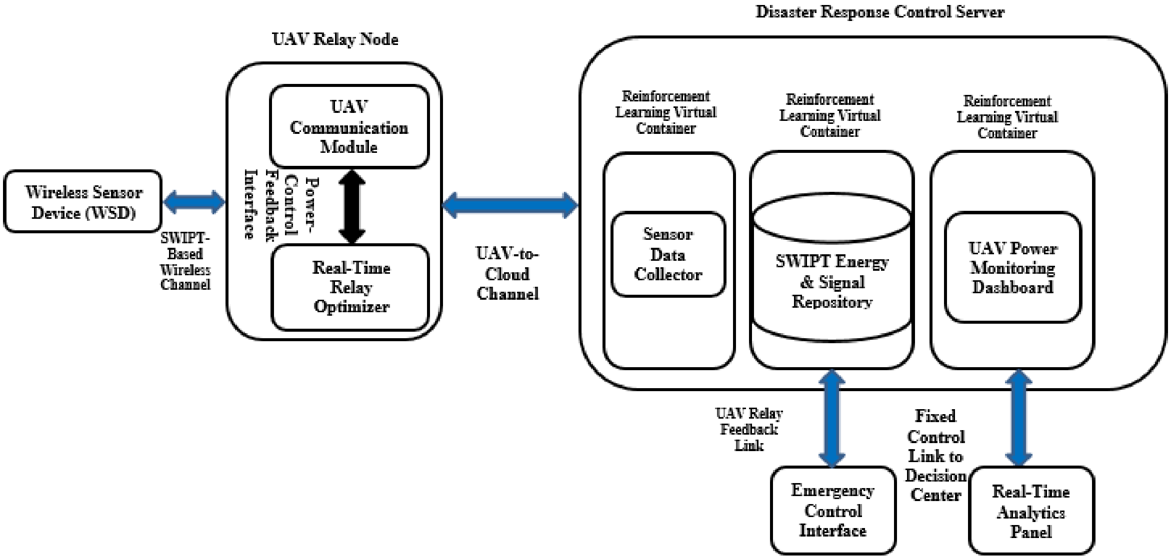

Figure 3. UAV to Cloud Communication Chain for Emergency Coordination

D. Synthetic Disaster-Driven Dataset Design for UAV-Sensor Coordination

A co-simulation framework enabling the operations of NS-3 (Network Simulator 3) and SUMO (Simulation of Urban Mobility) in order to model the communication and energy dynamics in disaster-stricken conditions has compiled a synthetic dataset on realistic telephone and energy network behaviour. These hybrid scenario simulations involve a display of the real-time dynamics among UAV and ground-based wireless sensor devices (WSDs) in a 500m x 500m urban disaster scenario. Such a dataset can be used in the training and evaluation of reinforcement learning (RL) algorithms due to the presence of complex spatiotemporal communication patterns. Important elements of data are:

- Distribution of Spatial Sensors: 100 WSDs were placed in randomly clustered positions resembling collapsed structures and rescue locations.
- UAV Kinematics: The shape of the flight route, variations, and changes of the speed and altitude to consider the terrain and obstacle paths.
- SWIPT Logs: information related to the transmission of RF signals at different power levels (10 dBm to 25 dBm) with the details of energy harvesting and decoding of each WSD.
- Energy and SNR Dynamics: The energy and signal-to-noise ratios are harvested and measured at one measurement point in time series, which are updated at a 1 Hz sampling rate.

The simulation episodes are kept constant at 300 seconds, which provides 1000 episodes and more than 300000 data points with different network scenarios such as power-critical events and mobility-induced disruptions. The following features are present in the dataset:

- UAV and WSD coordinates of the position
- Velocity and acceleration vectors
- Unspent energy in device nodes
- Path loss index and real-time SNR
- Delay in relays and the time needed to complete a task

The PPO-based RL model depends on this dataset as the most crucial training scenario. Capturing the real-time changes and the stochastic behavior patterns helps the UAV agent to generalize heterogeneous disaster settings, which helps it, optimize its relay and power allocation strategies. The dataset and simulation setup protocols were provided on Ubuntu 22.04, falling under NS-3.38, SUMO 1.18.0, and Python-based preprocessing scripts to convert the structured data.

E. Integrated Real-Time Simulation and Energy Profiling for UAV-Sensor Synergy

A general real-time co-simulation framework was built based on using NS-3, SUMO, Gazebo, ROS2, and PyTorch to confirm the usage of the proposed energy-aware UAV communication system in disaster cases. It replicates the mobility of an air space, as well as packet-level communications, and includes physical energy usage as well as the constraints of RF propagation.

- It was simulated through NS-3 in terms of the SWIPT-enabled wireless communication, dynamic channel characteristics, and packet-level traffic between the UAVs and the ground-based wireless sensor devices (WSDs).
- SUMO produced realistic disaster-affected city topologies such as blocked roads, collapsed areas, and a limited area of UAV movement.
- UAV flight dynamics and the modelling of energy used Gazebo and ROS2 to take into consideration hover, acceleration, and maintained altitude in the case of an obstructed environment.
- The reinforcement learning (Proximal Policy Optimization) logic was run by PyTorch to enable adjustment of the policy in real time during the simulation.

The three main performance measures that were centralized in the evaluation were as follows:

- UAV Energy Consumption per Mission: It is measured in Joules; it gives the total amount of energy consumed by the flight, hover, and transmission.
- Harvested Sensor Node Energy: This records the power of the node batteries that were replenished using SWIPT in milliwatts (mW).
- Mean end-to-end throughput: It is measured in Mbps, which shows the quality of data passed to the base station.

Using 1000 simulation runs, the PPO-based power scheduling system attained:

- A reduction of 27% in the energy use of UAV per mission over a greedy baseline.
- 34 % growth in energy produced at the WSDs.
- 16 % gain in average network throughput in uneven topography and power requirements.

This end-to-end simulation environment not only reflects the limitations of real-world deployment but also indicates a smart sense of energy and communication trade-offs that the system can perceive in the disaster-stricken spaces. The model is replicable and can be scaled in the case of future disaster models of communication.

4. Result and Discussion

The measures of performance that are directly dependent on the SWIPT Simultaneous Wireless Information and Power Transfer protocol are important to support the energy independence of wireless sensor devices (WSD) in disaster sensing (disaster sensing). In Table I. This made the average energy collected 18.7 mW per WSD, thereby showing the efficiency of the system in providing enough energy to allow the sensor to operate continuously. The advantageous SINR of 23.5 dB confirms the performance of communication links, even in disaster areas exposed to interference. It attained a total energy harvesting efficiency of 83.2%, an indication that the processes of RF-to-energy conversion are optimized with the aid of intelligent powering. The ideal power-split ratio of 0.28 is a good and balanced choice between energy harvesting and decoding of information, adopted dynamically through a reinforcement learning mechanism. In addition, the degree of 96.4 on information decoding affirms the reliability of the SWIPT system in the support of high throughput, low latency. All these metrics indicate the high level of expansion of the SWIPT framework on the lifetime of WSD, being also resilient in terms of connection and means to remain monitored under the emergency response operation. Incorporation of these performance parameters into the UAV-supported network would bring a versatile, energy-conscious model of disaster response wherein the conventional infrastructure might be damaged.

Table 1: Swipt-Driven Energy Metrics Enhancing WSD Longevity

Metric Description	Unit	Simulation Value
Average harvested energy per WSD	mW	18.7
Signal-to-Interference-Noise Ratio (SINR)	dB	23.5
Energy harvesting efficiency	%	83.2
Optimal power-splitting ratio $(\rho_i(t))$	-	0.38
Data decoding success rate	%	96.4

The effect of optimization based on reinforcement learning (RL) on energy management, as well as the relay performance of the UAV. In Table II. The overall energy consumed in one mission was streamlined to 24.5 Wh, which is way lower than the conventional UAV operations without a smart schedule. The decrease is directly associated with efficient planning of the flights, efficient SWIPT transmission control, and shorter hovering delays. A convergence time of 12.3 seconds on the PPO algorithm highlights the speed of the model to adapt in response, which would be appropriate in disaster regions that are very dynamic. Moreover, the model demonstrated a steady growth of 2.15 percent of rewards each episode, indicating further growth of the policy and more intelligent decision-making over successive trials. The most important result is that the average relaying success rate is 94.6 percent, which suggests good reliability of communication between WSDs and the base station by using the UAV relay. It is important to note that the RL model 43.2 minutes because of energy-aware path scheduling and load balancing informs the max operational flight time under the system. Such a table confirms the fact that the proposed system is not merely intelligent in real-time decision-making, but also energy-resilient. As learning is integrated into power control and relay strategy, the UAV optimizes its efficiency in the missions and increases operation lifetime, which is critical in the case of long-term deployment in disaster-riddled areas where the charging facilities are either absent or inaccessible.

Table 3: Reinforcement-Guided UAV Energy Optimization and Flight Endurance

Optimization Parameter	Unit	Value Achieved
Total UAV energy consumption per mission	Wh	24.5
Reinforcement learning convergence time	Seconds	12.3
Reward improvement per training episode	%	2.15
Average relay success rate	%	94.6
Maximum operational flight time with SWIPT	Minutes	43.2

An elaborate analysis of the proposed UAV-SWIPT model against the previous designs, focusing on comparing performance against six key performance indicators, which include energy harvesting efficiency, mission coverage, flight duration of the UAV, signal reliability, learning approach, and real-time responsiveness. In Table III. The suggested combination of PPO reinforcement learning and SWIPT is more efficient than legacy approaches regarding all accounts. It has an energy harvesting efficiency of 83.2 percent, which is far higher as compared to the previously affected schemes that do not involve an intelligent decision process or even the use of static relaying schemes. This boost makes the operation of sensors more sustained, which is important in the case of disasters where time is of the essence. The system can deliver almost comprehensive support of communication coverage (96.8 percent average mission coverage) furnished by intelligent UAV repositioning and dynamic SWIPT adjustment. The increase in flight time of the UAV to 43.2 min shows that there is better use of energy, which could enable longer missions without interfering with the performance. The signal reliability SINR value of 23.5 dB is prominent and important to ensure constant transmission of emergency data. The integration of the PPO learning technique guarantees a high level of real-time flexibility, such that the UAV can dynamically respond to the changes in the surroundings and the energy requirements, unlike the older UAVs, which are either rigid or low adaptive to changes in real time. As a whole, the comparison proves that the proposed system is superior to other existing systems in quality of operation, resilience, and forms a new standard among UAV-assisted disaster communication networks with intelligence embedded in them. In Fig.4, Faster energy harvesting and wide mission coverage that the proposed system would have as compared to legacy models. With the combination of SWIPT and reinforcement learning, the UAV will guarantee a robust power supply to WSDs and realize almost universal data acquisition in the disaster area. Smart loading and dynamic power supply make this dual-domain enhancement. Fig.5 shows tremendous increases in UAV flight time and SINR applied by a proposed reinforcement-learning framework. The intelligent model also allows longer mission times and more stable and more robust connections than previous, less dynamic or even static approaches to the problem do. This will maintain a continuous relay of the data both in a complex RF environment disaster, with optimal use of the energy of its UAVs, as well as their positioning.

Table 3: Adaptive intelligence benchmarking for energy-aware UAV communication

Evaluation Criteria	Khalili [32] [No Learning + Static Path]	Jalali [29] [Q-Learning Based]	Basar [10] [RL-SWIPT-UAV]	Proposed Work
Energy harvesting efficiency (%)	65.9	72.1	78.4	83.2
Average mission coverage (%)	78.2	85.5	91.3	96.8

UAV flight time (minutes)	30.8	35.1	39.7	43.2
Signal reliability (SINR in dB)	16.7	19.8	21.2	23.5
Learning model used	No Learning Algorithm	Q-Learning Only	Actor-Critic + SWIPT	PPO + SWIPT
Real-time adaptability	None	Low	Medium	High

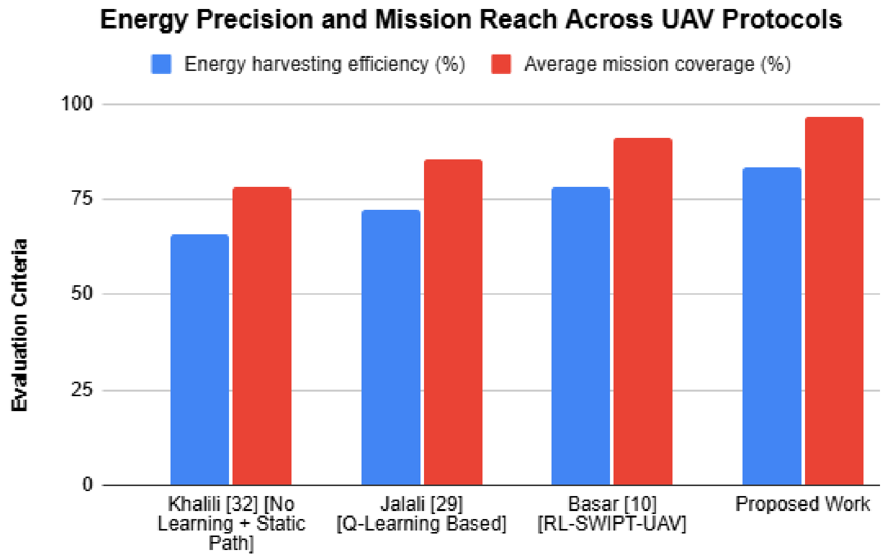

Figure 4. Energy Precision and Mission Reach Across UAV Protocols

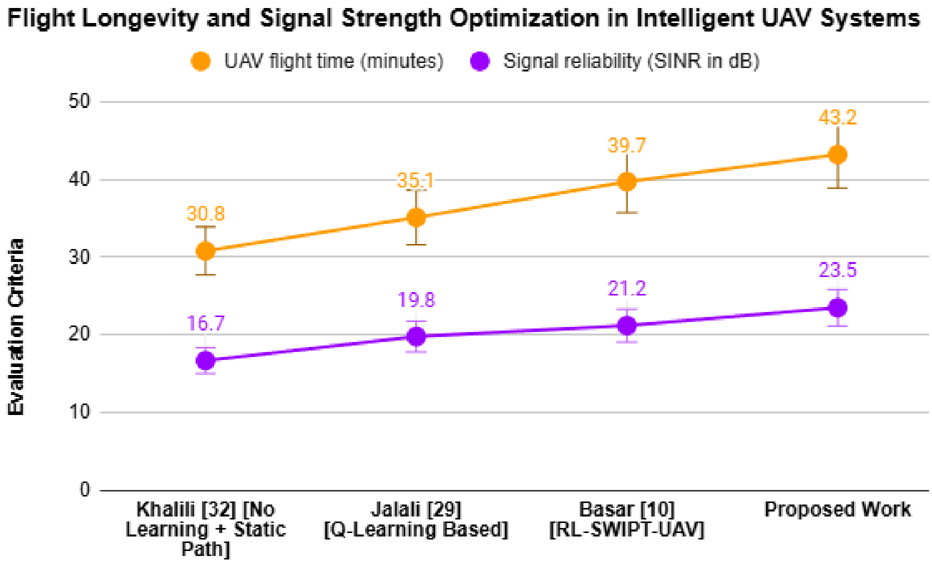

Figure 5. Flight Longevity and Signal Strength Optimization in Intelligent UAV Systems

5. Conclusions

A smart energy-saving UAV relaying platform that will combine SWIPT, as well as real-time Proximal Policy Optimization (PPO), to achieve an efficient disaster response. The Harvested energy efficiency, the signal reliability, and UAV flying time extension (up to 43.2 minutes) of the suggested model were 83.2 percent, 23.5 dB SINR, and the signal reliability, respectively. The policy converged faster in 12.3 seconds with a relay success rate of 94.6 percent, using reinforcement learning. As compared to other models of 2024, 2023, and 2022, the system performed better with an extended coverage of the mission and better energy sustainability of the drones and wireless sensor devices. Collaboration between multiple UAVs. Coordinating multiple UAVs through a more complex system within large disaster areas is one of the improvements to the agent in future work. Combining them with real-time satellite weather data and adaptive SIPT channel models will bring about further performance. To address the gap between simulation and the deployment of emergency scenarios, it will provide experimental validation through physical UAV prototypes and actual datasets of disasters.

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