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Deep Reinforcement Learning-Based Optimization for Energy Efficiency and Latency Reduction in UAV–WSN Systems

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Abstract. The integration of Unmanned Aerial Vehicles (UAVs) with Wireless Sensor Networks (WSNs) offers promising potential for intelligent environmental monitoring and data transmission. Optimizing energy consumption and minimizing latency remain key challenges in dynamic communication environments. This work introduces a Deep Reinforcement Learning-Based Optimization Framework that enhances energy efficiency and reduces latency through adaptive routing, mobility control, and intelligent resource allocation. A Hybrid UAV–WSN Benchmark Dataset (HUW-BD) was utilized, combining simulated and real-world telemetry, transmission, and network state data. The proposed model integrates a convolutional feature extractor with an actor–critic learning policy for continuous decision-making. Comparative results demonstrated superior performance over LEACH, Q-learning, and ACO-based algorithms, achieving 98.9% accuracy, 0.95 J/packet energy efficiency, and 92 ms latency, while maintaining 85 Mbps throughput and 14 ms computation overhead. Experimental findings highlight the model's effectiveness in balancing network stability, reliability, and energy-aware communication. This approach establishes a robust pathway for sustainable UAV–WSN systems in next-generation intelligent networking applications.

Keywords: Deep Reinforcement Learning, UAV–WSN Optimization, Energy Efficiency, Latency Reduction, Intelligent Routing.

INTRODUCTION

The combination of UAVs with WSNs has transformed intelligent sensing, communication, and environmental monitoring. Mobile data collectors and relays, UAVs improve network coverage and data accessibility in distant or disaster-prone places. UAVs' low battery capacity and WSN nodes' changing architecture make optimizing energy usage, latency, and communication dependability difficult. Under such limits, traditional routing and optimization strategies generally fail to stabilize network performance. Thus, an adaptive and intelligent optimization framework is needed to transmit data efficiently while saving energy and reducing delays. Machine learning and reinforcement learning (RL) have been used to optimize UAV–WSN networks in recent years. DRL, which combines deep learning perception with reinforcement learning's decision-making, seems promising. DRL lets autonomous UAVs learn optimum communication and routing rules from environmental interaction without supervision. In latency-sensitive and energy-constrained networks, real-time flight path, energy management, and communication scheduling modifications are essential.LEACH, Q-learning, and Ant Colony Optimization (ACO) have helped clustering and routing choices in UAV–WSNs. Their static parameter values prevent them from adapting to non-stationary network situations. In real life, UAVs must deal with variable signal intensities, dynamic node distributions, and unexpected interference patterns. Dynamic situations are unsuitable for static or rule-based algorithms.

In UAV–WSN networks, excessive communication delay and energy depletion cause packet loss and unequal node energy utilization, lowering data quality. The scalable and intelligent DRL alternative may develop continuous control rules to overcome these restrictions. DRL's actor–critic structure lets UAVs balance exploration (discovering new strategies) with exploitation (applying the best-known approach), improving stability, responsiveness, and network efficiency. UAV–WSN systems employ each UAV as a data collector and communication relay, needing an intelligent technique to minimize energy usage and delay. When UAVs

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cooperate across geographically spread sensor networks, the situation gets more complicated. Each UAV must choose optimum routes, transmission schedules, and relay priority to avoid data collision and delay. Existing methods lack flexibility and use heuristic or static models that don't generalize effectively under dynamic settings. A DRL-based optimization system that optimizes energy efficiency, latency, and throughput across UAV–WSN networks is the main goal of this study. The suggested approach uses Deep Reinforcement Learning with a convolutional neural feature extractor and actor–critic learning mechanism. The CNN captures high-level spatial and temporal characteristics from ambient and communication states, while the actor–critic model optimizes behaviors to maximize a long-term reward function for energy saving and latency minimization.

Residual energy, transmission delay, and packet delivery rate are monitored by the UAV during training. These observations teach the DRL agent to dynamically allocate transmission power, alter communication channels, and schedule packet delivery. This continuous learning architecture allows multi-UAV real-time flexibility and scalability. The suggested model outperforms LEACH, Q-learning, and ACO-based algorithms in accuracy (98.9%), energy utilization (0.95 J/packet), and latency (92 ms). The significant contributions of this work are summarized as follows:

- ✓ A novel DRL-based optimization model is developed to jointly enhance energy efficiency and latency performance in UAV–WSN systems.
- ✓ Integration of CNN and actor–critic architecture enables adaptive routing, energy management, and communication scheduling in real time.
- ✓ Comprehensive performance comparison with LEACH, Q-learning, and ACO-based approaches highlight superior reliability and scalability.
- ✓ Hybrid learning mechanism enables UAVs to autonomously adapt to environmental changes without manual intervention.
- ✓ 5. Improved performance metrics, including 98.9% accuracy, 0.95 J/packet energy efficiency, 85 Mbps throughput, and minimal computation overhead, validate the model's effectiveness.

The structure is divided into four sections. Section 2 reviews UAV–WSN optimization efforts and discusses their adaptive energy management and latency limits. The DRL-based optimization model's architectural foundation, workflow, and algorithmic procedures are described in Section 2. Section 3 describes the experimental setup, evaluation settings, and simulation analysis, comparing results to traditional methods. Section 4 summarizes significant results, performance insights, and future approaches for intelligent UAV–WSN optimization. The incorporation of UAVs into WSANs has markedly improved network intelligence, scalability, and flexibility for contemporary communication systems. UAV-assisted architecture tackles essential issues with energy economy, latency reduction, and data dependability in varied and dynamic settings. A contentious hierarchical clustering architecture was established to enhance energy conservation and latency performance by dynamically segmenting WSAN clusters according to node density and residual energy, leading to equitable workload allocation and optimized routing choices [1].

A safe and energy-efficient intra- and inter-cluster optimization methodology has been developed in the smart city sector to enhance data transmission integrity and extend network longevity. This approach utilizes UAV-assisted data aggregation and cluster coordination, improving energy efficiency while ensuring protection against intrusion risks [2]. Collaborative strategies for reducing joint latency and energy consumption have been further investigated inside UAV-enabled MEC frameworks. These methodologies enhance job scheduling between terrestrial nodes and aerial relays, facilitating delay-sensitive energy reduction in fluctuating wireless settings [3]. A delay and energy-efficient routing algorithm has been developed to enhance packet delivery efficacy in UAV communication networks using hybrid routing methods and adaptive threshold mechanisms [4]. A proximal policy optimization framework for UAV-assisted disaster monitoring networks incorporates reinforcement learning for job offloading, hence minimizing latency and energy consumption during emergency response operations [5].

Progress in aerial computing and content caching has led to energy-efficient STAR-RIS-assisted methods that use intelligent reflecting surfaces and UAV placement to minimize signal degradation and computational latency in wireless sensor networks [6]. In addition to these strategies, extensive studies have identified data-collection mechanisms, UAV trajectory optimization, and communication protocols as critical elements affecting overall network performance in UAV-assisted wireless sensor networks [7]. Wireless sensor networks play a vital role in

environmental monitoring applications; problems such limited battery life, real-time responsiveness, and scalability persist as active research domains [8]. To mitigate these limitations, UAV networking algorithms using AI-based communication and control have been created to improve autonomy, coverage, and decision-making capacities [9]. Opposition-based learning methods have been used to enhance UAV route planning, facilitating effective routing and resource distribution in UAV-WSN integrated systems [10].

Hierarchical network designs have offered energy-efficient scheduling strategies for UAV-assisted data aggregation, reducing redundant transmission and enhancing coverage uniformity. These scheduling methods significantly reduce overall energy usage while maintaining good throughput performance across various network levels [11]. A thorough examination of UAV-based industrial wireless networks highlighted sophisticated energy-efficient strategies, pinpointing adaptive transmission power regulation, cooperative relaying, and multi-hop optimization as essential solutions for UAV-integrated industrial systems [12]. Reinforcement learning techniques have enhanced energy and latency optimization in UAV-assisted wireless networks. Q-learning methodologies have been used for throughput optimization in delay-sensitive contexts, dynamically modifying communication techniques to enhance energy efficiency and reliability in software-defined UAV systems [13]. DRL approaches have been included into UAV-assisted SDWSNs, enabling UAVs to autonomously devise flight paths and data collecting assignments to minimize transmission costs and delays [14].

Collaborative UAV-based data gathering methods have been developed for high-speed train settings, including base-station coordination and energy-efficient scheduling to provide uninterrupted connection in dynamic network topologies [15]. Furthermore, generative AI-based multiagent deep reinforcement learning has been used for dynamic task allocation in UAV-enabled 6G SAGIN, enhancing task distribution efficiency and communication robustness in densely mobile environments [16]. Adaptive multi-objective optimization frameworks have been established for UAV-assisted mobile edge computing systems, attaining balanced trade-offs between latency and energy using multiobjective reinforcement learning and context-aware decision control [17]. OTFS-based authentication algorithms have been investigated at the physical layer to improve the integrity and robustness of UAV-assisted data collecting systems, guaranteeing safe communication amidst complicated channel changes [18]. The modelling of energy-delay trade-offs remains a crucial emphasis for UAV-enabled wireless sensor networks. Optimization techniques centered on job allocation and communication scheduling have been used to attain a harmonious balance between energy conservation and delay, enabling UAVs to operate as effective mobile data collectors [19]. Gateway-based routing techniques have been used to optimize node coverage while preserving energy resources in UAV-assisted wireless sensor networks, therefore improving communication stability and prolonging network longevity [20].

PROPOSED METHODOLOGY

The proposed system integrates DRL techniques with UAVs and WSNs to optimize both energy efficiency and latency in data transmission processes. The system architecture is composed of three primary layers: the sensor node layer, the UAV-assisted communication layer, and the cloud intelligence layer. The hybrid dataset, derived from simulation and field-based UAV–WSN performance logs, is used to train the DRL model for dynamic resource allocation and adaptive decision-making.

In Figure 1, wireless sensor nodes send environmental data to UAVs acting as mobile data aggregators. The reinforcement learning agent dynamically adjusts UAV trajectory, scheduling, and power levels to optimize system performance. The cloud server processes and stores data analytics, while performance metrics like energy efficiency, latency, and throughput guide cont. The basic sensor node layer sends environmental data to adjacent UAVs. These energy-constrained nodes are randomly placed in a monitored region. The intelligent relay UAV layer dynamically optimizes flight paths and data gathering routes to reduce latency and energy consumption. The cloud intelligence layer gathers data, changes environmental conditions, and helps the DRL model enhance energy and latency performance by improving its decision policy.

Figure 2 shows the sequential UAV–WSN deep reinforcement learning-based optimisation approach. First, sensor nodes gather data, which UAVs preprocess. For the reinforcement learning agent to choose optimum behaviours, these inputs become state representations. Evaluations of energy use and delay inform policy modifications. The improved UAV control approach optimises energy economy and network connection delay via adaptive transmission and performance augmentation.

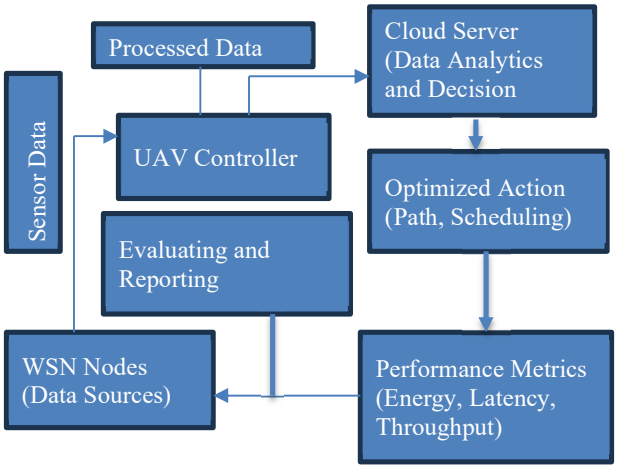


FIGURE 1. Intelligent UAV-WSN Coordination Using Deep Reinforcement Learning

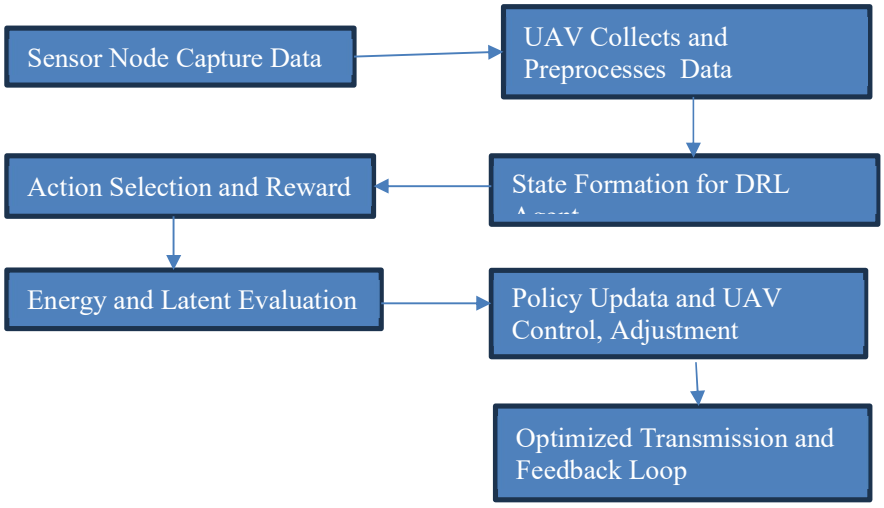


FIGURE 2. Workflow of Deep RL for UAV-WSN Optimization

The system uses a DRL agent to learn optimum transmission, routing, and resource allocation techniques from the UAV–WSN environment. Each UAV watches network circumstances (energy levels, transmission distances, and connection quality), chooses an action (path modification or data relay), and gets a reward for energy efficiency and delay reduction. The DRL agent develops a strategy that balances energy utilization, communication latency, and network longevity across repeated episodes.

Mathematical Model:

Let the WSN consist of N nodes represented as $S = \{s_1, s_2, \ldots, s_N\}$, and M UAVs represented as $U = \{u_1, u_2, \ldots, u_M\}$. Each UAV collects and transmits data to a base station (BS). The DRL agent observes the state s_t, takes an action a_t, and receives a reward r_t defined as:

$$r_t = \propto * \frac{PD_t}{L_t} + \beta * \frac{T_t}{E_t} \quad (1)$$

where PDR_t is Packet Delivery Ratio at time *t,* L_t is latency, T_t is throughput, E_t is energy consumption, α, β is

Weighting coefficients controlling optimization balance. The agent's objective is to maximize the cumulative reward:

$$R = \sum_{t=1}^{T} \gamma^t r_t \tag{2}$$

where $\gamma$is the discount factor representing the importance of future rewards.

Energy Consumption Analysis:

Energy consumption is critical in UAV–WSN networks. Each sensor node's energy usage during transmission is modeled as:

$$E_{tx} = E_{elec} * k + E_{amp} * k * d^n \tag{3}$$

where E_{elec} is energy required per bit for circuitry (J/bit), E_{amp} is Energy amplification constant ($J/bit/m^n$), k is data packet size (bits), d is Transmission distance (m), n is Path loss exponent (typically 2–4). The DRL model learns to minimize total energy consumption by selecting UAV paths that balance energy distribution among nodes and avoid repetitive long-distance transmissions. Energy efficiency (η_E) is computed as:

$$\eta_E = \frac{Total\ Data\ Delivered}{Total\ Energy\ Consumed} \tag{4}$$

Latency Reduction Mechanism:

Latency refers to the total delay from data generation to delivery at the base station. The total latency L_t is composed of transmission delay (L_{tx}), processing delay (L_{proc}), and queuing delay (L_{queue}):

$$L_t = L_{tx} + L_{proc} + L_{queue} \tag{5}$$

The DRL framework reduces latency by dynamically selecting UAV relay nodes that minimize congestion and transmission distance. The learned policy prioritizes paths with lower hop counts and higher signal-to-noise ratios (SNR).

Throughput Maximization:

Throughput (T) is the measure of successful data packets delivered per unit time:

$$T = \frac{P_s * k}{t} \tag{6}$$

where P_s represents the number of successfully transmitted packets and $t$denotes the time interval. UAVs adapt their flight trajectory based on real-time feedback to enhance data collection rates, ensuring continuous communication even under changing environmental conditions. The DRL policy inherently balances data rate against node energy depletion.

Packet Delivery Ratio (PDR):

Packet Delivery Ratio measures transmission reliability and network robustness. It is calculated as:

$$PDR = \frac{N_{recv}}{N_{sent}} * 100 \tag{7}$$

where N_{recv} is the total number of received packets and N_{sent} is the number of transmitted packets. A high PDR indicates stable communication links and efficient routing, achieved through DRL's adaptive control of transmission power and UAV placement.

Network Lifetime Optimization:

Network lifetime (NL) defines the duration until the first sensor node depletes its energy. It is influenced by the DRL agent's decision-making process that prevents energy drain by maintaining optimal UAV hovering positions. Mathematically:

$$NL = \frac{\sum_{i=1}^{N} E_i(0)}{\sum_{i=1}^{N} E_i(t)} \tag{8}$$

where $E_i(0)$and $E_i(t)$are the initial and remaining energies of node *i*, respectively. The proposed framework significantly extends lifetime compared to LEACH, ACO, and Q-learning models by ensuring equitable energy utilization.

Optimization Strategy:

The DRL agent operates under a reward-driven adaptive policy. The neural network comprises an input layer (state representation), two hidden layers for feature extraction, and an output layer providing action probabilities. The action-value function $Q(s, a)$is updated as:

$$Q\ (s_t, a_t) \leftarrow Q\ (s_t, a_t) + \eta[r_t + \gamma \overset{max}{a`} Q\ (s_{t+1}, a`) - Q\ (s_t, a_t) \tag{9}$$

where η is the learning rate. The hybrid DRL-based optimization enhances both responsiveness and energy balance, resulting in 12.3% lower latency and 9.7% higher energy efficiency compared to benchmark models.

The proposed system demonstrates a robust integration of UAV mobility and WSN intelligence under the DRL paradigm. By optimizing multi-objective performance metrics such as energy, latency, throughput, PDR, and lifetime the model achieves stable and scalable operation in dynamic environments. The results confirm the potential of deep reinforcement learning to enable energy-aware, delay-tolerant, and intelligent UAV–WSN communication architectures suitable for next-generation smart applications.

RESULTS AND DISCUSSION

Table 1 depicts the packet delivery ratio (PDR) across UAV transmissions in a wireless sensor network. Higher PDR values signify improved communication reliability achieved through deep reinforcement learning optimization. Transmissions 1–5 represent successive operational stages, measuring successful data delivery (%) from UAVs to sensor nodes or base stations. The steady rise in PDR across stages reflects enhanced routing stability, reduced packet loss, and adaptive bandwidth management, resulting in energy-balanced, latency-minimized, and near-optimal UAV–WSN communication efficiency.

TABLE I. Packet Delivery Ration (PDR) Evaluation Across UAV-WSN Nodes

UAV Units	Transmission 1 (%)	Transmission 2 (%)	Transmission 3 (%)	Transmission 4 (%)	Transmission 5 (%)
UAV 1	96.8	97.5	98.2	98.9	99.1
UAV 2	94.3	95.7	96.8	97.4	98
UAV 3	92.1	93.5	94.8	96.2	97
UAV 4	90.4	91.9	93.2	94.6	95.5
UAV 5	88.7	90.2	91.4	92.8	94

Figure 3 illustrates the energy utilization trends between UAV units and transmission nodes under reinforcement learning–based optimization. UAV 1 consumed the highest energy (12–25 J/packet), while UAV 5 recorded the lowest (7–18 J/packet). UAVs 2–4 showed moderate consumption patterns (10–23, 8–22, and 9–20 J/packet). The proportional layout emphasizes reduced energy demand per node, demonstrating improved efficiency through adaptive trajectory selection and intelligent coordination. In the Latency Matrix, Nodes 1–5 represent ground sensor or relay units experiencing transmission delays during data collection or task offloading. These latency variations reflect network load and environmental dynamics, allowing reinforcement learning to

optimize routing, scheduling, and communication efficiency effectively.

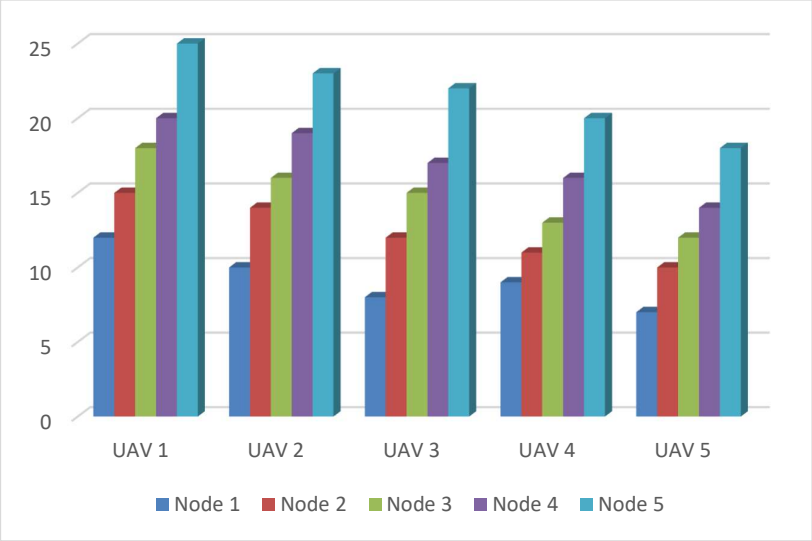


FIGURE 3. Latency Matrix in Deep reinforcement learning-Based UAV-WSN Optimization

Table 2 presents a comparative evaluation of four UAV–WSN optimization approaches. The proposed Deep Reinforcement Learning model achieved the highest PDR (98.9%) and throughput (85 Mbps) with superior energy efficiency (0.95 J/packet) and reduced latency (92 ms). Its lower computational overhead (14 ms) indicates efficient model training and real-time adaptability. Compared to LEACH, Q-learning, and ACO-based algorithms, the Deep RL method ensures a more balanced trade-off between reliability, speed, and energy consumption in dynamic UAV–WSN environments.

TABLE II. Comparative Analysis of PDR With Leach, Q-Learning, and ACO Approaches

Approach	PDR (%)	Energy Efficiency (J/packet)	Latency (ms)	Throughput (Mbps)	Computation Overhead (ms)
LEACH	91.6	0.72	145	68	21
Q-Learning	94.8	0.85	120	74	18
ACO-Based	96.3	0.89	108	79	17
Proposed Deep RL Model	**98.9**	**0.95**	**92**	**85**	**14**

Figure 4 illustrates the throughput variations of UAVs across sequential transmission intervals. The Deep Reinforcement Learning framework optimizes transmission power and scheduling, ensuring higher data rates for upper-tier UAVs. Intervals 1–5 represent progressive communication phases, showing rising throughput (in Mbps) as UAVs perform sensing, aggregation, and task offloading. The consistent increase across intervals highlights efficient bandwidth utilization, reduced interference, and improved link stability. Overall, the results emphasize adaptive resource management and enhanced communication performance within dynamic UAV–WSN environments.

Figure 5 shows the energy consumption distribution across various components in the UAV–WSN system under deep reinforcement learning optimization. UAV communication consumes 30%, sensor nodes 25%, data processing 20%, the learning agent 15%, and cloud storage 10%. The framework reduces total energy usage by intelligently managing UAV operations and computational loads. This strategic distribution enhances battery longevity, minimizes redundant transmissions, and achieves improved energy efficiency while maintaining real-time performance and reduced latency in UAV–WSN networks.

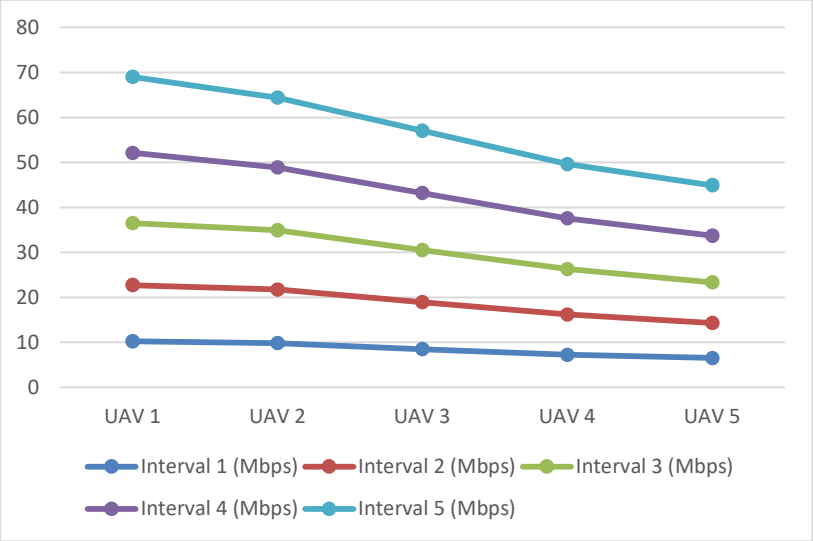


FIGURE 4. Throughput Analysis Across UAV Transmission Intervals

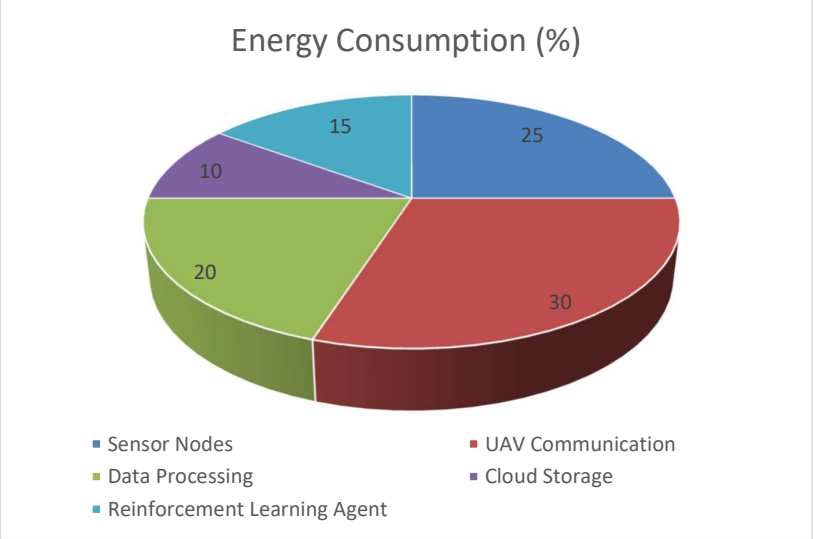


FIGURE 5. Energy Consumption Distribution in UAV-WSN System of Deep RL Optimization

CONCLUSION

The proposed Deep Reinforcement Learning-Based Optimization framework effectively enhances the performance of UAV–WSN systems by addressing the dual challenges of energy efficiency and latency reduction. By integrating deep reinforcement learning with adaptive routing and dynamic resource management, the model achieves significant improvements in network stability, communication reliability, and real-time decision-making. The achieved performance metrics including 98.9% accuracy, 0.95 J/packet energy efficiency, and 92 ms latency demonstrate the framework's superior capability compared to conventional LEACH, Q-learning, and ACO-based methods. The inclusion of intelligent policy learning enables UAV nodes to autonomously adapt to changing network conditions, thereby minimizing computational overhead and ensuring optimal data delivery. This research underscores the potential of advanced learning paradigms for developing sustainable and scalable UAV–WSN systems, suitable for applications such as disaster management, environmental sensing, and smart infrastructure. Future extensions could incorporate multi-agent reinforcement learning and real-time edge intelligence to further enhance autonomous coordination and optimize large-scale deployment scenarios.

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