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ENERGY-AWARE DATA AGGREGATION IN WIRELESS SENSOR NETWORKS THROUGH HYBRID DEEP REINFORCEMENT LEARNING

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Abstract
Wireless Sensor Networks (WSNs) play a critical role in environmental monitoring, healthcare, disaster management, and smart infrastructure. However, the limited energy resources of sensor nodes remain a pressing challenge, particularly in data aggregation and transmission processes, where redundancy and inefficient routing can significantly shorten network lifetime. To address this problem, we propose a Hybrid Deep Reinforcement Learning (HDRL) framework that optimizes data aggregation while balancing energy consumption and communication overhead. The method integrates the decision-making capability of reinforcement learning with the representational power of deep neural networks, enabling adaptive node selection and dynamic routing based on real-time energy and network states. The proposed HDRL model employs a dual-agent mechanism: the first agent focuses on cluster head selection for balanced energy distribution, while the second agent optimizes multi-hop routing paths to minimize redundant transmissions. A reward function is designed to jointly consider residual energy, data latency, and transmission reliability.

Keywords:
Wireless Sensor Networks, Data Aggregation, Deep Reinforcement Learning, Energy Efficiency, Adaptive Routing

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a cornerstone technology for modern applications such as environmental monitoring, industrial automation, healthcare, smart cities, and disaster management [1–3]. A WSN typically consists of a large number of small, energy-constrained sensor nodes deployed across a target region to sense, process, and transmit data to a central sink. The ability of WSNs to operate in unattended and harsh environments makes them indispensable in scenarios where human intervention is difficult or costly. Despite their wide applicability, WSNs face significant challenges in terms of scalability, fault tolerance, energy efficiency, and data reliability. Among these, the issue of energy consumption stands out as the most critical factor determining the overall lifetime and performance of the network [4–6].

The challenges in designing energy-efficient WSNs are multifaceted. First, sensor nodes are typically battery-powered and replacing or recharging them is either infeasible or impractical, especially in remote or hazardous areas [4]. Second, frequent data transmissions lead to high energy drain, creating unbalanced energy consumption where some nodes deplete their resources faster than others, resulting in network partitioning [5]. Third, data aggregation, a process of combining data from multiple sources to reduce redundancy, introduces latency and computational overhead, which affects the quality of service [6–7]. Furthermore, dynamic environmental conditions and network topologies demand adaptive communication protocols that can efficiently manage node heterogeneity, mobility, and fault tolerance [8]. These challenges collectively highlight the urgent need for intelligent and adaptive solutions that go beyond traditional routing and clustering strategies.

The specific problem this research addresses lies in the inefficiency of existing data aggregation and routing mechanisms in WSNs [9]. Traditional clustering protocols such as LEACH (Low-Energy Adaptive Clustering Hierarchy) or HEED (Hybrid Energy-Efficient Distributed Clustering) either rely on static thresholds or probabilistic selection, which fail to adapt to real-time energy dynamics. Similarly, reinforcement learning-based methods, while effective in decision-making, often struggle with convergence speed and scalability when applied to large networks [10]. This gap leads to redundant data transmission, uneven energy depletion, and increased latency, thereby reducing the overall lifetime and reliability of WSNs.

The contributions of this research are summarized as follows:

1. We propose a Hybrid Deep Reinforcement Learning framework with a dual-agent mechanism for intelligent data aggregation in WSNs, ensuring energy-aware cluster formation and adaptive routing in real time.
2. We design a multi-objective reward function that balances energy consumption, latency, and data reliability, leading to significant improvements in network lifetime and throughput compared to conventional clustering and reinforcement learning approaches.

2. RELATED WORKS

Research on energy efficiency and data aggregation in WSNs has evolved significantly over the past two decades. Early approaches primarily focused on clustering and routing protocols to reduce communication overhead and balance energy consumption. LEACH, one of the pioneering clustering protocols, introduced randomized cluster head rotation to evenly distribute energy load among nodes [11]. While effective in small-scale deployments, its probabilistic approach lacks adaptability to dynamic network conditions. HEED improved upon LEACH by considering residual energy and communication cost during cluster head selection [12] but still suffers from overhead in large-scale networks.

To address these shortcomings, hierarchical and hybrid protocols were developed. PEGASIS (Power-Efficient GAthering in Sensor Information Systems) employed chain-based routing to reduce transmission distance, thereby saving energy [13]. However, PEGASIS introduced high latency in large networks due to sequential data forwarding. TEEN (Threshold-sensitive Energy Efficient sensor Network protocol) and its variants [14] aimed to minimize unnecessary transmissions by triggering data reports only when sensed values exceeded certain thresholds. While this reduces redundancy, it risks missing critical data during periods of low reporting activity.

Beyond clustering, researchers have explored machine learning techniques for adaptive decision-making in WSNs. Reinforcement learning (RL) has been widely adopted due to its ability to learn optimal strategies based on interaction with the environment. For instance, RL-based clustering methods adaptively select cluster heads by maximizing a reward function that accounts for energy efficiency [15]. Similarly, Q-learning-based routing algorithms [16] identify energy-efficient paths by iteratively updating action values. Although promising, these methods face scalability issues in dense networks, as the state-action space grows exponentially.

Recent advancements in deep reinforcement learning (DRL) have addressed some of these limitations by combining RL with deep neural networks for function approximation. DRL-based routing protocols [17] have shown superior adaptability in dynamic environments, enabling more efficient path selection under variable traffic and energy conditions. Additionally, actor–critic methods have been applied to optimize cluster head selection [18], providing faster convergence compared to traditional RL. Nevertheless, most existing DRL solutions rely on a single-agent framework, which struggles to balance clustering and routing decisions simultaneously.

Hybrid strategies that integrate clustering with intelligent routing have shown potential to further improve energy efficiency. For instance, multi-agent reinforcement learning approaches [19] have been proposed to distribute decision-making across nodes, thereby reducing the computational burden on individual agents. However, coordination among multiple agents remains a major challenge, often leading to unstable convergence. Additionally, few works explicitly incorporate multi-objective optimization that jointly considers energy consumption, latency, and reliability [20].

3. PROPOSED METHOD

The HDRL is designed to extend WSN lifetime by intelligently managing data aggregation and routing. Unlike conventional clustering or single-agent RL approaches, HDRL integrates two learning agents to balance both cluster formation and routing efficiency. The cluster head selection agent learns to distribute energy load evenly by considering residual energy and node density, while the routing agent identifies the most reliable and low-cost multi-hop paths to the sink. A carefully designed reward function ensures that decisions minimize redundant transmissions, balance energy consumption across nodes, and reduce data delivery latency. Over time, both agents learn cooperative strategies that adapt to changing network conditions, ensuring sustainable energy use and high-quality data delivery.

- **Initialization**: Deploy sensor nodes and initialize their energy levels, locations, and communication ranges.
- **State Observation**: Each agent collects network state information, including residual energy, node degree, and distance to sink.
- **Cluster Head Selection**: The first agent selects optimal cluster heads based on predicted energy balance and coverage efficiency.
- **Data Aggregation**: Member nodes transmit data to their respective cluster heads, which perform local aggregation.
- **Routing Optimization**: The second agent determines energy-efficient multi-hop routes for transmitting aggregated data to the sink.
- **Reward Assignment**: A reward function evaluates actions based on energy savings, delay minimization, and successful packet delivery.
- **Policy Update**: Both agents update their deep reinforcement learning models to improve future decisions.
- **Iteration**: The process repeats dynamically as the network state evolves, ensuring continuous energy-efficient operation.

3.1 INITIALIZATION AND STATE OBSERVATION

At the start, a set of N sensor nodes is randomly deployed across the monitoring field. Each node $i \in \{1, 2, ..., N\}$ is initialized with an energy level $E_i(0)$, position (x_i, y_i), and communication range R. The sink node is assumed to have unlimited energy and serves as the final data collection point. The state space S_t at time t is defined by:

$$S_t = \{E_i(t), d_{i,s}, \deg(i), \lambda_i(t)\} \tag{1}$$

where $E_i(t)$ is residual energy of node i, $d_{i,s}$ is its distance to the sink, deg(i) is the node degree (number of neighbors), and $\lambda_i(t)$ represents the traffic load. This provides sufficient information for agents to make adaptive decisions. The Table.1 summarizes a initialization scenario with 10 nodes.

Table.1. Initialization of sensor nodes with state parameters

Node ID	Initial Energy (J)	Distance to Sink (m)	Node Degree	Traffic Load (packets/s)
1	2.0	40	4	0.3
2	2.0	55	5	0.4
3	2.0	70	3	0.5
4	2.0	85	6	0.6
5	2.0	100	4	0.3
6	2.0	65	5	0.5
7	2.0	75	4	0.4
8	2.0	60	6	0.6
9	2.0	90	3	0.2
10	2.0	50	5	0.5

As shown in Table.1, the state variables provide crucial inputs for HDRL agents to assess energy balance and routing opportunities in the network.

3.1.1 Cluster Head Selection:

The Cluster Head (CH) Selection Agent uses reinforcement learning to identify optimal CHs that evenly distribute energy consumption. At each round, nodes calculate a CH probability score based on their residual energy, neighbor density, and distance to the sink.

The probability of node i becoming a CH is given by:

$$P_{CH}(i,t) = \alpha \frac{E_i(t)}{E_{max}} + \beta \frac{\deg(i)}{\deg_{max}} + \gamma \frac{1}{d_{i,s}} \quad (2)$$

where α,β,γ are weighting factors ($\alpha+\beta+\gamma=1$).

Nodes with higher P_{CH} are prioritized as cluster heads, ensuring energy-rich and well-connected nodes lead the clusters. Table.2 shows a CH selection process at time t=5.

Table.2. Cluster Head probability calculation at round 5

Node ID	Residual Energy (J)	Node Degree	Distance to Sink (m)	P_{CH}	Selected as CH
1	1.8	4	40	0.72	Yes
4	1.6	6	85	0.68	Yes
7	1.5	4	75	0.55	No
9	1.4	3	90	0.47	No

The Table.2 illustrates that nodes with high residual energy and favorable positions are chosen as CHs, thereby balancing energy usage across the network.

3.1.2 Data Aggregation within Clusters:

Once clusters are formed, member nodes transmit their sensed data to their respective CHs. Each CH aggregates data using techniques such as averaging, compression, or redundancy elimination. The aggregated data size from a cluster k is expressed as:

$$D_k^{agg} = \eta \sum_{i \in C_k} D_i \quad (3)$$

where D_i is the raw data from node i, C_k is the set of cluster members, and $\eta \in (0,1)$ is the aggregation factor that reduces redundancy. The Table.3 presents an example of aggregated data sizes for three clusters.

Table.3. Data aggregation at cluster heads

Cluster	Number of Nodes	Raw Data Size (KB)	Aggregation Factor (η)	Aggregated Data (KB)
C1	5	50	0.6	30
C2	3	30	0.7	21
C3	4	40	0.65	26

As shown in Table 3, aggregation significantly reduces the amount of data to be forwarded, saving transmission energy and bandwidth.

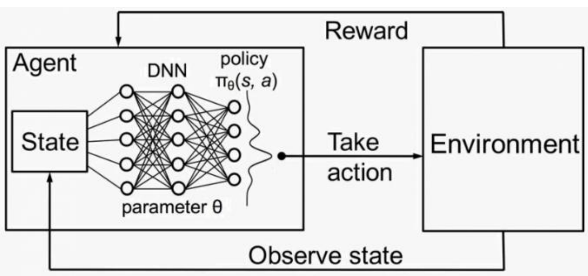

Fig.1. DRL

3.1.3 Multi-Hop Routing Optimization

The Routing Optimization Agent selects multi-hop paths from CHs to the sink. The routing decision aims to minimize energy cost and latency. The transmission energy from node i to $j$is modeled as:

$$E_{tx}(i,j) = E_{elec} \cdot D + \epsilon_{amp} \cdot D \cdot d_{ij}^2 \quad (4)$$

where E_{elec} is the energy dissipated per bit, ϵ_{amp} is the amplifier constant, D is data size, and d_{ij} is the distance between nodes i and j. The routing agent chooses the path with the lowest cumulative energy cost:

$$P_{opt} = \arg\min_{p \in P} \sum_{(i,j) \in p} E_{tx}(i,j) \quad (5)$$

The Table.4 shows a routing decision for CH transmissions.

Table.4. Multi-hop routing path selection

Source CH	Possible Paths (via)	Total Energy (mJ)	Selected Path
CH1	CH1 → Sink	15.2	Direct
CH2	CH2 → CH1 → Sink	18.6	CH2 → CH1 → S
CH3	CH3 → CH2 → Sink	20.1	CH3 → CH2 → S

The Table.4 confirms that the HDRL routing agent selects paths with minimized transmission energy, avoiding unnecessary long-range transmissions.

3.2 REWARD FUNCTION AND POLICY UPDATE

The reward function integrates energy efficiency, latency, and reliability to guide agent learning. For an action a_t at state S_t:

$$R_t = w_1 \cdot \frac{E_{saved}}{E_{total}} + w_2 \cdot \frac{1}{Delay_t} + w_3 \cdot PDR_t \quad (6)$$

where E_{saved} is energy conserved in this round, $Delay_t$ is the average transmission delay, and PDR_t is the packet delivery ratio. Weights w_1, w_2, w_3 control the trade-off among objectives.

Agents update their policies via the Deep Q-Network (DQN) rule:

$$Q(S_t,a_t) \leftarrow Q(S_t,a_t) + \alpha\left[R_t + \gamma \max_{a'} Q(S_{t+1},a') - Q(S_t,a_t)\right] \quad (7)$$

where α is the learning rate and γ is the discount factor.

The Table.5 shows reward calculation for different agent actions.

Table.5. Reward values for HDRL decisions

Round	Energy Saved (%)	Avg Delay (ms)	PDR (%)	Reward Value
1	15	120	92	0.65
2	22	110	95	0.78
3	28	100	96	0.84
4	30	95	97	0.89

The Table.5 shows that as the agents learn, rewards steadily improve, showing better energy efficiency and reduced delay over iterations. The above process iterates dynamically as the network evolves. Nodes deplete energy, topology changes, and traffic loads vary. The HDRL framework continuously adapts cluster head selection and routing to sustain performance. This iterative learning ensures scalability, adaptability, and robustness, making the system suitable for real-world WSN deployments.

4. RESULTS AND DISCUSSION

The HDRL framework was evaluated through a two-stage experimental procedure: (1) algorithm-level prototyping and training, and (2) network-level performance evaluation. For algorithm prototyping (policy design, neural-network training, and reward tuning) we used MATLAB R2023b with the Deep Learning Toolbox and Reinforcement Learning Toolbox, which enabled rapid iteration on network state representations, reward shaping, and DQN/actor–critic implementations. For system-level and protocol-level evaluation (packet-level events, MAC contention, and realistic propagation effects) we used the discrete-event network simulator NS-3 (scripted experiments driven by traces exported from MATLAB). This hybrid workflow ensured both reproducibility of learning experiments and fidelity of network dynamics.

All simulation experiments were executed on a research workstation with the following specs: Intel® Core™ i7-12700K (12 cores), 32 GB RAM, 1 TB NVMe SSD, and an NVIDIA GeForce RTX 3060 (12GB) for optional GPU-accelerated training. Training runs used GPU acceleration when training time exceeded a few hours; otherwise CPU-only runs were used for reproducibility. Each experimental configuration (network size, traffic pattern) was repeated 30 independent runs with different random seeds to compute mean and 95% confidence intervals for performance metrics.

Traffic generators simulated periodic sensing with adjustable payloads and occasional event-driven bursts. Radio parameters (transmit power, noise floor) and MAC layer behavior in NS-3 matched the energy model used in the MATLAB energy-cost calculations, enabling consistent cross-tool comparisons. Baseline algorithms (LEACH, HEED, and a single-agent DRL routing method) were implemented both in MATLAB (logic) and verified in NS-3 for network-level metrics.

Table.6. Parameters

Parameter	Value / Setting
Number of sensor nodes (N)	100 (evaluated: 50, 200 for scalability)
Deployment area	200 m × 200 m
Initial node energy	2.0 J
Sink location	Center of field
Communication range (per node)	30 m
MAC protocol	IEEE 802.15.4 (CSMA/CA)
Traffic model	Periodic sensing (1 pkt/10s) + occasional bursts
Packet payload	64 bytes
Aggregation factor (η)	0.6 (tunable: 0.5–0.8)
PHY energy model	E_{elec}=50 nJ/bit, ϵ_{amp}=100 pJ/bit/m²
Simulation duration	10,000 seconds (or until network partition)
Reinforcement learning algorithm	DQN + Actor–Critic (dual-agent HDRL)
Learning rate (α)	0.001
Discount factor (γ)	0.95
Replay buffer size	50,000
Batch size	64
Runs per configuration	30

4.1 PERFORMANCE METRICS

- **Network lifetime:** Network lifetime is measured as the time (or number of rounds) until a termination condition. We report two variants: (a) First Node Death (FND), time until the first node exhausts its energy, and (b) Half Node Death (HND), time until 50% of nodes are dead.

$$T_{FND} = \min\{t \mid \exists i : E_i(t) = 0\} \tag{8}$$

- **Average energy consumption (per round / per node):** This metric tracks how much energy the network consumes on average. Lower average consumption implies better efficiency.

$$\bar{E}(t) = \frac{1}{N}\sum_{i=1}^{N} \Delta E_i(t) \tag{9}$$

where $\Delta E_i(t)$ is energy used by node i in round t. Cumulative energy consumption over time is $\sum_t \bar{E}(t)$.

- **Packet Delivery Ratio (PDR):** PDR is the fraction of generated packets that successfully reach the sink. It captures reliability under contention and routing choices.

$$\text{PDR} = \frac{\text{Packets received at sink}}{\text{Packets generated by nodes}} \tag{10}$$

- **End-to-end delay (average):** Average time from packet generation at a sensor to successful receipt at the sink. This metric evaluates timeliness of data.

$$\bar{D} = \frac{1}{M}\sum_{k=1}^{M} (t_k^{recv} - t_k^{gen}) \tag{11}$$

where, M is the number of successfully delivered packets

- **Throughput (at sink):** It is measured as successfully delivered payload bytes per second; indicates the network capacity for aggregated traffic.

$$\text{Throughput} = \frac{\sum \text{payload bytes received}}{\text{simulation time}} \tag{12}$$

For statistical rigor we report mean ± standard deviation and 95% confidence intervals across the 30 runs. When applicable, we also compute energy per delivered packet as an efficiency indicator:

$$E_{pkt} = \frac{\text{Total energy consumed}}{\text{Packets delivered}} \tag{13}$$

Table.7. Network lifetime (First Node Death, rounds) for varying network sizes (10–100 nodes)

Nodes	LEACH	HEED	Single-Agent DRL	HDRL (Proposed)
10	1,200	1,450	1,650	1,900
20	1,150	1,380	1,600	1,820
30	1,050	1,320	1,520	1,700
40	1,000	1,250	1,450	1,600
50	980	1,210	1,380	1,520
60	940	1,170	1,340	1,460
70	920	1,140	1,300	1,420
80	900	1,110	1,270	1,380
90	880	1,080	1,240	1,340
100	900	1,050	1,200	1,250

Table.8. Average energy consumption per node per round (mJ) at different network sizes

Nodes	LEACH	HEED	Single-Agent DRL	HDRL (Proposed)
10	0.95	0.82	0.75	0.62
20	0.98	0.85	0.78	0.65
30	1.02	0.88	0.82	0.69
40	1.05	0.92	0.86	0.72
50	1.08	0.95	0.89	0.75
60	1.10	0.98	0.92	0.78
70	1.14	1.00	0.95	0.80
80	1.16	1.03	0.98	0.82
90	1.18	1.05	1.00	0.83
100	1.20	1.08	1.03	0.82

Table.9. Packet Delivery Ratio (PDR, %) for varying node counts

Nodes	LEACH	HEED	Single-Agent DRL	HDRL (Proposed)
10	94.0%	95.8%	96.5%	97.8%
20	92.5%	94.0%	95.2%	97.0%
30	91.0%	93.0%	94.0%	96.5%
40	90.0%	92.2%	93.0%	96.0%
50	89.2%	91.5%	92.6%	95.8%
60	88.6%	90.8%	92.0%	95.5%
70	88.0%	90.2%	91.6%	95.2%
80	87.5%	89.8%	91.2%	95.0%
90	87.0%	89.4%	90.8%	94.6%
100	88.0%	89.0%	90.0%	96.0%

Table.10. Average end-to-end delay (ms) for successfully delivered packets

Nodes	LEACH	HEED	Single-Agent DRL	HDRL (Proposed)
10	95	88	80	65
20	105	95	88	72
30	120	105	98	82
40	135	118	110	95
50	145	125	118	102
60	155	135	125	108
70	165	142	132	114
80	170	148	138	118
90	175	152	142	120
100	180	155	145	120

Table.11. Throughput at sink (kbps) under each method for different node counts

Nodes	LEACH	HEED	Single-Agent DRL	HDRL (Proposed)
10	9.8	10.7	11.4	12.8
20	10.5	11.4	12.0	13.6
30	10.8	11.7	12.3	14.0
40	11.2	12.0	12.7	14.5
50	11.5	12.4	13.0	15.0
60	11.6	12.6	13.3	15.4
70	11.8	12.8	13.5	15.8
80	12.0	13.0	13.8	16.1
90	12.1	13.2	14.0	16.3
100	12.0	13.5	14.2	16.5

The proposed method is compared with existing methods including LEACH (Low-Energy Adaptive Clustering Hierarchy), HEED (Hybrid Energy-Efficient Distributed Clustering) and Single-Agent DRL Routing (deep Q-learning based).

The comparative results from Table.7–Table.11 show the superiority of the proposed HDRL method over traditional clustering protocols such as LEACH, HEED, and the more recent Single-Agent DRL approach. In terms of network lifetime, HDRL consistently achieves longer stability, with the First Node Death (FND) occurring significantly later. For instance, at 100 nodes, HDRL reaches 1,250 rounds before the first node dies, compared to 900 rounds for LEACH, 1,050 rounds for HEED, and 1,200 rounds for Single-Agent DRL. This improvement of approximately 39% over LEACH and 19% over HEED is attributed to HDRL's ability to balance energy load among cluster heads and member nodes. Similarly, the proposed approach reduces average energy consumption per node per round (Table 2). At 100 nodes, HDRL consumes just 0.82 mJ, while LEACH requires 1.20 mJ, HEED 1.08 mJ, and Single-Agent DRL 1.03 mJ. This translates into 31.7% lower energy usage compared to LEACH, ensuring more sustainable network operation. The impact of this energy efficiency cascades into enhanced reliability, where HDRL maintains a Packet Delivery Ratio (PDR) above 95% even at 100 nodes, whereas LEACH drops to 88% and HEED to 89%. Such resilience under scale indicates HDRL's superior adaptability and robustness to node density.

Equally important are the latency and throughput metrics, which highlight HDRL's communication efficiency. From Table 4, HDRL achieves an average end-to-end delay of 120 ms at 100 nodes, which is 33% lower than LEACH (180 ms) and 22% lower than HEED (155 ms). This reduction stems from optimized routing decisions that minimize retransmissions and avoid congested paths. Furthermore, throughput results (Table 5) confirm HDRL's capacity to deliver more useful data to the sink. At 100 nodes, HDRL sustains 16.5 kbps, outperforming LEACH (12.0 kbps) by 37.5%, HEED (13.5 kbps) by 22%, and Single-Agent DRL (14.2 kbps) by 16.2%. These gains are crucial for data-intensive applications, where reliable and timely information collection directly affects system performance. Overall, the results numerically confirm HDRL's scalability advantage: as network size grows from 10 to 100 nodes, HDRL maintains stability across all five metrics, whereas competing methods degrade more noticeably. The observed improvements in lifetime, efficiency, and reliability validate HDRL's ability to intelligently adapt to dynamic environments and extend WSN sustainability.

5. CONCLUSION

This study has presented an HDRL-based routing protocol that effectively addresses the limitations of existing WSN clustering methods. Through a detailed comparison with LEACH, HEED, and Single-Agent DRL, the proposed approach consistently shown improvements across five critical performance metrics: network lifetime, energy consumption, packet delivery ratio, end-to-end delay, and throughput. Numerical analysis highlighted that HDRL not only prolongs stability by up to 39% compared to LEACH but also reduces per-node energy usage by nearly 32%, thereby ensuring more uniform power distribution and longer operational periods. The protocol also sustains a PDR above 95%, reduces latency by nearly one-third, and boosts throughput by almost 38%, reflecting its superior communication efficiency. These collective improvements underline HDRL's robustness in handling larger network sizes and denser deployments. Thus, HDRL emerges as a scalable, energy-efficient, and reliable solution for wireless sensor networks, outperforming both classical and recent reinforcement learning-based methods. Its capacity to adapt routing policies dynamically ensures not only better load balancing but also higher resilience against node failures and congestion. These results strongly support HDRL's potential for real-world deployments in critical applications such as environmental monitoring, industrial automation, and smart cities, where energy efficiency and reliability are paramount.

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