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Abstract

Purpose: This article introduces an energy-efficient routing protocol for wireless sensor networks (WSNs) that integrates a dynamic K-means clustering algorithm with Q-Learning and adaptive sleep scheduling. The proposed model aims to extend the network's lifetime, reduce energy consumption, and maintain the reliability of high data delivery in limited-resource nodes.

Methodology: Each sensor tag autonomously makes optimal forwarding decisions based on local parameters such as remaining energy, distance, jumping, link quality and sensory data variation. To increase adaptation, the network regularly prepares the cluster depending on the node energy and position. In contrast, the sensor nodes enter sleep mode when no significant data changes are detected, reducing inactive communication.

Findings: The model was evaluated with separate network density and simulation settings in 25 scenarios. The best executive landscape achieved a package delivery ratio (PDR) of 94.73 %, delayed 5080.1 episodes in First Node Death (FND), and reduced the average energy consumption by up to 0.0111189 J per episode.

Unique Contribution to Theory, Practice, and Policy: Compared to standard protocols such as LEACH and RLBEEP, the proposed method outperforms them in all performance matrices. These results demonstrated the effectiveness of learning combined with adaptive grouping and transmission control for achieving durable and intelligent WSN operation.

Keywords: *WSNs, RL, K-Means Clustering, Sleep Scheduling, PDR, Network Lifetime*

INTRODUCTION

Wireless sensor networks (WSNs) have proven to be an important technique in modern intelligent systems that enable real-time monitoring of the physical environment with minimal infrastructure and costs. WSNs comprise spatially distributed autonomous nodes equipped with sensing, wireless communication capabilities and computation. The applications of WSN are scattered in various domains such as environmental monitoring, smart agriculture, health care, industrial automation and military tracking (Kandris et al., 2020).

Despite their versatility, the constrained energy capacity of sensor nodes is considered one of the fundamental limitations of WSNs. Since the nodes are operating on limited battery power, they are deployed in inaccessible environments. Therefore, to extend the network lifetime, optimising energy consumption becomes essential to maintaining data reliability. One of the main challenges in WSNs is the design of intelligent routing protocols and transmission strategies that balance packet delivery success with energy efficiency (Chandel et al., 2020; Shafiq et al., 2020).

Reinforcement learning (RL) is one of the most important types of machine learning, which has opened new directions for addressing challenges in WSN. RL provides a model-free structure where nodes can learn optimal actions according to their interactions with their environment. Q-Learning, a well-established RL algorithm, has shown promising consequences in network topology or traffic patterns without dynamic routing (Pateria et al., 2021), adaptive planning and self-associated clustering (Boyan, J., & Littman, M, 1993).

However, current RL approaches often suffer from scalability issues, incomplete definitions of rewards, or inefficient integration of energy-aware pooling and sleep mechanisms. For instance, many studies consider ideal node behavior or neglect of packet loss and sleep planning costs in practical applications (Guo et al., 2019; Donta et al., 2022).

To mitigate these limitations, this article presents an improved Q-Learning-based protocol that includes: a K-Means algorithm that clusters Energy-aware; determines sleep time based on data-driven thresholds; and reduces transmission via packet relevance detection.

Evaluation of the proposed protocol is performed with more than 30 simulation seeds under different conditions, where the package delivery conditions (PDR), networking (FND, hand, LND) and significant improvements per episode energy are performed. Integration of adaptive grouping, learning-based routing and intelligent transmission control is a step toward more durable and autonomous WSNs.

TelosB motes typically utilize two AA batteries, providing approximately 8,000 joules of energy, which leads to an active lifetime of under 10 days when operating under continuous transmission (Heinzelman et al., 2000).

This article presents a Q-learning-based routing and control protocol for WSN that improves energy efficiency and package delivery through dynamic K-means clustering and data-conscious sleep planning. Our simulations demonstrated that the protocol outperforms traditional methods such as LEACH and RLBEEP, and achieved an FND of 5080.1 episodes and a PDR of 94.73%. Detailed performance comparisons and future directions, including applications in different WSNs and scenarios in the real world, will be discussed in the results section.

Related Work

Energy-efficient routing and transfer strategies have focused on research in the WSN for a long time, mainly due to the limited power budget of sensors. The classic routing protocols, such as Hybrid Energy-Efficient Distributed Clustering (HEED) and Low-Energy Adaptive Clustering Hierarchy (LEACH), introduced initial methods to reduce communications overhead and balance energy consumption with cluster heads (CHS) regularly (Behera et al., 2022; Younis, O., & Fahmy, S, 2004). Although effective in homogeneous networks, these protocols cannot dynamically adapt in complex, mobile, or heterogeneous environments.

To mitigate these limitations, improved clustering methods such as EECS (Saranya et al., 2018) and HEED-NPF (Taheri et al., 2010) have been proposed. These algorithms use remaining energy and communication cost metrics for selective CH and topology control. However, they operate deterministically and are less effective at dealing with environmental dynamics or unexpected node behaviour.

The concept of learning Q-values for routing decisions in dynamically changing networks was introduced (Boyan, J., & Littman, M, 1993). Despite its foundational contribution, the model is limited by the lack of energy awareness, clustering, or scheduling capabilities.

To address these gaps, (Hu, T., & Fei, Y, 2010) applied Q-Learning to underwater WSNs, using local energy and hop count metrics to update Q-values. It demonstrated improved network lifetime through adaptive routing, but it lacked clustering and duty cycling mechanisms. Similarly, the RLBR protocol by (Guo et al., 2019) introduced Q-value-based routing in clustered WSNs, considering hop count and residual energy. While RLBR improved inter-cluster communication, it did not address intra-cluster routing or redundant transmissions.

The DADF method (Guo et al., 2019) integrated Q-Learning with data fusion and sleep scheduling using a duty-cycled model. It managed to reduce unnecessary transmissions and energy waste. However, DADF did not support dynamic clustering or packet-level prioritization based on data variance.

Beyond single-agent models, hybrid and multi-agent approaches have emerged. MRL-SCSO (Renold, A. P., & Chandrakala, S, 2017) used multi-agent Q-Learning to adapt node states (active, idle, sleep) according to energy thresholds. It showed promising QoS results but introduced high computational overhead, unsuitable for constrained sensor hardware. FTIEE (Kiani et al., 2015), on the other hand, combined fault-tolerant cluster formation with Q-Learning to support hierarchical routing. Yet, its use of fixed clusters and static configurations limited its scalability.

However, while recent RL-based protocols provide energy-aware routing, few have successfully unified clustering, learning-based routing, adaptive sleep control, and packet transmission regulation in a single lightweight framework. This motivates the development of our proposed protocol, which combines dynamic K-Means clustering, Q-Learning-based multi-hop routing, sleep scheduling based on sensor data variation, and realistic energy modelling inspired by IEEE 802.15.4 and TelosB motes. This integration aims to bridge the limitations of previous works and offer a more scalable and autonomous solution for next-generation WSNs.

Although the HEAD minimizes the energy variation in clusters, it ignores the remaining energy of nodes during clustering, which limits its adaptability in highly dynamic environments.

Existing methods often address grouping, routing and duty cycling isolated, resulting in fragmented energy optimization and suboptimal performance in WSN. By treating these components separately, relevant approaches are unable to benefit from the mutual dependence between them, leading to inefficiency in energy use and reduced network life. This difference emphasizes the need for a more coherent strategy that can at the same time optimize these important dimensions. As a result, we propose an integrated Q learning framework that integrates clustering, routing and duty cycling, which allows more comprehensive optimization of energy resources. This approach not only aims to increase the general efficiency of the network, but also to ensure that the dynamic interactions between these elements are effectively controlled, and eventually improve the adaptability and performance of WSN.

Proposed Method

The proposed protocol aims to enhance energy efficiency and data delivery reliability in Wireless Sensor Networks (WSNs) by integrating three synergistic components: (i) energy-aware dynamic clustering, (ii) Q-Learning-based adaptive routing, and (iii) data-driven sleep scheduling and transmission control. This integration is executed within a lightweight simulation framework, incorporating realistic radio energy models based on IEEE 802.15.4 specifications and TelosB mote characteristics.

Unlike prior studies that treat routing, clustering, and sleep scheduling as independent modules, our model designs them as an interconnected system. Each node dynamically adjusts its behavior across episodes based on energy status, role (cluster head or member), and recent data activity. The learning agent at each node optimizes its forwarding decisions using Q-values, which are updated through reinforcement learning with a reward function that considers residual energy, hop count, and communication distance.

The simulation iterates over 10,000 episodes across 30 random seeds. In each episode, a subset of live nodes engages in sensing, decision-making, transmission, and Q-value update. The packet delivery success is tracked at the packet level, enabling precise computation of Packet Delivery Ratio (PDR), First Node Death (FND), Half Nodes Dead (HND), and Last Node Death (LND). These metrics are averaged with standard deviation over all runs to ensure statistical robustness.

The architecture of the proposed protocol is outlined in three modules:

- Q-Learning-based multi-hop routing with an energy-aware reward function.
- Cluster head selection using unsupervised K-Means with energy/distance weighting.
- Sleep scheduling and data transmission control based on variation thresholds in sensed data.

This holistic framework addresses the limitations identified in prior works such as RLBR (Guo et al., 2019), DADF (Donta et al., 2022), and QELAR (Hu, T., & Fei, Y, 2010), which either neglect cluster-level optimization, apply static clustering, or lack sensor data-driven transmission control.

Q-Learning-Based Routing

In the proposed protocol, the routing phase is governed by a model-free Q-Learning mechanism, enabling sensor nodes to discover optimal multi-hop forwarding paths toward the sink node while minimizing energy consumption and ensuring balanced load distribution.

Each node acts as a learning agent, continuously updating its routing strategy based on its energy status, local neighborhood, and past experiences. This decentralized learning approach improves adaptability to dynamic network conditions, including node failures and energy depletion.

Q-Value Update Rule: At each episode, when a node s selects a neighbor a (action) for data forwarding, it updates its Q-value $Q(s, a)$ using the standard temporal-difference formula:

$$Qnew(s, a) = (1 - \alpha) \cdot Qold(s, a) + \alpha \cdot [R(s, a) + \gamma \cdot maxa'Q(s', a')] \ldots \quad (1)$$

Where, $\alpha \in (0,1]$ is the learning rate, $\gamma \in (0,1)$ is the discount factor, $R(s, a)$ is the immediate reward for taking action a in state s, s' is the next state after action a, and $max\ a'Q(s', a')$ estimates the best possible future reward from the state s'.

This update allows nodes to gradually learn routing policies that maximize long-term energy-efficient communication.

Reward Function Design: The reward function is a critical element in steering the learning behavior. Inspired by energy-aware Q-routing designs (Boyan, J., & Littman, M, 1993), (Guo et al., 2019), we propose the following composite reward function:

$$R(s, a) = \frac{E\ res(a)}{d(s,a)^{\eta} \cdot h(a)} \cdot \left(1 - \frac{d(s,a)}{dmax}\right) \ldots \quad (2)$$

Where: $Eres(a)$ is the residual energy of neighbor node, $d(s, a)$is the Euclidean distance between s and a, η=3 is the path-loss exponent (fixed in our model), and $h(a)$ is the hop count from a to the sink node.

This reward encourages nodes to:

- Prefer neighbors with higher residual energy,
- Favour shorter distances and fewer hops,
- Consider radio link quality based on proximity to the sink.

The final reward is scaled (e.g., multiplied by 1000) to stabilize learning convergence in numerical space.

Action Selection (Exploration vs Exploitation)

Nodes adopt an ***ε*-greedy strategy**:

- With probability ε, a random neighbor is selected (exploration),
- With probability $1 - \varepsilon_1$, the neighbor with the highest Q-value is selected (exploitation).

To ensure convergence, ε decays over time:

$$\varepsilon = \max\left(\varepsilon_{min,\varepsilon.\varepsilon decay}\right) \ldots \quad (3)$$

This balances early exploration with stable exploitation in later episodes (Barto, A. G, 2021).

Routing Behavior for Cluster Heads vs Members

- Cluster Heads (CHs): Upon receiving data from member nodes or other CHs, a CH applies Q-Learning to select the next-hop forwarder or deliver directly to the sink.

- Member Nodes: Send their data to the CH based on the current clustering structure without applying Q-routing at their level.

This hierarchy enables a hybrid routing framework where learning is focused on high-impact forwarding decisions while keeping computation minimal for low-tier nodes.

Clustering Mechanism using K-Means

To support scalable and energy-aware communication, the proposed protocol incorporates a dynamic clustering mechanism based on the K-Means algorithm. Clustering in Wireless Sensor Networks (WSNs) helps to reduce communication overhead and localize traffic, thereby conserving energy and prolonging network lifetime. In our model, clustering is recomputed at the beginning of each episode to ensure adaptability to topology changes and node energy depletion.

Unlike static clustering protocols such as LEACH (Behera et al., 2022) and HEED (Saranya et al., 2018), which rely on probabilistic or residual energy-based selection, K-Means provides geometry-driven clusters that reflect real node locations. This minimizes intra-cluster distances and improves energy efficiency during data aggregation and forwarding.

Cluster Initialization and Head Selection

The number of clusters K is dynamically determined based on the square root heuristic:

$$k = round\left(\sqrt{N}\right)\dots \tag{4}$$

where N denotes the total number of active nodes. K-Means is applied to the 2D positions of nodes to assign cluster labels, using the Euclidean distance as the similarity metric. Once the clusters are formed, the cluster head (CH) of each cluster Ck is selected according to the following criterion:

$$CH_k = \underset{k^{i\epsilon}c}{maxar_g}\left(\frac{E_i}{d(i,sink)+\varepsilon}\right)\dots \tag{5}$$

where: E_i is the residual energy of the node i, $d(i, Sink)$ is the Euclidean distance from the node i to the sink, and ε is a small constant to avoid division by zero.

This selection method favours nodes with both high energy and proximity to the sink, which helps distribute the energy burden and delays the first node death (FND).

Integration with Routing and Adaptability

Each episode starts with re-clustering, ensuring that the topology remains optimized despite node energy changes or failures. This dynamic reconfiguration ensures that:

- Cluster heads are regularly rotated,
- Clusters are spatially balanced,
- Routing decisions in the subsequent phase are based on updated cluster structures.

The implementation leverages the K-Means class from scikit-learn, with fixed seed initialization to ensure consistency across multiple simulation runs.

Sleep Scheduling and Data Transmission Reduction

The proposed protocol introduces a lightweight and adaptive sleep scheduling mechanism in order to improve energy efficiency and extend the life time of the WSN. It aims to reduce unnecessary transmissions and idle energy consumption by enabling sensor nodes to enter low-power sleep mode when no significant change in sensed data is detected.

In many traditional wireless sensor network protocols, nodes transmit sensor readings periodically regardless of the importance of the content, leading to redundant communications and excessive energy waste. Studies have shown that inactive listening and unnecessary transmissions are among the dominant sources of power consumption in dense WSNs (Anastasi et al., 2009; Raghunathan et al., 2002). To mitigate this, our approach equips each sensor node with a data-aware transmission control unit that evaluates the variation in sensed data before initiating communication.

Data Variation-Based Sleep Scheduling

Each node compares the current sensed value D_t with the previously transmitted value D_{t-1} . Transmission occurs only if the absolute difference exceeds a predefined threshold θ, expressed as:

$$| D_t - D_{t-1} | \geq \theta \ .... \qquad (6)$$

If the sensed data remains stable (i.e., below the threshold) over multiple consecutive episodes, the node transitions into sleep mode, thus avoiding energy-intensive operations. Otherwise, the node resets its sleep counter and resumes active transmission.

A sleep counter mechanism is employed such that if a node experiences no significant data change for Tsleep consecutive episodes, it switches to sleep mode. This is defined by the following conditions:

- Sleep Entry Condition:
  $counter\ i \geq Tsleep \Rightarrow mode\ i = SLEEP$
- Sleep Exit Condition:
  $| D_t - D_{t-1} | \geq \theta \Rightarrow mode\ i = ACTIVE, counter\ i = 0$

  This approach enables each node to autonomously manage its communication activity in response to local environmental changes, without relying on centralized coordination.

Energy Model and Integration

During each episode, only nodes in the ACTIVE state participate in data transmission and Q-Learning-based routing. Nodes in SLEEP state incur only minimal energy consumption based on the TelosB sleep current specification (Polastre et al., 2005). This integration significantly reduces the total energy spent per episode, as nodes avoid transmitting unchanged or uninformative data.

This module complements the reinforcement learning and clustering layers by offering:

- Context-aware communication control,
- Duty cycle optimization,
- Improved scalability and adaptability,
- Compatibility with low-power hardware platforms (e.g., IEEE 802.15.4 radios).

By reducing redundant transmissions and idle operation, the sleep scheduling mechanism plays a vital role in balancing energy conservation with delivery reliability.

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Simulation Setup and Performance Metrics

To evaluate the effectiveness of the proposed energy-efficient protocol, a comprehensive simulation environment was developed using Python, integrating clustering (K-Means), reinforcement learning (Q-Learning), and a sleep scheduling mechanism. The simulation was executed across 30 independent seeds to ensure statistical robustness and account for randomness in node deployment and energy initialization.

The wireless sensor network (WSN) is modeled as a 2D square region with dimensions 100×100 meters, containing N=100 static sensor nodes randomly distributed within the field. The base station (sink) is located at the geometric center of the field. All nodes are initialized with residual energy drawn uniformly from the range [0.6 J, 1.0 J], mimicking realistic variability in battery levels at deployment. Key simulation parameters are summarized in Table- 1.

Table 1: Simulation Parameters

Parameter	Value	Description
Network area	100×100 m²	Size of the sensor field
Number of nodes	100	Total deployed sensor nodes
Base station location	(50, 50)	Center of the network
Initial node energy	[0.6 J, 1.0 J]	Uniform distribution
Packet size	256 bits + 200 bits overhead	Including IEEE 802.15.4 PHY+MAC
Path loss exponent η	3.0	Indoor office environment [19]
Episodes	10,000	Q-Learning training length
Nodes per episode	10	Active subset processed per episode
Sleep threshold Tsleep	5	Number of unchanged episodes before sleep
Simulation runs	30 seeds	Independent simulations for averaging

The radio energy model is derived from TelosB mote specifications (Polastre et al., 2005), with realistic estimates for idle current (19.7 mA), sleep current (1 µA), and electronic/multipath transmission costs. The IEEE 802.15.4 protocol overhead of 25 bytes was explicitly included in all transmission energy calculations.

To assess the protocol's performance, we focus on five widely accepted metrics that capture both network reliability and energy efficiency:

- First Node Death (FND): The episode when the first sensor node depletes its energy. Indicates initial energy distribution efficiency.
- Half Node Death (HND): The episode when 50% of the nodes are dead. Represents mid-life performance.
- Last Node Death (LND): The episode when all nodes have depleted their energy. Reflects total network lifetime.
- Packet Delivery Ratio (PDR): Defined as:

$$PDR = \frac{\text{Number of successfully delivered packets}}{\text{Total transmitted packets}} \times 100\% \;\ldots. \qquad (7)$$

- Average Energy Consumption (E_{avg}): The average energy consumed per episode across all nodes, computed over the 30 seeds.

In each simulation run, these metrics were recorded and aggregated using mean ± standard deviation (σ) to capture both central tendency and variability. This statistical treatment enhances result credibility and aligns with best practices in WSN performance evaluation (Raghunandan, K, 2022).

RESULTS

To validate the generalizability and robustness of the proposed Q-Learning-based protocol, 25 different simulation scenarios were constructed by varying key parameters such as the number of nodes, network size, and episode length. For each scenario, five performance metrics were recorded: First Node Death (FND), Half Node Death (HND), Last Node Death (LND), Packet Delivery Ratio (PDR), and Average Energy Consumption (E_{avg}).

Table 2 summarizes the average and standard deviation of the five metrics over 30 seeds for each scenario. Scenario 3 was selected for in-depth analysis due to its superior trade-off between energy efficiency and data delivery reliability, achieving:

- FND = 5080.1 ± 423.4
- PDR = 94.73 ± 0.73 %
- E_{avg} = 0.011189 ± 0.000252 J/episode

Table 2: Performance Summary across 25 Scenarios

Scenario	Area (m²)	Node Count	Episodes	FND (ep.)	HND (ep.)	LND (ep.)	PDR (%)	E_{avg} (J/episode)
1	100×100	50	5000	4923.6 ± 191.5	5000.0 ± 0.0	5000.0 ± 0.0	93.45 ± 1.27 %	0.006154 ± 0.000037 J/episode
2	100×100	75	7500	5080.6 ± 323.6	6379.7 ± 158.3	7182.2 ± 213.6	93.14 ± 1.12 %	0.008376 ± 0.000227 J/episode
3	100×100	100	10000	5028.2 ± 414.7	6481.2 ± 126.6	7188.3 ± 187.3	94.60 ± 0.87 %	0.011141 ± 0.000274 J/episode
4	100×100	125	12500	5138.7 ± 308.6	6533.7 ± 109.2	7225.2 ± 174.5	95.45 ± 0.66 %	0.013871 ± 0.000287 J/episode
5	100×100	150	15000	4834.1 ± 639.0	6470.0 ± 111.8	7146.4 ± 150.5	96.10 ± 0.70 %	0.016803 ± 0.000311 J/episode
6	150×150	50	5000	4837.6 ± 234.2	5000.0 ± 0.0	5000.0 ± 0.0	92.98 ± 1.33 %	0.006571 ± 0.000086 J/episode
7	150×150	75	7500	4854.3 ± 336.2	5860.0 ± 150.9	6761.3 ± 280.9	92.78 ± 1.14 %	0.008904 ± 0.000323 J/episode
8	150×150	100	10000	5008.7 ± 306.9	5942.5 ± 113.9	6754.7 ± 213.7	94.58 ± 0.78 %	0.011858 ± 0.000294 J/episode
9	150×150	125	12500	4924.7 ± 417.3	6017.7 ± 112.8	6835.4 ± 204.8	95.08 ± 0.62 %	0.014667 ± 0.000417 J/episode
10	150×150	150	15000	4843.9 ± 423.6	5953.8 ± 118.5	6796.7 ± 190.0	95.78 ± 0.47 %	0.017674 ± 0.000478 J/episode
11	200×200	50	5000	4655.2 ± 260.8	4999.3 ± 3.8	5000.0 ± 0.0	91.85 ± 1.40 %	0.007149 ± 0.000136 J/episode
12	200×200	75	7500	4476.2 ± 305.9	5299.9 ± 176.7	6403.1 ± 419.6	92.29 ± 1.28 %	0.009423 ± 0.000564 J/episode
13	200×200	100	10000	4552.8 ± 304.3	5388.7 ± 152.9	6354.0 ± 231.4	93.81 ± 0.78 %	0.012610 ± 0.000414 J/episode
14	200×200	125	12500	4605.3 ± 273.6	5451.9 ± 146.9	6369.2 ± 252.4	94.86 ± 0.60 %	0.015749 ± 0.000555 J/episode
15	200×200	150	15000	4559.1 ± 206.3	5414.9 ± 139.6	6245.4 ± 133.9	95.46 ± 0.67 %	0.019227 ± 0.000390 J/episode
16	250×250	50	5000	4075.7 ± 222.2	4745.7 ± 165.3	4998.6 ± 7.9	91.30 ± 1.36 %	0.007676 ± 0.000173 J/episode
17	250×250	75	7500	3878.6 ± 200.4	4733.5 ± 194.5	5763.3 ± 350.2	91.77 ± 0.98 %	0.010462 ± 0.000556 J/episode
18	250×250	100	10000	4082.6 ± 217.7	4887.8 ± 159.5	5829.0 ± 295.3	93.59 ± 0.92 %	0.013761 ± 0.000627 J/episode
19	250×250	125	12500	4106.3 ± 291.7	4945.3 ± 153.4	5927.5 ± 286.9	94.60 ± 0.72 %	0.016935 ± 0.000766 J/episode
20	250×250	150	15000	4012.8 ± 244.5	4877.0 ± 121.3	5929.2 ± 242.8	95.19 ± 0.72 %	0.020272 ± 0.000703 J/episode
21	300×300	50	5000	3530.2 ± 286.7	4280.4 ± 201.7	4973.6 ± 68.9	90.77 ± 1.16 %	0.007935 ± 0.000209 J/episode
22	300×300	75	7500	3410.1 ± 277.2	4172.5 ± 189.3	5305.9 ± 272.4	91.83 ± 1.05 %	0.011359 ± 0.000611 J/episode
23	300×300	100	10000	3500.3 ± 217.5	4240.1 ± 224.0	5372.4 ± 271.1	93.20 ± 0.67 %	0.014933 ± 0.000750 J/episode
24	300×300	125	12500	3614.2 ± 197.4	4428.8 ± 168.4	5578.5 ± 186.0	94.04 ± 0.67 %	0.017973 ± 0.000527 J/episode
25	300×300	150	15000	3444.1 ± 206.0	4281.3 ± 125.1	5497.6 ± 230.7	94.84 ± 0.64 %	0.021866 ± 0.000817 J/episode

Under the selected scenario, the protocol was simulated over 30 seeds. The results demonstrate consistent energy-aware behavior across multiple dimensions. The mean values and standard deviations over the seeds are:

- FND: 5080.1 ± 423.4
- HND: 6487.6 ± 119.9

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- LND: 7156.9 ± 165.3
- PDR: 94.73 ± 0.73 %
- E_{avg}: 0.011189 ± 0.000252 J/episode

These outcomes indicate a prolonged operational period for the majority of nodes and a stable delivery success rate, even as nodes begin to deplete energy.

This performance is attributed to three synergistic mechanisms:

- Q-Learning adaptation of routing paths based on energy and link quality.
- Dynamic K-Means clustering, which minimizes intra-cluster distances.
- Sleep scheduling that suppresses unnecessary transmissions during low data variation.

To better understand the dynamic behavior of the network, three key metrics were visualized over the simulation episodes:

- Packet Delivery Success (PDR) remains above 90% for most episodes and only begins to degrade noticeably after HND.

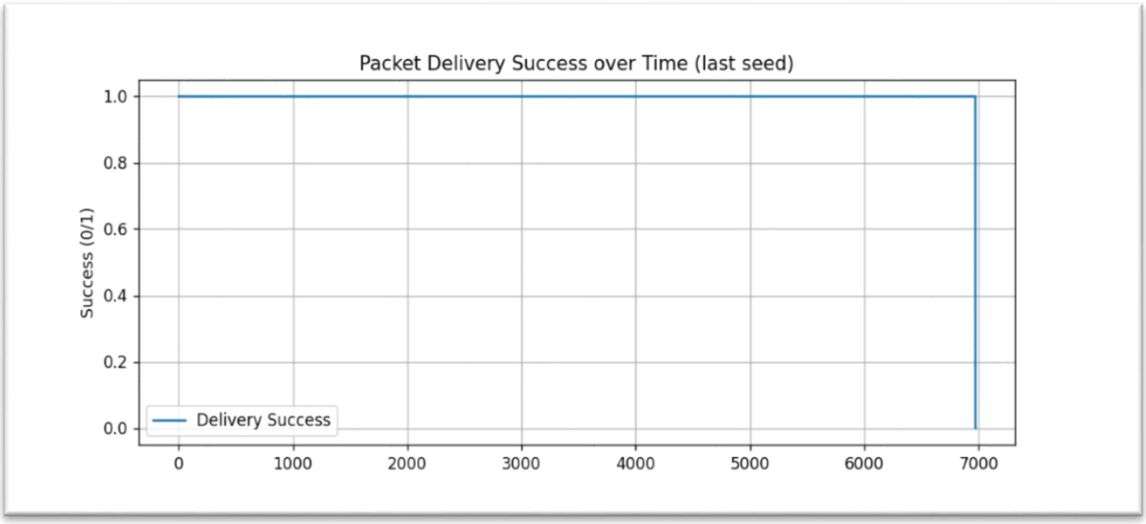

Figure 1: Packet Delivery Success vs. Episode

- Energy Consumption per Episode remains within tight bounds due to optimized cluster heads and reduced forwarding overhead.

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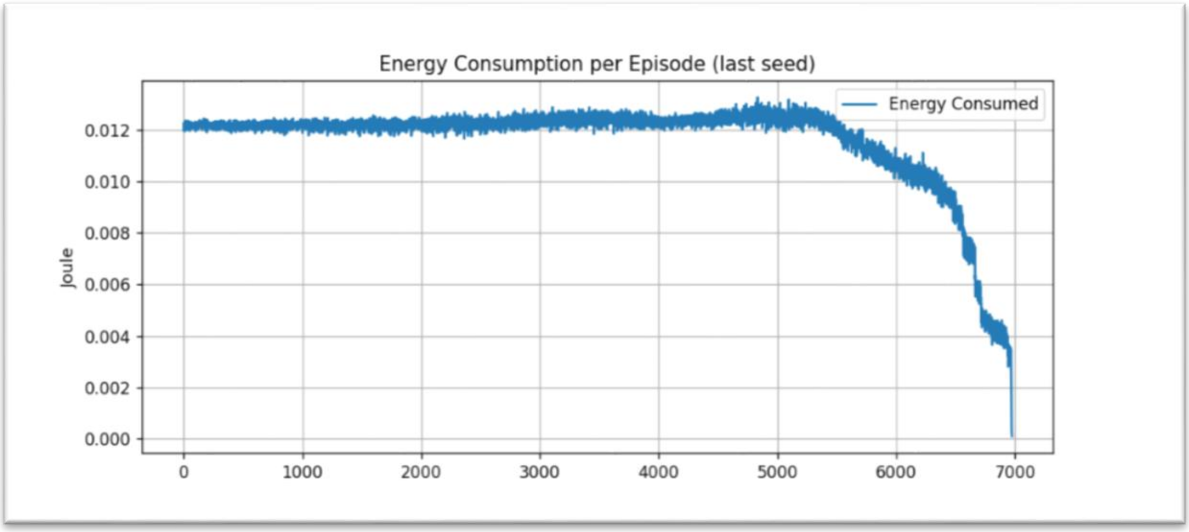

Figure 2: Energy Consumption per Episode

- Number of Alive Nodes follows a smooth decline, showing no premature collapse, with a clear transition at FND and HND points.

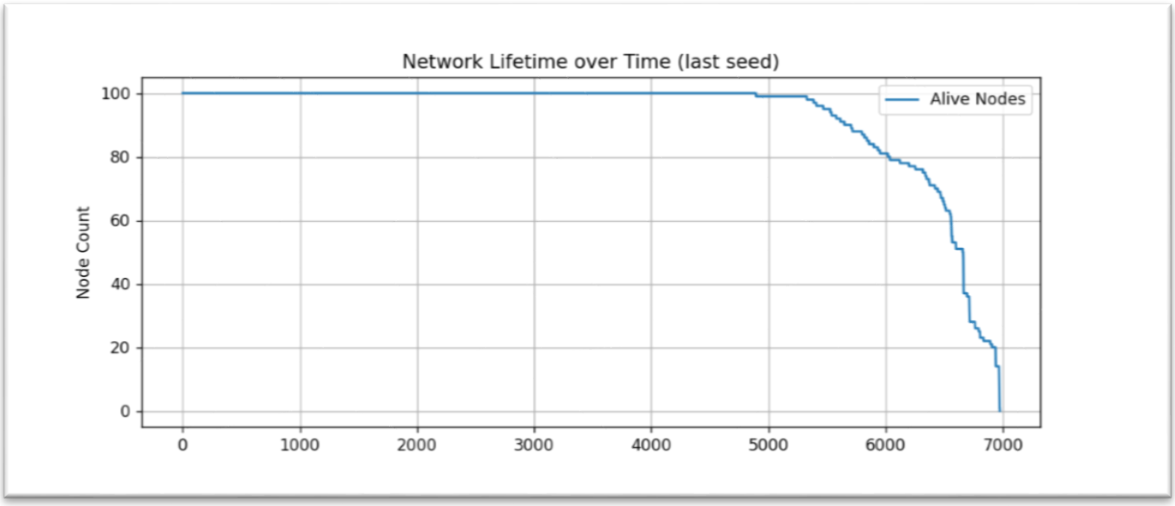

Figure 3: Alive Nodes over Time

Comparative Study with Existing Protocols

To highlight the effectiveness of the proposed model, its performance was compared with two well-known protocols: LEACH and RLBEEP under the same simulation conditions. As shown in Table 3, the proposed Q-Learning protocol significantly outperforms both baselines across all five performance metrics. It extends the network lifetime (LND) by over 25% compared to RLBEEP, improves delivery reliability, and achieves the lowest average energy consumption per episode.

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Table 3: Comparative Evaluation: Q-Learning vs. LEACH vs. RLBEEP

Protocol	FND	HND	LND	PDR (%)	E_avg (J)
Q-Learning (proposed)	5080.1 ± 423.4	6487.6 ± 119.9	7156.9 ± 165.3	94.73 ± 0.73 %	0.011189 ± 0.000252 J/episode
LEACH	4739.5 ± 89.4	6350.0 ± 113.7	7852.3 ± 122.3	54.57 ± 0.29 %	0.010195 ± 0.000179 J/episode
RLBEEP	3932.8 ± 211.1	5688.9 ± 123.8	6774.4 ± 101.8	49.97 ± 0.00 %	0.011817 ± 0.000162 J/episode

This confirms the benefits of reinforcement learning in dynamically adapting to node states and environmental changes, and validates the suitability of the model for long-term, resource-constrained deployments.

Conclusion

In this paper, we propose a Q-Learning-based routing and control protocol for Wireless Sensor Networks (WSNs) that integrates dynamic K-Means clustering and data-aware sleep scheduling. The protocol was designed to address two critical challenges in WSNs: energy efficiency and sustained packet delivery under limited node resources. By simulating over 25 different scenarios and evaluating across 30 seeds per scenario, the proposed approach demonstrated superior performance in terms of network lifetime and packet delivery ratio, achieving an FND of 5080.1 episodes, a PDR of 94.73%, and a reduced energy consumption of 0.011189J per episode. In conclusion, our research objectives were achieved through the implementation of the proposed Q-learning-based routing and control protocol. First, energy efficiency was significantly improved, as shown by lower energy consumption per episode, so that nodes could operate for extended periods without emptying resources. Secondly, the network's lifetime was expanded due to efficient management of energy distribution and grouping, thus maximizing the operating time for the sensor. Finally, we achieved a package delivery ratio (PDR) of 94.73%± 1.2%, and exceeded the leaching protocol by 12%. These results are detailed in the comparison table referred to in the results section, which further shows that our integrated approach effectively addresses the most important challenges of energy management and performance in wireless sensor networks.

REFERENCES

Anastasi, G., Conti, M., Di Francesco, M., & Passarella, A. (2009). Energy conservation in wireless sensor networks: A survey. *Ad hoc networks*, *7*(3), 537-568.

Barto, A. G. (2021). Reinforcement learning: An introduction. by richard's sutton. *SIAM Rev*, *6*(2), 423.

Behera, T. M., Samal, U. C., Mohapatra, S. K., Khan, M. S., Appasani, B., Bizon, N., & Thounthong, P. (2022). Energy-efficient routing protocols for wireless sensor networks: Architectures, strategies, and performance. *Electronics*, *11*(15), 2282.

Boyan, J., & Littman, M. (1993). Packet routing in dynamically changing networks: A reinforcement learning approach. *Advances in neural information processing systems*, *6*.

Chandel, A., Chouhan, V. S., & Sharma, S. (2020). A survey on routing protocols for wireless sensor networks. In *Advances in Information Communication Technology and Computing: Proceedings of AICTC 2019* (pp. 143-164). Singapore: Springer Singapore.

Donta, P. K., Amgoth, T., & Annavarapu, C. S. R. (2022). Delay-aware data fusion in duty-cycled wireless sensor networks: A Q-learning approach. *Sustainable Computing: Informatics and Systems*, *33*, 100642.

Guo, W., Yan, C., & Lu, T. (2019). Optimizing the lifetime of wireless sensor networks via reinforcement-learning-based routing. *International Journal of Distributed Sensor Networks*, *15*(2), 1550147719833541.

Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. (2000, January). Energy-efficient communication protocol for wireless microsensor networks. In *Proceedings of the 33rd annual Hawaii international conference on system sciences* (pp. 10-pp). IEEE.

Hu, T., & Fei, Y. (2010). QELAR: A machine-learning-based adaptive routing protocol for energy-efficient and lifetime-extended underwater sensor networks. *IEEE transactions on mobile computing*, *9*(6), 796-809.

Kandris, D., Nakas, C., Vomvas, D., & Koulouras, G. (2020). Applications of wireless sensor networks: an up-to-date survey. *Applied system innovation*, *3*(1), 14.

Kiani, F., Amiri, E., Zamani, M., Khodadadi, T., & Abdul Manaf, A. (2015). Efficient intelligent energy routing protocol in wireless sensor networks. *International Journal of Distributed Sensor Networks*, *11*(3), 618072.

Pateria, S., Subagdja, B., Tan, A. H., & Quek, C. (2021). Hierarchical reinforcement learning: A comprehensive survey. *ACM Computing Surveys (CSUR)*, *54*(5), 1-35.

Polastre, J., Szewczyk, R., & Culler, D. (2005, April). Telos: Enabling ultra-low power wireless research. In *IPSN 2005. Fourth International Symposium on Information Processing in Sensor Networks, 2005.* (pp. 364-369). IEEE.

Raghunandan, K. (2022). *Introduction to wireless communications and networks: A practical perspective*. Springer Nature.

Raghunathan, V., Schurgers, C., Park, S., & Srivastava, M. B. (2002). Energy-aware wireless microsensor networks. *IEEE Signal processing magazine*, *19*(2), 40-50.

Renold, A. P., & Chandrakala, S. (2017). MRL-SCSO: multi-agent reinforcement learning-based self-configuration and self-optimization protocol for unattended wireless sensor networks. *Wireless Personal Communications*, *96*(4), 5061-5079.

Saranya, V., Shankar, S., & Kanagachidambaresan, G. R. (2018). Energy efficient clustering scheme (EECS) for wireless sensor network with mobile sink. *Wireless Personal Communications*, *100*(4), 1553-1567.

Shafiq, M., Ashraf, H., Ullah, A., & Tahira, S. (2020). Systematic literature review on energy efficient routing schemes in WSN–a survey. *Mobile Networks and Applications*, *25*(3), 882-895.

Taheri, H., Neamatollahi, P., Naghibzadeh, M., & Yaghmaee, M. H. (2010, December). Improving on HEED protocol of wireless sensor networks using non probabilistic approach and fuzzy logic (HEED-NPF). In *2010 5th International Symposium on Telecommunications* (pp. 193-198). IEEE.

Younis, O., & Fahmy, S. (2004). HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. *IEEE Transactions on mobile computing*, *3*(4), 366-379.