International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(15s) 2026 pp. 244-258
https://doi.org/10.70917/ijcisim-2026-4401
Article

# Energy-Efficient WSNs by Integrating DQL with LEACH Protocol

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**Abstract:** Longer life of wireless sensor networks is achieved with energy saving methods for advanced applications. The up gradation in low energy adaptive clustering hierarchy (LEACH) protocol is proposed in this paper with the use of deep Q-learning (DQL) which becomes adaptive network for saving energy and increasing life. The most popular machine learning strategy that make use of Support Vector Machine is compared with the proposed method which shows improved decision making ability of the protocol. The selection of cluster heads is improved with consideration of changing conditions of environment, residual energy, along with topological combinations. For larger area networks, DQL shows improved performance with increasing lifetime of the network. The comparative with state of the art methods shows DQL based approach shows better performance in terms of not only extended lifetime but also optimum throughput, packet delivery ratio and end to end delay.
**Keywords:** Wireless Sensor Networks (WSNs), Energy Efficiency, Deep Q-Learning (DQL), LEACH Protocol, Comparative Study.

## 1. Introduction

In various fields of applications such as farms, smart cities and industrial zones, wireless sensor network (WSN) are deployed for collection of data. Collection of data from sensors and sending them at base station (Sink Node) is main task of the nodes deployed in the WSNs. The battery operated these nodes are required to be energy efficient for maximum life of the network operations. The energy efficiency is achieved with various approaches in which clustering is popular with use of LEACH as base protocol for such applications. The enhancement of lifetime with modified version of leach protocol is the main objective of the work presented in this article. The challenging task of energy saving in WSN is associated with the fundamental concerns which includes how long the network lasts, how well it works, and how stable it is [1]. Here are some main problems:

1. Limited Energy: With no facilitation for frequent changing of batteries or charging them, the power of sensor nodes need to last longer [2].
2. High Energy Use: Along with sensing, processing and packetizing of them in efficient manner is the fundamental task in the sensor node. [3].
3. Data Sending Costs: Collected data need to be sent at the base station for further processing requirements and monitoring of the field which is main task of the WSN in any application. The data collection at the base station is through forwarding of many nodes which involves smart routing strategies [4].
4. Changing Environments: As per the task of sensor nodes, the environmental conditions must be accommodated and adaptable for any sensor node in WSN [5].
5. Reliability and Fault Handling: In some cases, if some of the node fail due to running out of energy, the in between distance gets increased during forwarding tasks which again increases energy consumption and thereby decrease in lifetime. [6].
6. Protocol Layers: In protocol layers configuration, routing is important layer which takes care of shortest and energy efficient path selection during data forwarding mechanism.

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7. Scaling Up: As size of the network increases along with number of nodes in the WSN, energy saving mechanism become complex to be handled.

Solving these issues together may not be feasible while working on single task, but balancing the fundamental parameters with optimum performance can be achieved. Considering this fundamental perspective, this article focuses on energy efficiency enhancement of WSN with modification of clustering based LEACH protocol. The selection of cluster head is improved for more energy efficient mechanism. For this purpose, deep Q learning (DQL) an approach with reinforcement learning technique that makes protocol adaptive in nature while selecting cluster heads for assigning the data forwarding tasks within small zones of the larger networks. The smart nodes are thus designed with use of DQL to save energy and balancing the network parameters. The important contribution of this work are,

- DQL based improved network management to increase energy efficiency and keep maximum nodes running for longer time.
- Decentralized approach of CH selection within small zones with use of DQL which minimizes network overhead.
- Energy saving by selecting best routes, less retransmissions and increased successful data transmission rate.
- Scalable approach with improved performance for larger networks with large number of nodes in WSN.

Along with the introduction and significance of the work mentioned in section I, section 2 discusses the related methods used in WSN for energy efficiency enhancement. Section III discusses the details of protocol along with DQL method used in the proposed modified LEACH protocol. Section IV discusses the analysis and comparative study of the proposed protocol with other existing contemporary protocols and methods. Finaly section V concludes the paper with achievements and future directions.

## 2. Literature Review

Many researchers consider clustering as fundamental energy saving method which has made use of lightweight LEACH protocol quite popular. The additions of methods including artificial intelligence based approaches have improved LEACH protocol in many perspectives. The base LEACH protocol introduced by Heinzelman et al. [7] is clustering based strategy for forwarding the data from sensor nodes to base station with different aspects in which location of base station changes from central place to one side of the network. The configuration of topology is thus done by the designers of the network topology for better efficiency and network performance. Mainly central place of the base station considered as base topology by many researchers. In neural network based modification of protocols, Zhang et al. [10] modified the cluster head selection for improving the network performance parameters.

Gupta et al. [8] applied fuzzy logic for energy balancing with node prioritization based on energy, centrality, and distance to balance load. K. Amirthalingam et al. [9] enhanced LEACH by modifying the probability function to include energy and distance, improving cluster head energy efficiency. Zhao et al. [10] suggested a modified LEACH that considers energy changes and adds a vice cluster head to reduce re-clustering energy costs. Daanoune et al. [11] focused on remaining energy and cluster size, identifying unused nodes to boost efficiency.

Nabavi et al. [12] developed a dual optimization technique using genetic and gravitational search algorithms for clustering and routing, minimizing energy and transmission costs. Bhola et al. [13] optimized LEACH using genetic algorithms, reporting up to 17.39% energy savings. Khan et al. [14] identified weaknesses in LEACH and proposed a method to enhance energy efficiency and network lifespan. In the modification approaches with use of optimization based strategies, Dogra et al. [15] used Tunicate Swarm Intelligence which was used for cluster head selection with parameters like energy, distance, and node density. In smart city based application scenario, Verma [16] proposed EI-CSC protocol which used the Sooty Tern Optimization Algorithm for increased network lifetime and stability. In AI based approach, AGRIC [24] improved routing with energy efficiency.

Gaidhani et al. [17], combined K-mean in LEACH protocol base mechanism for energy efficiency. Initial steps is to form zones of nodes with sue of K-means and then selecting CH based on energy levels. Similarly, Ramesh et al. [18] combined k-means clustering with LEACH, which improved energy saving by almost 48%. With addition of distance parameter in clustering by improved K-Means algorithm, Panchal et al. [19] used distance of node from base station.

In Machine learning (ML) based techniques [20] models learn from the network environment and adjust their behavior to improve overall performance. In many popular approaches conventional rule based approaches such as Fuzzy logic, or evolutionary and support vector machines are used [21].Table 1 shows the summary of the review.

Table 1: Summary of the energy efficient techniques in WSN

| Technique | Outcome | Advantages | Disadvantages |
|---|---|---|---|
| LEACH [Heinzelman et al. [7]] | Basic clustering strategy with centralized base station | Simple, energy-efficient clustering method | Static CH selection, limited scalability |
| Fuzzy Logic LEACH [Gupta et al. [8]] | Node prioritization using energy, centrality, and distance | Balanced load distribution, energy-aware CH selection | Higher computation overhead |
| Modified Probability LEACH [Amirthalingam et al. [9]] | Energy and distance used in probability function | Improved CH energy efficiency, better performance | Requires additional parameters, may complicate selection logic |
| Vice-CH LEACH [Zhao et al. [10]] | Adds vice cluster head to reduce reclustering | Reduced reclustering overhead, improved network stability | More control overhead for vice CH coordination |
| Residual Energy LEACH [Daanoune et al. [11]] | Uses cluster size and remaining energy to improve efficiency | Avoids idle nodes, boosts energy savings | Cluster formation complexity |
| Dual Optimization (GA + GSA) [Nabavi et al. [12]] | Optimized clustering and routing | Lower transmission cost and energy consumption | High computational cost |
| Genetic Algorithm LEACH [Bhola et al. [13]] | Achieved ~17.39% energy savings | Effective optimization, better CH selection | Convergence time may be slow |
| Enhanced LEACH [Khan et al. [14]] | Addressed energy inefficiencies and extended network lifespan | More efficient than base LEACH | May lack generalizability across scenarios |
| Tunicate Swarm Intelligence [Dogra et al. [15]] | CH selection based on energy, distance, and node density | Intelligent CH selection with good trade-offs | Complex algorithm |
| EI-CSC with Sooty Tern Optimization [Verma [16]] | Designed for smart city WSNs with increased network lifetime | Stable clusters, good energy management | Specific to smart city scenarios |
| K-Means LEACH [Gaidhani et al. [17]] | Zones created via K-means, then CH based on energy | Structured CH formation, improved energy efficiency | Overhead in zone formation |
| Improved K-Means LEACH [Ramesh et al. [18]] | K-means with 48% energy savings | Significant energy improvement | Needs synchronization across zones |

| | | | |
|---|---|---|---|
| Distance-based K-Means LEACH [Panchal et al. [19]] | Adds distance from base station in clustering | Enhanced CH placement, reduced path cost | Needs distance calculation at every round |
| ML-based LEACH [General ML Approaches [20], [21]] | Learning-based behavior adaptation to network conditions | Smart decision making, adaptability | Requires training, computational overhead |
| AGRIC [24] | AI-based routing with energy efficiency | Improved routing, adaptable | Implementation complexity |
| General Observation | Tradeoff between energy efficiency and QoS metrics like PDR and E2E delay | Neural networks offer balance between adaptability and light computation | Path optimization in large WSNs remains underexplored |

While achieving the energy efficiency, improving the network parameters such as throughput, packet delivery ratio and end to end delays is also important. While achieving such tradeoff requires lightweight as well as adaptable neural network use which further balances the network efficiently. There is need to design the protocols with smart decision making capabilities to select right cluster heads in the network to improve energy efficiency along with optimum performance of other network parameters. The communication path length in larger WSNs is important challenge and is not addressed in many works. The work presented in this paper addresses these gaps with detailed methodology and analysis.

## 3. Proposed Work

The objectives involved in this work which makes use of base LEACH protocol for modification with DQL are based on energy efficiency, smart decision making for route and CH selection and dynamic cluster formation in the WSN. The objectives are,

1. To incorporate distance, energy levels of the nodes and load handling capacity of the nodes.
2. To incorporate reinforcement learning framework in the WSN for improved adaptability of the protocol.
3. To Reduce node failure by energy drain by balancing the CH tasks amongst small zones within the network.
4. To design smart route selection mechanism with adaptive decision making with learning of past events.
5. To optimize the dynamic clustering method while maintain the network performance parameters at optimum levels.

Figure 1 shows framework for energy efficient WSN strategy for cluster head selection which makes use of residual energy, communication cost and location details. The framework uses deep reinforcement learning approach to dynamically adapt CH selection in WSN.

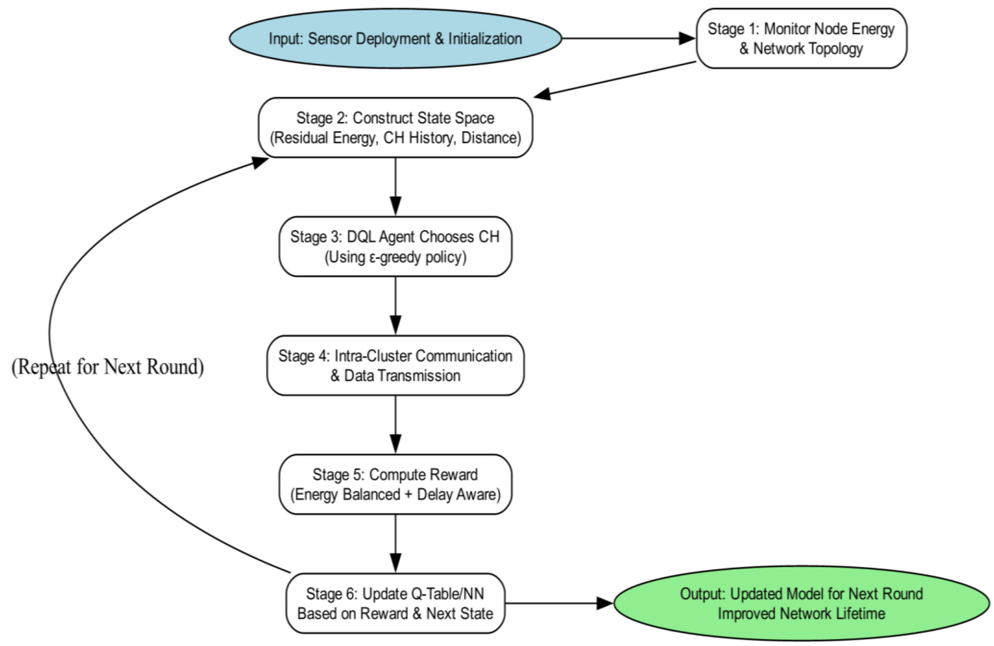


Figure 1: Block diagram of stages in proposed strategy

The designed framework with use of DQL is a holistic and intelligent routing solution that offers scalability and energy efficiency with optimum network performance.

In DQL, deep learning is used with integration of Q-Learning. In dynamic cluster head selection with adaptive to changing network applications, DQL is well suited approach. In this work, the main challenges includes balancing of energy consumption, maintaining connectivity and adaptability to the changes in the network.

Required Factors in Reinforcement Learning:

- Agent: The entity that makes decisions (e.g., a central controller or individual nodes).
- Environment: The WSN with all its nodes and their states (e.g., energy levels, positions).
- State (S): Represents the current status of the WSN, including factors like nodes' energy levels, locations, and previous cluster heads.
- Action (A): The decision of selecting a particular node as CH.
- Reward (R): The feedback mechanism that supports the decision making in right direction for selecting CH.

The complex tasks are easily solved with use of DQL [22]. Q-Learning is a type of reinforcement learning where an agent learns to take the best action in a particular state by evaluating the value of state-action pairs. This value is known as the Q-value and it reflects the expected cumulative reward.

Bellman Equation (Q-value Update):

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \qquad \ldots(1)$$

- $\alpha$: Learning rate (0 to 1), controls how much new information overrides old.
- $\gamma$: Discount factor (0 to 1), represents future reward significance.
- $r$: Reward received after taking action $a$ in state $s$.
- $s'$: New state after performing action $a$.
- $a'$: Varied action in new state

DQL combines Q-learning with deep neural networks to approximate Q-values over large state-action spaces. This approach is especially useful in complex environments like WSNs.

Key Components:

1. Evaluation Network: Predicts the Q-value for each state-action combination.

2. Target Network: Periodically updated to stabilize learning.
3. Replay Buffer: Stores experiences ($s$, $a$, $r$, $s'$) to break correlation and improve learning stability.

Steps in Deep Q-Learning

1. Initialize Q-network with random weights.
2. For each episode:
a. Observe initial state $s$.
b. Select action $a$ using an $\epsilon$-greedy strategy.
c. Execute action $a$ and receive reward $r$ and new state $s'$.
d. Store transition $(s, a, r, s')$ in replay buffer.
e. Sample random mini-batch from buffer.
f. Compute target Q-value:

$$y = r + \gamma \max_{a'} Q_{\text{target}}(s', a') \quad \ldots(2)$$

g. Update Q-network by minimizing loss:

$$\mathcal{L} = \left(y - Q(s, a)\right)^2 \quad \ldots(3)$$

h. Update target network weights from Q-network periodically.

**Configuring the experiment:**

State Representation: A vector comprising node energy levels, CH history, and topology metrics. Actions: Selecting a node as CH from the candidate list.

Reward Function: Encourages actions that enhance energy efficiency, balance load, and improve longevity.

Training Goal: The DQL model helps sensor nodes make clustering and routing decisions that result in longer network operation with optimal energy usage.

**Algorithm:**
**Initialization**
- Set up sensor nodes and energy parameters.
- Initialize performance metric arrays.
- Define DQL parameters and initialize the Q-network.

**Repeat for each round:**
For each active node:
- Construct the current state: energy level, distance to sink, number of neighbors, and round index.
- Choose an action using an $\epsilon$ -greedy strategy:
  - With probability $\epsilon$, pick a random action.
  - Otherwise, select the action with the highest Q-value.
- Assign the node as CH or normal based on the action.

For each normal node:
- Connect to the nearest CH.

Update energy use and DQL-related metrics.
For each active node:
- Define the next state based on updated conditions.
- Compute the reward considering energy savings and role assignment.
- Store the experience (state, action, reward, next state) in a replay buffer.
  If replay buffer has enough samples:
- Sample a mini-batch.
- For each experience in the batch:
  - Calculate target Q-values.
  - Update the Q-network by minimizing the loss between predicted and target values.
  - Gradually reduce $\epsilon$ to encourage exploitation over exploration.

**Post-processing:** Compare and plot metrics between traditional LEACH and DQL-enhanced LEACH.

## 4. Results and Analysis

Table 2 shows the network configuration parameters considered during simulated experimentation.

Table 2: Configuration of WSN

| Parameter | Value |
|---|---|
| Number of Nodes | {50,100,150,200} |
| Network Area (X, Y) | 100m x 100m |
| Sink Node Position (X, Y) | (50m, 50m) |
| Initial Energy per Node | 0.5 Joules |
| Size of the Data Packet | 4000 bits |
| Size of the Control Packet | 100 bits |
| Energy of Transmission (ETX) | 50 nJ/bit |
| Energy of Reception (ERX) | 50 nJ/bit |
| Free Space Model (Efs) | 10 pJ/bit/m^2 |
| Multipath Model (Emp) | 0.0013 pJ/bit/m^4 |
| Amplifier Energy (Eamp) | 100 pJ/bit/m^2 |
| Energy for Data Aggregation (EDA) | 5 nJ/bit/signal |
| LEACH Probability (p) | 0.1 |
| Maximum Number of Rounds | 800 |
| DQL Rate of Learning (α) | 0.01 |
| DQL Factor of Discount (γ) | 0.99 |
| DQL Epsilon (ε) Initial Value | 1 |
| DQL Epsilon Decay Rate | 0.995 |
| DQL Minimum Epsilon (ε_min) | 0.01 |
| DQL Batch Size | 32 |
| DQL Replay Memory Size | 10000 |
| DQL Target Network Update Frequency | 100 erations |

## A. *Number of Dead Nodes Analysis*

1. With respect to number of nodes in the network

Figure 1 illustrates the number of dead nodes recorded under different routing protocols as the initial number of nodes in the network increases from 10 to 50. The LEACH protocol shows the highest node mortality, peaking at 39 dead nodes with 50 total nodes, indicating inefficient energy utilization. Similarly, ML-EERP variants based on SVM, Decision Tree (DT), Naïve Bayes (NB), and Discriminant Analysis (DA) also exhibit a rising trend in node deaths as network size grows. For instance, ML-EERP (DA) records 35 dead nodes at its peak.

In contrast, the proposed DQL protocol demonstrates a more balanced and energy-efficient performance. It consistently maintains a lower number of dead nodes across all node counts. Notably, with 50 initial nodes, the DQL-based approach results in only 18 dead nodes—the fewest among all tested protocols. This outcome clearly reflects the protocol's ability to optimize energy consumption and extend the operational lifetime of the network, outperforming both traditional and machine learning-driven methods.

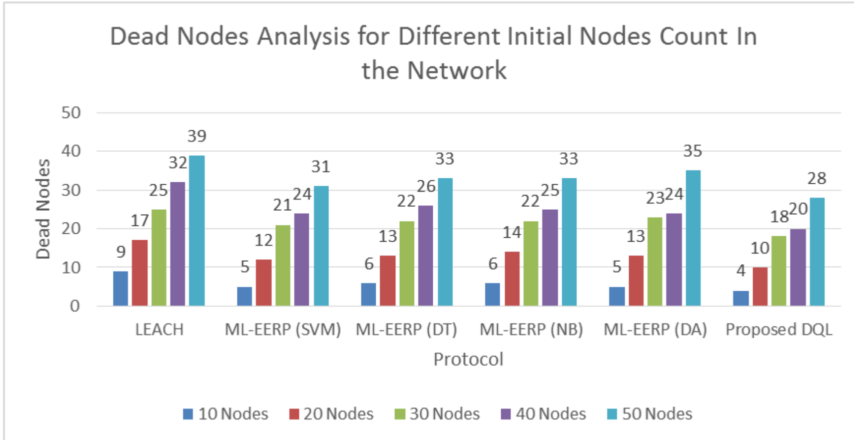


**Figure 1: Dead Nodes Analysis**

2. With respect o iterations for fixed nodes count

Figure 2 shows the analysis of the 50-nodes WSN with respect to iterations. The comparative analysis includes LEACH, ML-EERP (SVM) [23], and the proposed DQL-based LEACH protocol. The energy is depleted with resepect to iterations. For LEACH maximum dead nodes are 39 at 800 iterations. For ML-EERP (SVM) sthis number is 31 and for proposed DQL based LEACH only 20 dead nodes are seen. This consistent high performance of proposed DQL based LEACH shows its effectiveness for enhancing the network lifetime.

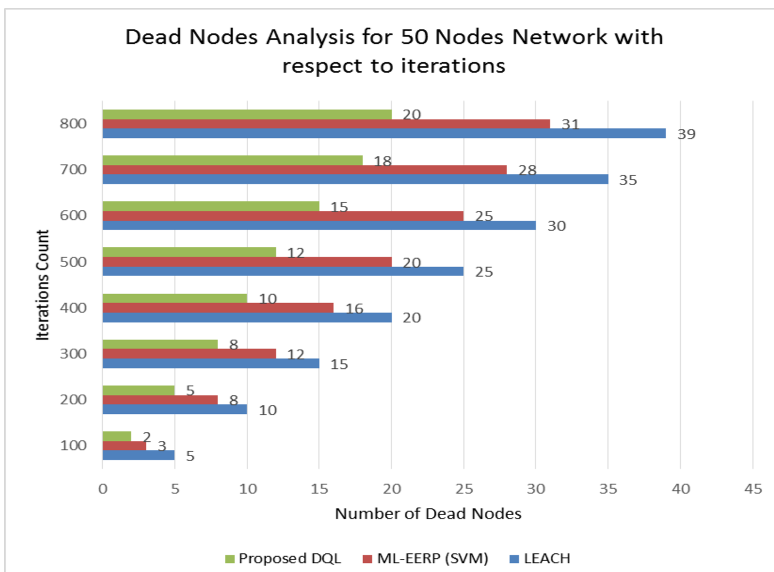


**Figure 2: Dead Nodes analysis for 50 Nodes Network with respect to iterations**

### B. *Residual Energy Analysis:*

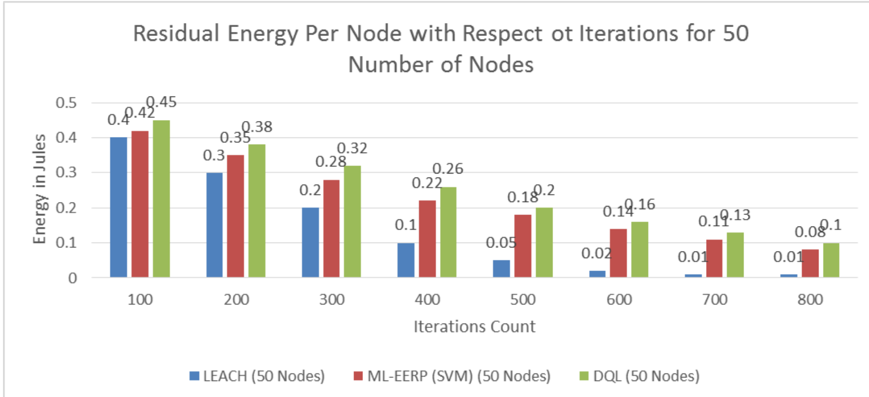


**Figure 3: Residual Energy Analysis for 50 Number of Nodes in the network**

Figure 3 compares the residual energy per node over increasing iteration counts (from 100 to 800) in a 50-node network for three protocols: LEACH, ML-EERP (SVM), and the proposed DQL-based method.

At the beginning (100 iterations), the DQL protocol preserves the highest energy level per node (0.45J), followed by ML-EERP (0.42J), while LEACH trails at 0.3J. As the iterations proceed, all protocols exhibit a downward trend in energy reserves due to continuous network operation. However, the DQL method consistently maintains a higher level of residual energy at each stage. Notably, at 400 iterations, DQL retains 0.26J per node compared to ML-EERP's 0.22J and LEACH's 0.1J. By the 800th iteration, DQL still holds 0.1J, outperforming both ML-EERP (0.08J) and LEACH (0.01J). These results highlight the DQL protocol's superior energy management capabilities, allowing it to conserve more energy over time. This directly enhances the network's operational lifespan and supports reduced node failure, confirming the DQL method's advantage in energy-efficient communication over both traditional and ML-based routing protocols.

Figure 4 shows how residual energy per node changes over time for a network of 100 nodes, tested across three protocols: LEACH, ML-EERP (SVM), and the proposed DQL method. At 100 iterations, the DQL protocol retains the most energy per node (0.44J), with ML-EERP at 0.4J and LEACH slightly lower at 0.38J. As the iteration count increases, energy decreases for all three methods due to ongoing communication and processing. However, DQL consistently maintains higher energy levels. For example, at 400 iterations, DQL still holds 0.24J, while ML-EERP drops to 0.2J and LEACH to just 0.09J. By the 800th iteration, DQL preserves 0.1J—far more than LEACH (0.01J) and ML-EERP (0.07J). These observations confirm that the DQL protocol is more energy-efficient, allowing nodes to operate longer with less energy loss. Its consistent performance demonstrates its effectiveness in reducing energy depletion and improving network lifetime when compared to traditional and machine learning-based alternatives.

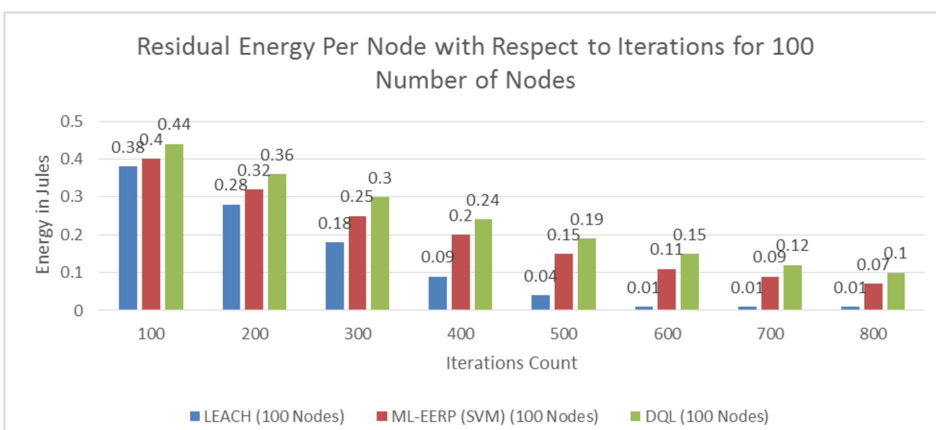


Figure 4: Residual Energy Analysis for 100 Number of Nodes in the network

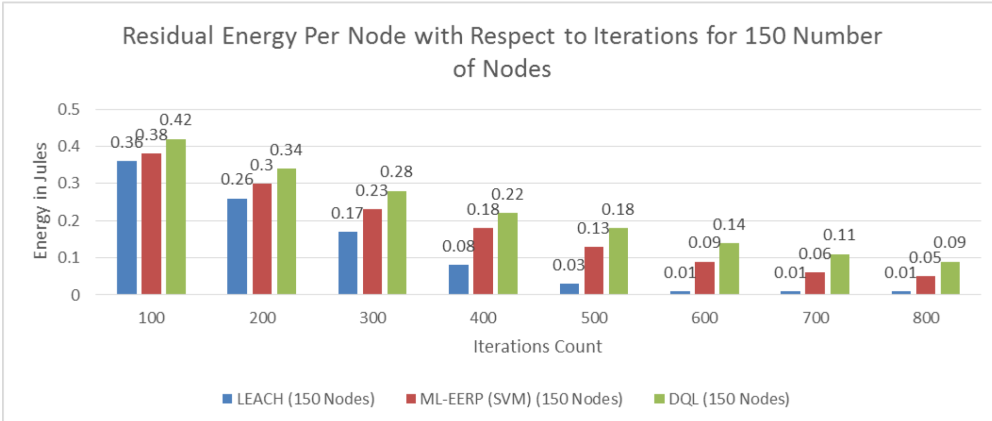


Figure 5: Residual Energy Analysis for 150 Number of Nodes in the network

The graph in Figure 5 shows how residual energy per node changes over iterations in a 150-node network using three different protocols: LEACH, ML-EERP (SVM), and the Proposed DQL. At 100 iterations, DQL shows the highest energy per node (0.42J), followed by LEACH (0.38J) and ML-EERP (0.38J). As iterations increase, energy drops in all protocols, but the rate of reduction is slower in DQL. For example, at 400 iterations, DQL retains 0.22J, while LEACH and ML-EERP drop to 0.08J and 0.18J respectively. At 800 iterations, DQL still maintains 0.09J of energy, compared to just 0.01J for LEACH and 0.05J for ML-EERP. These results demonstrate that DQL significantly improves energy efficiency and prolongs node life. Its intelligent decision-making helps manage energy more effectively than traditional and machine learning-based methods, making it more suitable for large-scale and long-duration sensor network deployments.

In comparative analysis shown in Figure 6, at 100 iterations, DQL shows the highest energy level (0.41J), compared to 0.37J and 0.34J energy for LEACH and ML-EERP respectively. As iterations progress, all protocols see a drop in energy, but DQL maintains a consistent advantage. At 400 iterations, DQL is showing 0.2J of energy, which is higher compared to 0.07J and 0.16J for LEACH and ML-EERP respectively. DQL retains 0.08J even at 800 iterations.

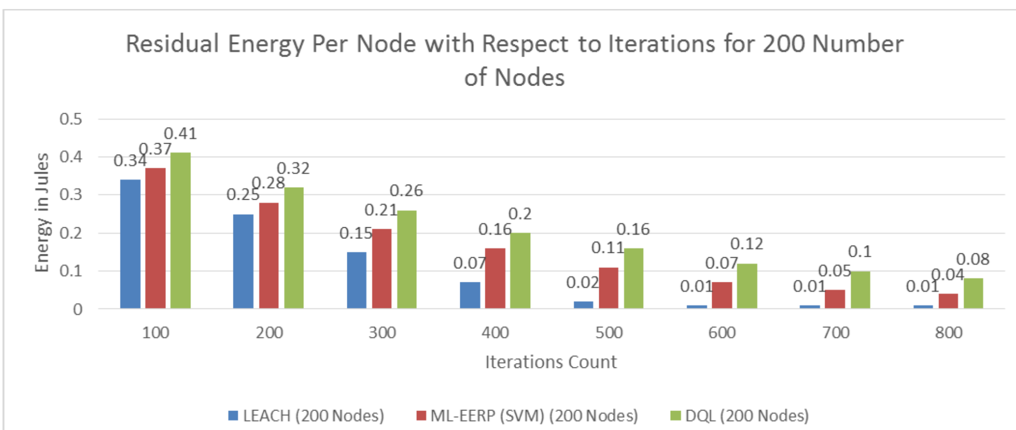


Figure 6: Residual Energy Analysis for 200 Number of Nodes in the network

### *C. Throughput Analysis:*

$$Throughput(kbps) = \frac{nuber\ of\ bits\ successfully\ received}{time\ taken\ for\ receiving\ all\ the\ bits}$$

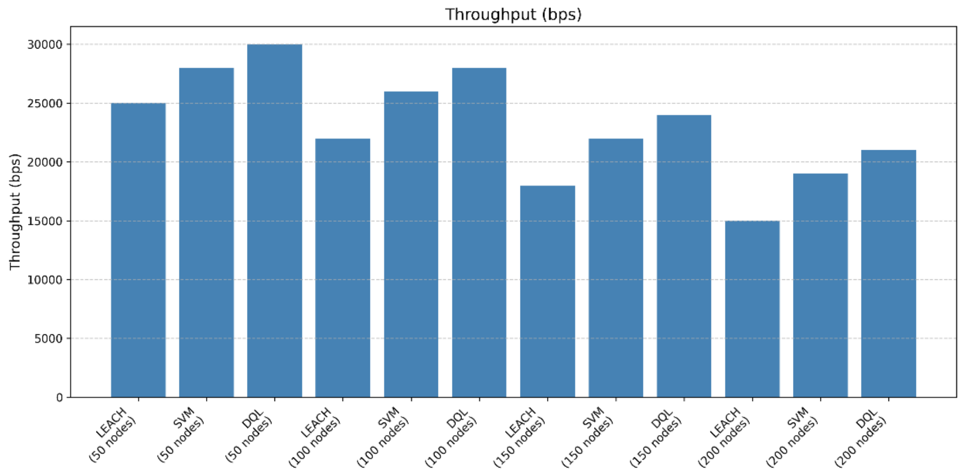


Figure 7: Analysis of throughput

The throughput graph in Figure 7 compares the performance of LEACH, ML-EERP (SVM), and the Proposed DQL protocols across networks with 50, 100, 150, and 200 nodes. At every node count, the DQL-based protocol achieves the highest throughput. For example, at 50 nodes, DQL reaches 30,000 bps, outperforming LEACH (25,000 bps) and SVM (28,000 bps). As the number of nodes increases, throughput decreases for all protocols, but DQL consistently maintains an edge. Even at 200 nodes, DQL achieves 21,000 bps higher than SVM (19,000 bps) and LEACH (15,000 bps). This demonstrates that DQL manages network traffic more effectively, resulting in better data delivery. The PDR graph reveals a similar trend. At 50 nodes, LEACH leads slightly with 95%, followed closely by DQL (94%) and SVM (92%). As network size grows, PDR drops in all protocols, but DQL maintains competitive performance. For instance, at 150 nodes, DQL achieves 83%, while LEACH and SVM manage 82%. At 200 nodes, DQL retains 79%, which remains close to the best. This shows DQL is stable and reliable for packet delivery, even as the network scales.

### *D. PDR Analysis:*

$$\text{PDR}\ (\%) = \frac{\text{Number of bits received}}{\text{Total number of bits sent}} \times 100$$

Figure 8 illustrates the Packet Delivery Ratio (PDR) in percentage for various protocol and network size combinations. The graph compares the performance of LEACH, ML-EERP (SVM), and the proposed DQL protocol across increasing node counts, ranging from 50 to 200 nodes. Among all configurations, LEACH shows the highest PDR values, especially at lower node densities (e.g., 50 nodes), indicating relatively efficient packet transmission under light network loads. However, as node density increases, PDR gradually declines for all protocols due to congestion and energy constraints. ML-EERP (SVM) follows closely behind LEACH in most scenarios, maintaining stable performance across moderate node sizes.

The proposed DQL protocol, while showing slightly lower PDR than LEACH and ML-EERP in high-density settings, provides a consistent and balanced trade-off between energy efficiency and delivery reliability. Notably, the PDR remains above 70% even at the highest tested node count, demonstrating the method's robustness in scalable deployments.

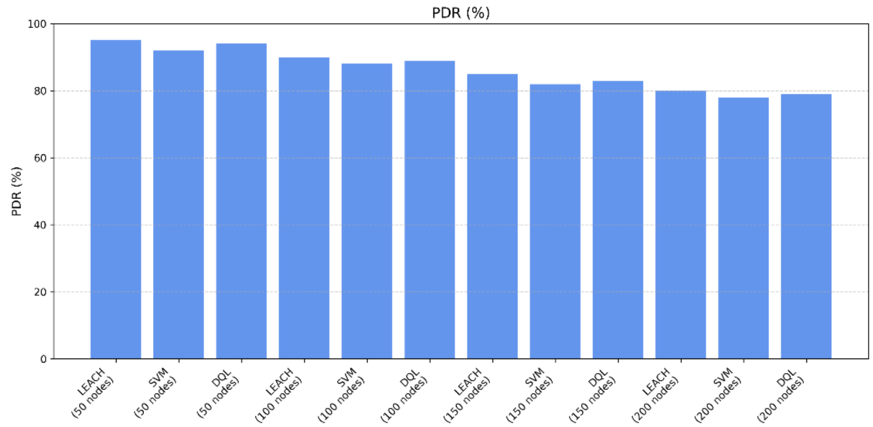


Figure 8: Analysis of PDR

## *E. End to end Delay Analysis:*

In average time taken for a packet to travel from source to destination node the average end-to-end delay (E2E) analysis is performed. The formula for average end-to-end delay can be expressed as:

$$Average\ end\ to\ end\ delay = \frac{\sum_{i=1}^{N} D_i}{N}$$

Where:

- N is the total number of packets transmitted.
- Di is the delay experienced by the i-th packet, defined as the difference between the time the packet is received by the destination and the time it was transmitted by the source.

$$D_i = T_i^{arrived} - T_i^{sent}$$

The average end-to-end delay gives an indication of the average time packets take to travel through the network, including queuing delays, transmission delays, propagation delays, and processing delays at nodes. The bar chart in Figure 9 illustrates the average end-to-end delay (in seconds) for different routing protocols—LEACH, ML-EERP (SVM), and Proposed DQL—across varying node densities (50, 100, 150, and 200 nodes). At 50 nodes, LEACH records the lowest delay (0.10s), while DQL follows closely at 0.12s, showing slightly better performance than SVM (0.15s). As node count increases, all protocols exhibit higher delays due to increased communication load. However, the Proposed DQL method consistently maintains a lower delay compared to the others. The tred analysis of DQL based LEACH shows its effectiveness in minimum latency based communication.

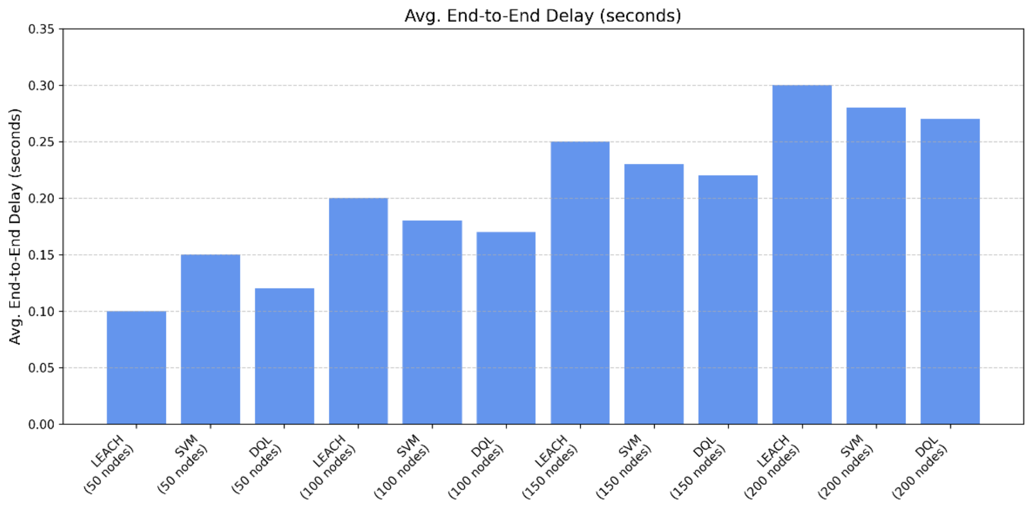


Figure 9: End to end delay analysis

### *F. Lifetime enhancement analysis*

As number of nodes in the network increase, mostly the [protocol show decrement in energy efficiency affecting network lifetime. With reference to required lifetime, the increased lifetime in percentage is analyzed for proposed DQL-based method and other state-of-the-art methods. TICHOR [24], Intelligent Clustering [25]v, DBN-RP [26] and ELPSO-PSO-BPNN [27] are considered for the analysis. Table 3 shows that DQL outperforms other existing methods that are developed for WSN lifetime enhancement.

Table 3: Comparative analysis of state-of-the-art methods for % network lifetime enhancement

| **Number of Sensor Nodes** | **DQL Bazsed LEACH (Proposed)** | **Intelligent Clustering Under Uncertainty** | **TIOCHR** | **ELPSO-PSO-BPNN** | **DBN-RP** |
|---|---|---|---|---|---|
| 50 | 98.35 | 95.35 | 96.35 | 92 | 94 |
| 100 | 98 | 94.35 | 96.25 | 91.15 | 92 |
| 150 | 97.45 | 93.25 | 95.15 | 90 | 91.33 |
| 200 | 96.35 | 92 | 94 | 89.15 | 91 |

### *G. Discussion*

The comparative analysis with consideration of energy efficiency, throughput, E2E analysis and PDR shows DQL based method outperforms the base LEACH and ML based ML-EERP (SVM) protocols. When number of nodes in the network are increased, the communication distance in between nodes decreases. This improves the path selection mechanism when smart decision capability is provided. The selection may ignore in-between nodes while reducing the hop counts and also distance metrics with respect to location of the sensor and base stations. This selection mechanism is not adaptive when other existing methods are studied. The change in environmental factors especially size of the network in terms of area and number of nodes must be adaptable when designing the general purpose protocols. This ensures the protocols scalability and efficiency for selective applications where network life time is important factor of consideration along with faster communication speed. Also, when particular protocol is modified with additional processing steps such as selection of CHs, the processing delays gets added in the end to end communication. Thus latency analysis should also show that protocol is not hampering the communication speed. This achievement in proposed method shows its reliability for fast data delivery applications.

## 5. Conclusion

This study has explored the enhancement of the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol through the integration of DQL in WSNs. The primary objective was to improve energy efficiency and network performance by leveraging autonomous learning and adaptive decision-making capabilities offered by DQL. Through analysis, it became evident that integrating DQL with LEACH significantly enhances the network's ability to manage energy resources more intelligently. By allowing sensor nodes to autonomously adjust clustering and routing strategies based on real-time environmental and network conditions, DQL mitigates energy wastage and prolongs the operational lifespan of WSNs. This capability is crucial in dynamic and unpredictable environments where traditional protocols may fall short in maintaining efficiency. Moreover, comparative evaluations with traditional machine learning approaches, such as Support Vector Machines (SVM), highlighted the superiority of DQL in terms of energy efficiency and adaptability. The reinforcement learning framework of DQL enables continuous improvement and adaptation to changing network dynamics, thereby optimizing network performance over time. Looking forward, the deployment of DQL-modified LEACH protocols presents promising avenues for future research and practical implementations in various WSN applications. Challenges such as computational complexity and training convergence need further exploration to fully harness the potential of DQL in real-world scenarios. In essence, this study contributes to advancing the state-of-the-art in WSNs by demonstrating how integrating advanced machine learning techniques like DQL can lead to more sustainable, efficient, and resilient wireless sensor networks.

6. **Funding Statement:** No financing / There is no fund received for this article.

7. **Data Availability:** The customized dataset was generated with the use of simulated environment. Data will be made available upon request.

8. **Conflict of interest: The authors declare that there is no conflict of interest.**

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