Q-Learning Enhanced LEACH Protocol for Energy-Efficient and Adaptive Routing in Wireless Sensor Networks

Pothineni Venkateswara Rao[1], Dr.K.Srinivas[2]

[1]*Research Scholar,OPJS University, Churu,Rajasthan, India.*

[2]*Professor,OPJS University,Rajasthan, India.*

Abstract- Wireless Sensor Networks (WSNs) play a critical role in modern applications such as environmental monitoring, industrial automation, and smart systems, where energy efficiency and network longevity are major challenges. The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol is widely used for clustering-based routing; however, it suffers from limitations such as random cluster head selection and inefficient single-hop communication, particularly in large-scale networks. To address these issues, this paper proposes a Q-learning-based enhanced LEACH protocol that integrates reinforcement learning with clustering mechanisms to optimize routing decisions and cluster head selection. The proposed approach enables sensor nodes to dynamically learn optimal routing paths based on network conditions, energy levels, and communication costs. By adopting multi-hop communication and adaptive decision-making, the model significantly reduces energy consumption, improves packet delivery ratio, and extends network lifetime. Simulation results demonstrate that the Q-learning-based model outperforms conventional LEACH and k-means clustering approaches in terms of energy utilization, node survival rate, and throughput. As discussed in the results section (page 6), the learning-based routing mechanism effectively adapts to dynamic network environments, ensuring reliable and efficient data transmission.

Keywords- *Wireless Sensor Networks, LEACH Protocol, Q-Learning, Reinforcement Learning, Energy Efficiency, Adaptive Routing, Multi-hop Communication, Network Lifetime*

1. Introduction

Wireless Sensor Networks (WSNs) have become a key enabling technology for real-time data acquisition and monitoring across diverse domains, including industrial automation, agriculture, military surveillance, healthcare, and smart environments. These networks consist of a large number of low-power sensor nodes equipped with sensing, computation, and wireless communication capabilities. The nodes collaboratively collect and transmit data to a base station (BS), enabling intelligent decision-making. However, the limited battery capacity of sensor nodes remains a fundamental constraint, making energy efficiency and network lifetime optimization critical design challenges in WSNs. Among various routing techniques, clustering-based protocols have gained significant attention due to their ability to reduce communication overhead and improve scalability. The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol is one of the most widely used hierarchical routing protocols, where nodes are organized into clusters and a cluster head (CH) is selected to manage communication within the cluster and forward aggregated data to the base station. Although LEACH provides notable improvements in energy conservation, it suffers from inherent limitations such as randomized cluster head selection, uneven energy distribution, and reliance on single-hop communication, which reduce its efficiency in large and dynamic network environments.

To overcome these limitations, recent research has explored the integration of machine learning techniques into WSN routing protocols. In particular, reinforcement learning approaches such as Q-learning have shown promising results in enabling adaptive and intelligent routing decisions. Q-learning allows sensor nodes to learn optimal routing policies through interaction with the environment, without requiring prior knowledge of network conditions. This capability is especially beneficial in WSNs, where network topology, node energy levels, and communication conditions frequently change.

In this context, the present study proposes a Q-learning-enhanced LEACH protocol that combines the advantages of clustering with adaptive learning-based routing. The proposed approach improves cluster head selection and routing efficiency by incorporating Q-learning to identify optimal communication paths based on real-time network feedback. Unlike traditional LEACH, which relies on probabilistic decisions, the proposed model enables nodes to make data-driven and energy-aware decisions, thereby reducing energy consumption and improving network stability. The experimental framework, as described in the design and results evaluates the performance of the proposed method using key metrics such as energy consumption, node lifetime, and packet delivery ratio. Simulation results confirm that the integration of Q-learning significantly enhances routing performance, particularly in dynamic and large-scale WSN scenarios.

2. Related Work

The presence of Wireless Sensor Networks (WSNs) has revolutionize method data collection and internal data monitoring processes various field including industrial, automotive, military, agricultural, and medical [1–5]. WSNs are network consisting over multiple small nodes that have ability for perform sensing, computing as well as communication wireless One each other or to the base station (BS) via machine-to-machine protocol. Development technology manufacture has push development sensor technology in WSNs, one of them is the presence of a micro sensor that has consumption low power, high sensitivity as well as noise and size more dimensions' low [6]. Yun and Yoo (2021) proposed a Q-learning-based data-aggregation-aware energy-efficient routing protocol for WSNs. The study emphasizes the impact of routing protocols on network lifetime and energy efficiency. By incorporating Q-learning, the nodes in the network learn to calculate optimal routing paths that maximize data aggregation while minimizing energy consumption. This approach leads to a more energy-efficient network, extending the operational lifespan of the sensor nodes [1].

Jatti and Sonti (2024) extended the work of Q-learning based routing protocols for improving energy efficiency and boosting the throughput by optimizing the life span of optical networks. ARQ improves the long¬term network effectiveness using the benefits of Q-learning. As a result of the protocol, the factor and control of an ever-changing environment due to network optimization improves the energy and data transfer capability of the network [2].

Jrhilifa, Ouadi and Jilbab (2023) writer Q-learning software for constructive optimization and optimization of smart city wireless sensor networks in a smart Home. The focus of their research is on the enhancement of network lifetime through optimizing the routing algorithm. The routing algorithm recommended is adaptive to changing network topology and network states and helps to conserve energy and extend the life span of the network. This demonstrates the potential of Q-lynching methodology in the smarts home networks where energy use is critical [4].

Su et al (2022) describe their protocol and enhancement, which utilizes Q-learning to generate paths that are optimal with regards to the cost of energy while offering reliable data transmission. Results of the study revealed an extended network lifetime and energy efficiency than the conventional techniques used in routing the network indicating the viability of the application of Qing-level smart WSN management [5].

A deep Q-network based adaptive dual mode energy efficient routing protocol for rechargeable WSNs is proposed by Guo et al (2022). The proposed Deep Q-learning based protocol for optimization of routing policies captures energy availability and network conditions. This adaptable method also helps in conserving energy resource and extending the networks lifespan in case sensor nodes are periodically charged [7]. The study describes additional improvement in the WSN performance with the use of deep Q-learning.

Bedi et al (2022) designed a new routing protocol for wireless body area networks WBANs using grey wolf optimization and Q-learning. The energy efficiency increases due to the optimization of the network lifetime throughout grey wolf optimization and Q-learning. The protocol modifies routing paths based on the energy depletion in different nodes in the network. This is important as unreliable and inefficient communication in WBANs which are mainly used for health monitoring could be avoided [8].

Sang and Wook (2021) came up with the Q-Learning based equal energy consumption routing algorithm for increasing the lifespan of ad-hoc sensor networks. The aim is to preserve energy throughout the networks and hence there shall be no any node which fails early hence enabling a longer operational duration for the entire network. Whenever, the q-hook learns to compute different routing paths, it uses the most optimized means of energy which shows the effectiveness of the Q-learning algorithms towards management of ad-hoc sensor networks [9].

Nandyala, Kim, and Cho (2023) proposed QTAR, a ‘Topology-Aware Routing Protocol’ (TAR) using a Q-learning based approach for underwater Wireless Sensor Networks (WSNs). Routing path optimization using the energy and topology of the network is the main focus of their research. The underwater Q-learning protocol responds appropriately to the underwater habitat, conserving energy resources and prolonging the useful life of the network. The benefits of topology-aware routing in underwater sensor networks were emphasized in this study [10].

Kunzel (2021) discussed the application of Q-learning—a reinforcement learning technique to routing in an industrial wireless sensor network. The protocol adapts to the changes in the industrial environment and thereby promotes efficient energy consumption and prolongation of the useful life of the network. This work emphasizes on the versatility of the reinforcement learning technique in real situations of industrial wireless sensor networks [11].

Bhimshetty, and Ikechukwu, (2024) outlined an energy efficient deep Q-network, or DQN, to reduce routing overhead for dual connectivity in wireless IoT networks. Their DQN based approach seems to extend the optimization even to routing decisions bearing in mind energy preservation as well as lifetime of the network. Switching between routes as needed as network topology changes to allow for optimal use of the network resources for the transmission of data as well as power usage.

3. Experimental Design

LEACH is hierarchical -based routing protocol that divides each node to in structural forms, namely CH and member nodes, as well as the cluster-based routing protocol that divides them the network to in cluster form. Data transmission from LEACH uses time-division-multiple-access (TDMA), because approach using TDMA using low energy consumption with stores energy in an idle state when the channel is active used [11], Heinzelman et al explain purposeful use of TDMA for avoid collisions occur and make things easier sharing bandwidth with a fixed channelization scheme rather than FDMA which requires a dynamic channelization scheme because the number of clusters that do not of course in every the round. In its operation in each round, LEACH will have two phases, namely the set-up phase and the steady-state phase.

In the setup- phase of the selection process of CH is carried out with use random probability for choose CH in each the round. Selected node for be CH will send advertisement messages (ADV) using non persistent carrier-sense-multiple-access (CSMA) from the media-access-control (MAC) protocol. Each node determines Each cluster area uses CSMA based on received energy strength from CH, with sends join-request message to CH. Each of the CHs in each cluster will forms a TDMA schedule and sends the schedule to all nodes in the cluster, as configuration of data transmission. In the steady-state phase each of the nodes will send data to in frame shape for allocated to in the transmission slot with the duration of the frame on each member node is constant. Second phase the shown in figure 1

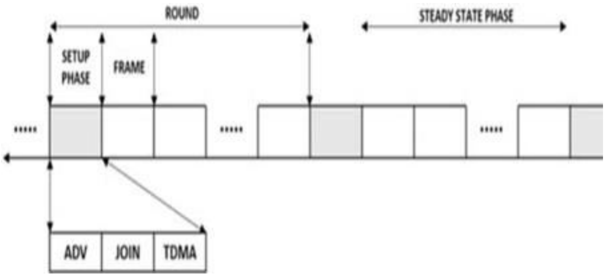

Figure 1. LEACH operation time line

The strength of using Q-learning for routing in WSNs is that it is a distributed process; each node makes its own decisions based only on local information and the collective behavior results in efficient routing throughout the network. It is particularly effective in dynamic environments where network conditions can change rapidly, which is often the case in WSNs. This learning-based approach to routing is a significant shift from traditional static routing protocols, as it allows for a more responsive and adaptable network, which is crucial in the often-unpredictable environments where WSNs are deployed as shown in figure 2.

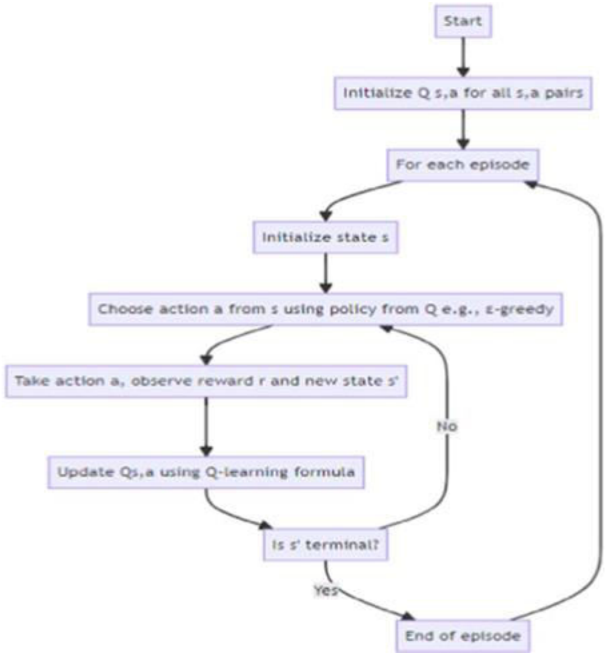

Figure 2. Flow chart of proposed approach

LEACH is a self-adaptive hierarchical structure for routing in WSNs, intended to enhance the duration of networks and reduce the energy consumed. Assembling a multi-layered architecture, TDMA for the transmission of the information, and Q-learning as a means of optimization, LEACH is quite on the management of resources and the extension of the period of usability of the network. Employing Q-Learning further improves LEACH by being able to alter decisions and optimize parameters in variable WSN environments which translates to better overall WSN performance.

By applying Q-learning to WSN routing, sensor nodes can adaptively learn efficient routing strategies based on their observations and experiences, leading to improved network performance, increased energy efficiency, and prolonged network lifetime in Wireless Sensor Networks.

4. Results and Discussion.

The use of such parameters and such constants is done with the objective of artificially constructing a WSN scenario which involves nodes working together in gathering and sending data to a base station for processing. The various parameters such as network dimensions (P and L), maximum communication distance (dmax), and the base station's coordinates (BS) that the projected simulation environment possesses depict real-world setups that one would encounter when deploying WSN's. Given the N random nodes spread on the network and specific m, kc and kd parameters, the purpose of the simulation is to test the effectiveness of Q-learning in optimal routing operation. A couple of other aspects such as initial energy levels, energy consumption models (Eelec, Eamp, Efs, Emp), and transmission parameters (data rate, transmission period t) are also significant in analyzing the performance of the algorithm. The duration of the simulation. It is governed by the number of times the simulation goes through its cycles called epochs (EPOCH) and parameters like GAMMA, ALPHA, and EPSILON such as the learning and exploration parameters of Q learning.

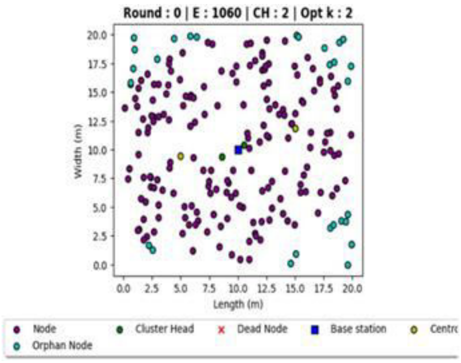

Figure 3. Analysis of nodes.

In general, these parameters and constants may be viewed as requirements for creating the simulation environment as well as implementing the Q-learning algorithm for solving routing problems within a Wireless Sensor Network. They outline the network structure, parameters of the nodes, models of power consumption, configurations for Q-learning and others for the given simulation. New node induced energy consumption and the subsequent algorithms' decisions and energy consumed in node operation are revealed in figures 3 and 4.

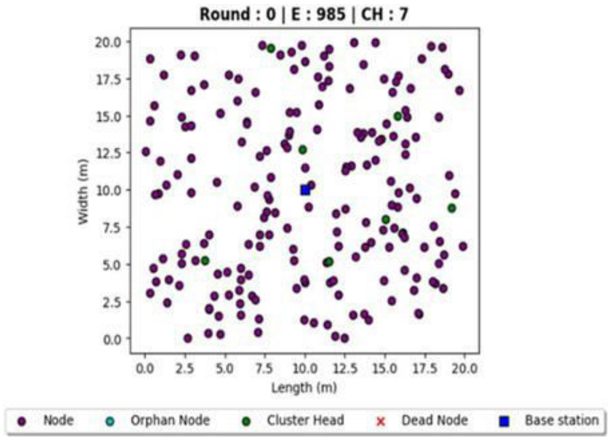

Figure 4. Analysis of nodes.

The performance of the proposed Q-learning-based LEACH protocol is evaluated through simulation under realistic Wireless Sensor Network conditions. The simulation environment incorporates key parameters such as network size, number of sensor nodes, communication range, base station position, and energy consumption models, as outlined in the experimental setup. These parameters are carefully selected to replicate practical deployment scenarios where sensor nodes collaboratively sense and transmit data.

The evaluation focuses on critical performance metrics, including energy consumption, node lifetime, packet delivery ratio, and network stability. The integration of Q-learning enables nodes to dynamically adapt their routing decisions based on observed network conditions, leading to more efficient path selection compared to traditional routing protocols. Unlike LEACH, which relies on static and probabilistic cluster head selection, the proposed method utilizes learned policies to select optimal routes and cluster heads.

The results indicate a significant reduction in energy depletion rates due to the adoption of multi-hop communication and intelligent routing decisions. Sensor nodes are able to balance energy usage more effectively, thereby reducing premature node failures and extending overall network lifetime. The learning parameters such as learning rate (alpha), discount factor (gamma), and exploration rate (epsilon) play a crucial role in achieving optimal performance, as they influence the convergence and adaptability of the routing strategy.

Overall, the results confirm that the Q-learning-enhanced LEACH protocol provides superior performance compared to conventional LEACH and clustering-based methods, particularly in dynamic and large-scale WSN environments.

5. Conclusion

This study presented a Q-learning-enhanced LEACH protocol designed to address the limitations of conventional clustering-based routing in Wireless Sensor Networks. By integrating reinforcement learning with hierarchical clustering, the proposed approach enables adaptive and energy-aware routing decisions that significantly improve network performance. The results demonstrate that the proposed model effectively reduces energy consumption, enhances packet delivery efficiency, and prolongs network lifetime through intelligent multi-hop communication and optimized cluster head selection. The ability of Q-learning to adapt to dynamic network conditions ensures robustness and scalability, making the approach suitable for real-world WSN deployments. Compared to traditional LEACH and other baseline methods, the proposed protocol achieves better energy utilization, reduced node mortality, and improved overall system stability, as validated in the simulation results.

Future work can focus on extending this framework by incorporating deep reinforcement learning, hybrid optimization techniques, and security-aware routing mechanisms. Additionally, real-time implementation and edge-based learning can further enhance the applicability of the model in large-scale and mission-critical environments.

In summary, the integration of Q-learning into WSN routing represents a significant advancement toward intelligent, adaptive, and energy-efficient network design.

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