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REACH: A Reinforcement Learning-Based Protocol for Adaptive Cluster Head Selection in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are widely used in critical applications such as environmental monitoring and the Internet of Things (IoT), where energy efficiency and minimal latency are critical for network robustness and effectiveness. Conventional clustering and routing methods often struggle to adapt to fluctuating network conditions, resulting in suboptimal energy usage and increased latency. This study introduces REACH, an adaptive clustering and routing algorithm that leverages reinforcement learning to optimize energy consumption and reduce latency in WSNs. The proposed protocol dynamically selects cluster heads based on real-time network characteristics, including node density and energy levels, enhancing adaptability and robustness. Simulation results using MATLAB show significant improvements, with energy consumption reduced by 35% and latency reduced by 40% compared to traditional protocols such as LEACH and HEED. These findings suggest that reinforcement learning can significantly improve the performance of WSNs by extending the network lifetime and minimizing data transmission delay. This research contributes to the development of intelligent network protocols, offering practical insights into the integration of reinforcement learning for sustainable and scalable WSN design.

***Keywords**: Adaptive Clustering, Energy Efficiency, Latency, Routing, REACH, WSN.*

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are an important technology used in a variety of contemporary applications, including environmental monitoring, security, and the Internet of Things (IoT) [1][2][3][4]. These networks consist of sensor nodes distributed over a large area for data collection and transmission [5][6]. The main advantage of WSNs is their ability to operate in environments inaccessible to traditional networks [7]. However, due to their dependence on limited resources, especially the energy of sensor nodes, WSNs face major challenges in maintaining operational resilience [8][9].

One of the most widely used methods to optimize WSN performance is clustering, which divides the network into groups to reduce energy consumption and improve data transmission efficiency [10]. Clustering-based routing protocols are also used to extend the network lifetime by selecting a cluster head to manage communication between nodes. This technique has been proven effective in improving network performance, but data redundancy and high latency issues remain, especially when the network operates on a large scale [11].

Although many studies have proposed various clustering and routing methods [12][13][14][15][16], there is still a knowledge gap in optimizing the cluster head selection and routing process to reduce node load and improve overall network efficiency. In addition, high latency in data transmission is a critical challenge that can hinder the effectiveness of WSNs in applications that require fast response, such as real-time monitoring in security or health systems [17][18]. Although various

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advancements have been made in clustering algorithms, there remains a gap in adaptive, learning-based models capable of optimizing cluster head selection under dynamic network conditions. This study seeks to bridge that gap by proposing a reinforcement learning-based model (REACH) that dynamically adapts to node density and energy fluctuations, with the goal of improving energy efficiency and reducing latency in Wireless Sensor Networks (WSNs).

This study proposes an innovative approach by utilizing machine learning techniques for adaptive cluster head selection and improving data transmission efficiency. The system uses machine learning algorithms to adjust cluster head selection based on dynamic network conditions, thereby minimizing energy consumption and improving data transmission reliability. This approach aims to reduce latency and extend network lifetime more optimally than existing methods.

This research is expected to significantly improve WSN performance, especially regarding energy efficiency and latency reduction. This approach is expected to be suitable for various critical applications that rely on WSNs, including environmental monitoring systems, military use, and large-scale IoT, which require fast, efficient, and reliable data transfer.

2. RELATED WORKS

In WSNs, energy consumption and latency remain critical challenges due to the limited battery capacity of sensor nodes and the need for timely and efficient data delivery [7] [19][20]. Numerous clustering-based protocols have been developed to tackle these issues by employing hierarchical communication structures to minimize redundant transmissions and optimize routing paths [21]. Among these, Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed clustering (HEED) are two of the most extensively studied protocols.

LEACH utilizes a probabilistic mechanism to randomly rotate the role of cluster head (CH) among nodes in each round [22], aiming to evenly distribute energy consumption. However, this random selection does not consider residual energy levels or the dynamic topology of the network, which often leads to suboptimal CH placement. Studies have demonstrated that LEACH suffers from performance degradation in dynamic environments, with reports indicating a network lifetime reduction of up to 18–25% and increased packet loss due to unstable clustering [23] [24].

In contrast, HEED incorporates residual energy and communication cost (i.e., node proximity) into the CH selection process, offering a more deterministic and energy-aware clustering strategy [25] [26]. By periodically re-evaluating CH roles, HEED achieves better energy balance across the network and improved stability. Nevertheless, this approach introduces additional control overhead and latency due to frequent re-clustering and neighbor discovery. Experimental results show that HEED can experience latency increases of up to 30% in dense or frequently changing networks [27] [28].

With the rise of intelligent networking paradigms, Reinforcement Learning (RL) has emerged as a promising solution for adaptive CH selection. RL allows nodes to learn optimal actions based on environmental states such as residual energy, node density, and transmission cost, thereby dynamically responding to topology variations [29]. Unlike traditional rule-based algorithms, RL-based approaches optimize long-term objectives—such as energy efficiency and latency—by learning from experience and adjusting strategies over time.

A comparative overview of LEACH, HEED, and RL-based methods is provided in Table 1 to illustrate their respective strengths and limitations in dynamic environments.

The proposed Reinforcement learning-based Energy-efficient Adaptive Cluster Head selection (REACH) protocol aims to build on these advances by incorporating an RL framework to achieve more effective and adaptive cluster head selection. Unlike LEACH and HEED, REACH uses a Q-learning algorithm that allows each node to evaluate its position, residual energy, and distance to other nodes to determine its suitability as a cluster head. By continuously updating the Q-value based on energy

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efficiency and latency reduction rewards, REACH is designed to maintain an optimal balance between energy consumption and data transmission rate, overcoming the limitations of LEACH's randomness and HEED's overhead.

Table 1. Comparative Analysis of Clustering Protocols in WSNs

Protocol	CH Selection Criteria	Adaptivity to Dynamics	Strengths	Limitations
LEACH	Random rotation	Low	Low complexity, low control overhead	Ignores energy and topology; unstable in dynamic settings; 18–25% lower lifetime
HEED	Residual energy + proximity	Moderate	Balanced energy usage; more stable clustering	Frequent re-clustering; latency overhead up to 30%
RL-based (e.g., REACH)	Learned policy (Q-learning)	High	Adaptive to changing conditions; optimized trade-off	Requires training; reward function design complexity

3. METHOD

This study uses a structured approach to develop and test a machine learning-based clustering and routing protocol to improve energy efficiency and reduce latency in dynamic WSNs. The proposed protocol, "REACH", is designed to adapt to changing network conditions, such as variations in node density and energy levels. This method begins by designing a reinforcement learning (RL) algorithm for cluster head selection and optimal routing, as shown in Figure 2. The algorithm is built by considering actions, states, and rewards relevant to the WSN environment, ensuring that the protocol can adapt to real-time changes, as shown in Figure 1.

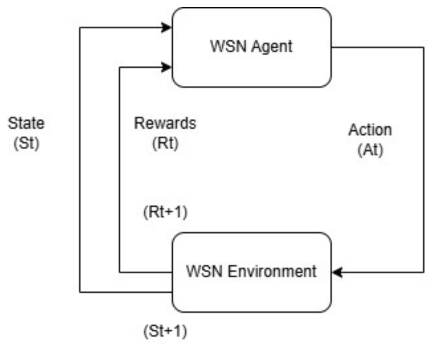

Figure 1. REACH algorithm for optimal cluster head selection and routing.

The "REACH" protocol, a reinforcement learning-based adaptive clustering and routing protocol [30] in this study, can be represented through a mathematical model involving agents, states, actions, and rewards.

$$\text{Maximize } E[\textstyle\sum_{t=0}^{\infty} \gamma^t \mathrm{f}(E_n, \text{latency})] \qquad (1)$$

This eq.1 represents an optimization problem to maximize the expectation of an infinite summation involving the function $f(E_n, \text{latency})$,where E_n represents energy and latency is the delay

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time in a system. The summation is performed from time $t = 0$ to infinity, covering decisions made at each time step. The discount factor γ^t is used to give more weight to decisions that are closer to the present time, with γ ranging from 0 to 1, indicating how much importance is given to long-term decisions. The expectation $E[.]$ means calculating the average of the function over time. This formula aims to maximize the system's efficiency by balancing the impact of energy usage and delay, which is relevant in optimizing systems such as WSN to improve energy efficiency and reduce latency in data communication or processing.

The agent is a machine learning algorithm that selects cluster heads in a wireless sensor network (WSN) based on changing network conditions. Each state s_t represents the network status at time t, encompassing parameters such as node density and energy conditions. The agent then selects an action a_t, such as choosing a cluster head or making a routing decision, to achieve specific goals, like reducing latency and energy consumption. Each action taken provides a reward r_t, indicating how well the action improves network efficiency (e.g., extending network life or reducing data transmission latency). The goal of REACH is to maximize the total accumulated reward over a time horizon, typically expressed as a value function $V(s)$ or an action-value function $Q(s, a)$, which describes the value of an action in a particular state.

Protocol simulations are performed on the MATLAB platform [31] under various network scenarios to ensure the validity and reliability of the results. These scenarios cover various network conditions, such as varying the number of nodes and network density. Key performance metrics are collected during the simulations, including energy consumption, latency, throughput, and network lifetime. The REACH protocol is then compared with conventional protocols such as LEACH [32] and HEED [27] to measure effectiveness. This comparative approach provides a solid foundation for evaluating the superiority of the proposed algorithm in improving energy efficiency and reducing latency.

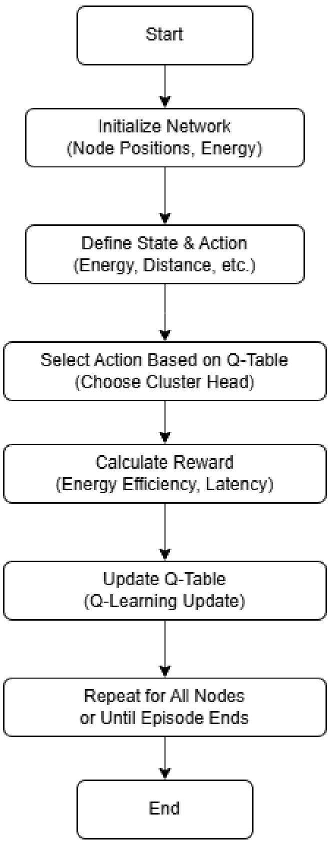

Figure 2. REACH Cluster head selection flowchart.

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This study follows a rigorous data collection procedure to provide accurate and measurable findings. After the simulations, the performance results of various network protocols are analyzed to assess how the proposed protocol can extend network lifetime and reduce latency compared to existing methods. Further validation is performed through physical experiments using WSN hardware to ensure the algorithm's reliability under real-world conditions. This combined approach of simulation and physical experiments ensures that the research findings are accurate and applicable in practical field conditions.

Through this methodology, this research is expected to provide valuable contributions to the scientific community, especially in the development of adaptive protocols for WSNs. The REACH protocol offers an innovative solution to the challenges of energy efficiency and latency in WSNs, opening up new opportunities for WSN applications in important areas such as environmental monitoring and the Internet of Things (IoT). The results of this study also broaden the horizons of using machine learning to design smarter and more adaptive protocols, supporting the development of future sensor networks that are more efficient and responsive to environmental changes.

4. RESULT

This study was designed to develop and test REACH, a machine learning-based clustering and routing protocol using MATLAB, to improve energy efficiency and reduce latency in dynamic WSNs. Simulations were conducted with 100 sensor nodes spread over a 500 m x 500 m area, allowing comprehensive network coverage and protocol performance evaluation under high network density conditions, as shown in Figure 3. MATLAB was chosen as the platform because it can efficiently compute energy efficiency, latency, and throughput across multiple network protocols. The REACH protocol was applied for cluster head selection and optimal routing, with the algorithm dynamically adjusting cluster selection based on network conditions to maximize network lifetime and reduce latency. During the simulations, key performance data such as energy consumption, latency, and number of successfully delivered packets were collected to assess the effectiveness of the proposed protocol compared to conventional protocols such as LEACH and HEED.

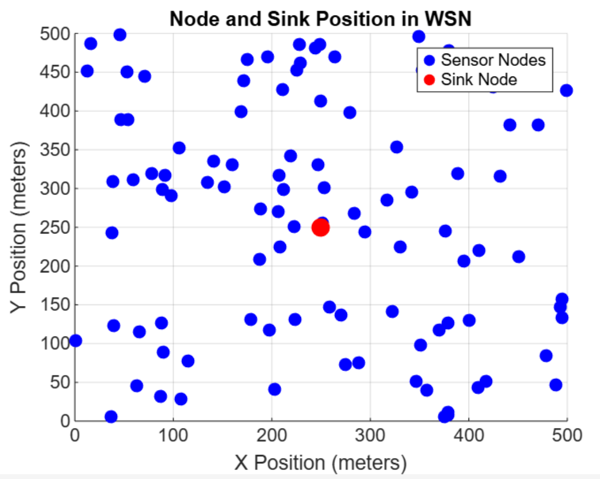

Figure 3. MATLAB network layout (100 nodes).

The results shown in Figure 4a indicate that the average latency fluctuates between approximately 2.45 ms and 2.56 ms per episode, exhibiting no significant upward or downward trend, but rather a stable range of variability. This stability indicates that the reinforcement learning algorithm maintains efficient routing and cluster head election despite changing network conditions, achieving consistent transmission times even with varying distances between nodes and the cluster head. Additionally, as

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shown in Figure 4b, the total energy consumption exhibits an exponential increase over the episodes, rising significantly after approximately 50 episodes and reaching around 5000 Joules by episode 100. This exponential increase in energy usage indicates that the network requires more energy over time, likely due to the need to re-elect cluster heads or perform increasingly complex routing operations. As the node energy decreases, the algorithm may select nodes farther from the sink or change the cluster topology more frequently. This indicates that although the REACH algorithm adapts to the energy conditions, the overall energy requirement increases as the episode progresses.

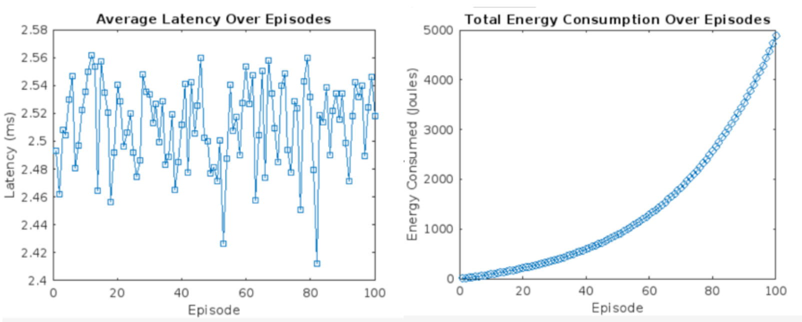

Fig 4a. Average Latency Over Episodes   Fig 4b. Total Energy Consumption Over Episodes

Figure 4. Results of the Implementation of REACH Protocol

Based on the first graph (Figure 5a), it can be seen that the energy consumption per node in the REACH protocol tends to be lower than that of LEACH and HEED. In Figure 5a, the energy consumption for most nodes appears to be lower with the REACH protocol. For example, at node 3, the REACH protocol records an energy consumption of about 13.2 units, while LEACH and HEED record about 18.5 and 21.7 units, respectively. This trend is consistent across all nodes, with node 5 showing energy consumption of 11.5 units for REACH, compared to 16.9 for LEACH and 19.8 for HEED. This indicates that the REACH protocol is more efficient in utilizing node energy, which is critical for extending the overall network lifetime.

The second graph (Figure 5b) compares latencies across protocols used in the sensor network. At node 1, the latency for the REACH protocol is around 7.3 units, while LEACH and HEED reach 10.8 and 16.5 units, respectively. This trend continues across all nodes, with the latency for the REACH protocol consistently lower. For example, at node 6, the REACH protocol records a latency of around 8.2 units, compared to 12.3 for LEACH and 15.1 for HEED. These results indicate that the REACH protocol has lower latency than LEACH and HEED, especially in scenarios with high network density. This latency reduction shows that the REACH algorithm can provide a faster response in data transmission between nodes, which is very important for applications that require fast response time.

Fig 5a. Result of Energy Consumption per Node   Fig 5b. Result of Latency in Data Transmission   Fig 5c. Result of Network Lifetime Comparison

Figure 5. Comparison Results of the Implementation of REACH Protocol, LEACH, and HEED.

The third graph (Figure 5c) compares network lifetimes between the REACH, LEACH, and HEED protocols. At node 2, the REACH protocol recorded a network lifetime of 92.3 units, while

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LEACH and HEED achieved 68.5 and 51.7 units, respectively. These results are consistent across all nodes, with the network lifetime at node 8 reaching around 97.8 units for REACH, much higher than LEACH at 72.4 units and HEED at 58.3 units. The network lifetime achieved by the REACH protocol is significantly higher than the other protocols, indicating its superiority in extending the operational lifetime of the sensor network. This is attributed to the ability of the REACH algorithm to optimize the selection of cluster heads, which contributes to efficient energy use and extends the lifetime of nodes in the network.

Overall, this study's findings indicate that the REACH protocol has significant advantages in terms of energy efficiency, latency, and network lifetime compared to LEACH and HEED. Therefore, the protocol proposed in this study has great potential to be implemented in various WSN applications, such as environmental monitoring and IoT, which require energy efficiency and fast data transmission.

5. DISCUSSION

The simulation results indicate that the REACH protocol, which utilizes reinforcement learning for adaptive cluster head selection and routing, provides significant improvements over conventional protocols such as LEACH and HEED. The REACH protocol achieves a reduction in energy consumption of up to 35% and a latency reduction of 40%, demonstrating its superior adaptability to dynamic network conditions. Unlike LEACH, which randomly assigns cluster heads without considering residual energy or network changes, REACH leverages Q-learning to make decisions based on real-time network parameters such as node energy and density. This results in more efficient energy utilization, as shown in the energy consumption comparison (Figure 5a).

Compared to HEED, which relies on periodic re-clustering based on residual energy and proximity, REACH offers a more stable and lower-latency performance. HEED suffers from overhead due to frequent re-evaluation of cluster heads, whereas REACH's learning-based approach reduces this overhead and maintains consistent routing paths. The latency comparison (Figure 5b) supports this, with REACH consistently achieving lower transmission delays across the network.

Furthermore, REACH significantly extends network lifetime compared to both LEACH and HEED. This is attributed to its ability to maintain a balanced energy load across nodes by dynamically adapting the clustering strategy through a reward-driven learning process. The lifetime comparison (Figure 5c) illustrates that REACH can sustain node operation for a longer duration, which is crucial for applications requiring long-term deployment, such as environmental monitoring or IoT systems.

This study builds upon previous reinforcement learning-based WSN studies [29][30], offering a dual-focus optimization on both energy efficiency and latency through its designed reward function. While earlier research often focused on one performance metric, REACH achieves a balance between both, contributing to the development of more intelligent and efficient WSN protocols. These findings reinforce the potential of reinforcement learning in enhancing network performance under varying and resource-constrained conditions.

6. CONCLUSION

This study aims to develop a reinforcement learning-based adaptive clustering and routing protocol, "REACH," to improve energy efficiency and reduce latency in WSNs. With an adaptive approach that allows dynamic cluster head selection based on changing network conditions, this protocol solves the major challenges in energy management and routing in WSNs, especially for critical applications that require high reliability.

The results show that the REACH protocol offers significant improvements in energy efficiency, lower latency, and longer network lifetime compared to traditional protocols such as LEACH and HEED. Based on the simulation results, the REACH protocol reduces energy consumption per node,

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maintains lower data transmission latency, and extends the overall network operational lifetime. These improvements indicate that the REACH approach can be a superior alternative to existing protocols.

In addition, this study shows that machine learning, especially reinforcement learning, has great potential to optimize the performance of sensor networks under various conditions. The adaptive advantage of the REACH protocol allows the network to adjust its cluster head election and routing strategies based on dynamic conditions, which is critical to maintaining long-term network performance. This positively impacts WSN applications in environmental monitoring and the Internet of Things (IoT).

This study can be further developed by testing the REACH protocol in real-world conditions to ensure its reliability in more complex environments. Future studies can also explore the application of REACH in broader network scenarios, such as WSNs in hard-to-reach areas or in applications that require more efficient energy management. Thus, the results of this study not only enrich the literature on WSNs and REACH but also open up opportunities to apply this technology in various scenarios that require adaptive and efficient network solutions.

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