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Smart Data Routing System using Deep Reinforcement Learning For IOT-Enabled WSN

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Abstract: In this work, we propose DRLEER (Dynamic Reinforcement Learning-Based Energy-Efficient Routing), a novel routing protocol designed to maximize energy efficiency and prolong the operational lifespan of Internet of Things (IoT) networks. DRLEER aims to minimize energy consumption while optimizing data delivery by employing a dynamic Reinforcement Learning approach to routing decisions. The protocol comprises three key phases: network design and Cluster Head (CH) selection, clustering, and energy-aware data transmission.

During the first phase, DRLEER calculates Q-values for CH selection by considering both hop count and initial energy, allowing the network to identify the most appropriate CHs for efficient communication. Subsequently, in the clustering phase, CHs broadcast invitation messages to nearby nodes, while nodes farther from the base station associate with the closest clusters. This process results in an optimally organized network structure.

The final phase utilizes Reinforcement Learning to enable energy-conscious routing decisions based on residual energy and network conditions. An energy threshold is defined to control CH replacement and maintain the stability of the network. Simulation results show that DRLEER significantly outperforms existing protocols, extending network lifespan to 5866 rounds, reducing average end-to-end delay to 55ms, and conserving energy with an average consumption of 2.75 per round. Furthermore, DRLEER successfully delivers 14.2 × 10^5 packets, demonstrating its ability to efficiently handle data delivery under energy constraints.

Overall, DRLEER provides a scalable, adaptable, and energy-aware solution for IoT routing, extending network service life and conserving resources through a low-power Reinforcement Learning framework

Keywords: IOT, WSN , Deepa Reinforcement Learning , Energy Efficiency

I. INTRODUCTION

"IoT" has ushered in a transformative era by connecting physical objects and individuals to the vast landscape of the internet, enabling seamless communication and interaction among them. This technological paradigm shift holds tremendous promise for enhancing the quality of life. However, IoT devices, by their very nature, face substantial constraints, primarily in relation to limited power and memory resources. In light of these constraints, energy efficiency has emerged as a critical factor that underpins the sustainable operation and longevity of IoT networks.

Within the intricate fabric of IoT networks, the routing operation plays a pivotal role. It determines how data traverses the network, making it a central element in optimizing network performance and efficiency. Therefore, devising energy-efficient routing protocols has become an imperative in the IoT ecosystem.

To address this challenge, this research introduces a groundbreaking approach centered on deep reinforcement learning (RL) as a means to enhance data routing within IoT networks. Deep RL leverages the principles of machine learning, allowing IoT devices to make intelligent routing decisions and adapt dynamically to changing network conditions. These conditions encompass factors like device mobility and energy levels, both of which significantly impact routing decisions.

The core innovation presented in this study is the Deep Reinforcement Learning Energy-Efficient Routing (DRLEER) protocol. DRLEER is designed to achieve multiple objectives simultaneously, including the optimization of network lifetime, efficient energy consumption, and scalability within IoT networks. One notable feature of DRLEER is its consideration of parameters such are the number of hops and energy left. Which collectively contribute to reducing end-to-end latency in data routing. The efficacy of DRLEER is underscored by simulation results, which consistently demonstrate its superiority over existing energy-efficient routing protocols.

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DRLEER's ability to strike a balance between energy usage and network lifespan positions it as a significant advancement in the IoT networking domain. In a broader context, this investigation represents a significant contribution to the continuing efforts aimed at strengthening the efficiency together with the longevity of IoT networks. IoT technology has far-reaching applications, spanning smart cities, healthcare, environmental monitoring, and more. Energy-efficient routing protocols, exemplified by DRLEER, play an essential part in ensuring the seamless functioning of IoT networks, especially in resource-constrained environments. This, in turn, extends the potential and impact of IoT technology across diverse domains, fostering a more connected and intelligent world.

II. PROPOSED MODEL

This section presents the DRLEER protocol, which is a routing system designed for IoT wireless networks with a focus on energy efficiency, utilizing reinforcement learning (RL). Additionally, the energy consumption model is outlined. To facilitate better understanding, we provide definitions, terminology, and assumptions. DRLEER empowers devices to acquire the ability to make more optimal routing decisions, aiming to maximize the selection of the next-hop and conserve energy. This is achieved by sharing local information with neighboring devices. Each nearby device that can potentially intercept a packet extracts the data from the packet header, and the sender includes local information in this header. Subsequently, the sender updates its routing table with this information. The regional data conveyed comprises the identification number of the gadget, remaining energy, positional coordinates, and hop total.

DRLEER follows a structured three-step approach similar to additional routing techniques based on clusters: setup of a network and the election of cluster heads, cluster establishment, and the transfer of data.

2.1 Three-Step Operational Structure:

DRLEER adheres to a structured three-step approach, which is a common framework seen in cluster-based routing protocols:

Configuring the Network and Electing the Cluster Head: In this initial phase, the network is organized into clusters, together with cluster heads are elected. Heads of clusters play a pivotal role in managing and optimizing data routing within their respective clusters.
Cluster Construction: Once the clusters are established, DRLEER ensures efficient intra-cluster communication and data aggregation. Cluster heads take responsibility for routing decisions within their clusters based on the local information collected.
Data Transfer: With the clusters in place, data transfer within the IoT network becomes streamlined. DRLEER's routing decisions, refined through RL and local information, guide the efficient delivery of data packets to their intended destinations.

Assumptions for Network Model:

In our network model, several fundamental assumptions lay the foundation for its operation:

i) Static Nodes with Unique IDs: Following deployment, both sensor nodes and base stations remain stationary, each identifiable by a distinct ID.
ii) Lack of GPS Capability: Nodes do not possess GPS-capable antennas, meaning they lack awareness of their physical locations.
iii) Energy Heterogeneity: While all nodes possess comparable processing and communication capabilities, variations in energy levels exist due to heterogeneity.
iv) Limited Battery Life: Once deployed, nodes remain unattended and cannot recharge their batteries.
v) Centralized Base Station: The network features a single primary base station with a continuous energy source, devoid of vitality, recall, and processing constraints.
vi) Data Aggregation Capability: Each node has the capacity to aggregate data, enabling the compression of multiple data packets into a single packet.
vii) Separation Calculation: Node-to-node distances can be determined based on the intensity of received signals.
viii) Adjustable Transmission Power: Nodes can adapt their transmission power based on the proximity of obtaining nodes as well as node failures are only taking into account when vitality levels deplete significantly.
ix) Symmetrical Data Transfer: Data transfer involving nodes A and B consumes identical amount of energy as transfer in the opposite direction, indicating symmetrical radio connections.
x) Uniform Random Node Distribution: Nodes are dispersed evenly and at random in an area measuring 100 by 100 square units.
xi) Nodes "Death" at Zero Energy: Nodes with depleted battery levels are designated as "dead nodes."

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2.2 Cluster-Based Communication Paradigm

The diagram in Figure 1 illustrates the paradigm for cluster-based single-hop communication in an IoT network with support from Wireless Sensor Networks (WSN). This research endeavors to develop an efficient path routing system for an IoT network aided by WSN, employing a deep neural network approach to machine learning.

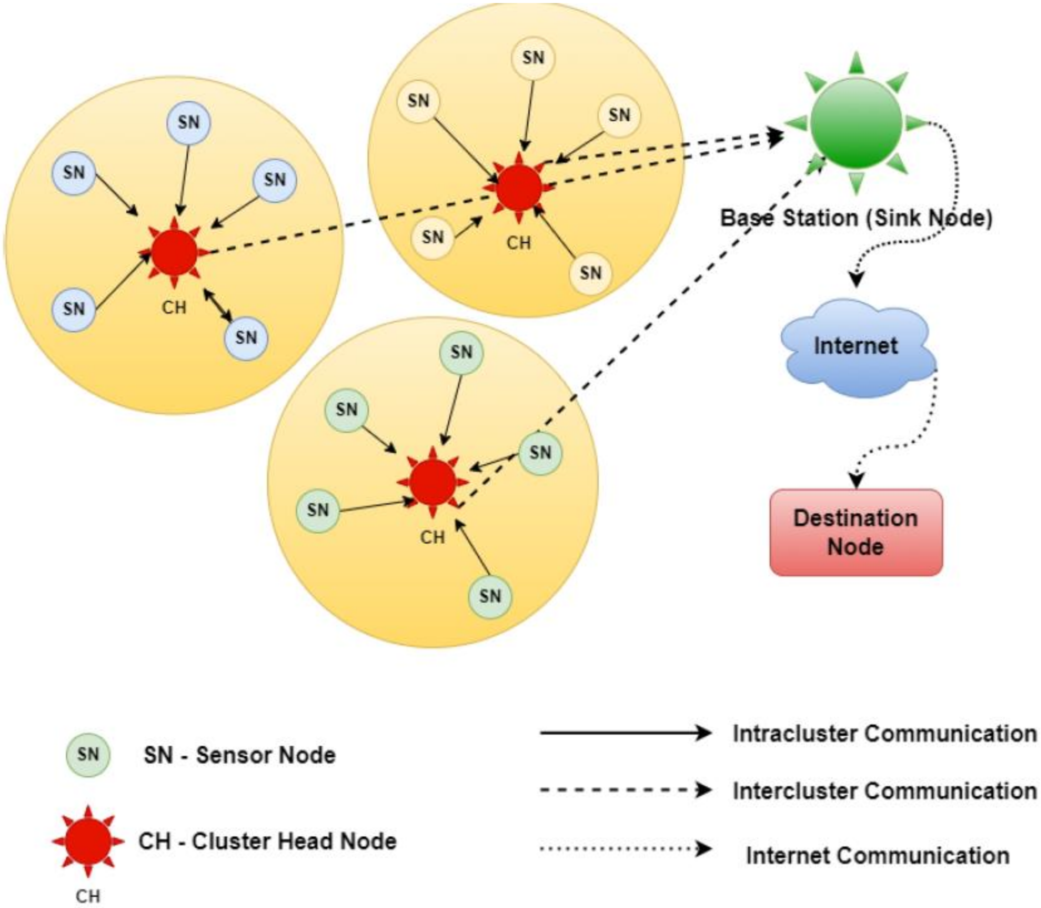

Figure 1 WSN-assisted IoT cluster-based single-hop communication.

2.3 Importance of Clustering

Before initiating the method of routing, it’s imperative to cluster the sensors into groups among nodes. This assembling strategy holds significant importance for achieving energy-efficient transmission, ultimately enhancing network resilience and minimizing energy consumption. In this investigation, we utilize a Reinforcement Learning (RL) strategy for perform clustering, recognizing its pivotal role in optimizing network performance and energy efficiency.

2.4 Formation of Clusters and CH Picking:

In this procedure, the responsibility of clustering is centralized and assigned either the sink node or the Base Station (BS). The BS, equipped with a comprehensive overview of the network's geographical layout, categorizes each individual Sensor Node (SN) into specific clusters based on their precise locations within the network's spatial domain. Once the SNs are organized into these clusters, an optimization process comes into play, tasked with the critical role of selecting the Cluster Heads (CHs).

However, it's important to acknowledge that hierarchical clustering Regarding Wireless Sensor Networks (WSN) often introduces complex challenges. These challenges manifest in the form of potential data aggregation overload and an excess of data reception from member SNs. Such situations can lead to a surge in energy consumption, which, in turn, could jeopardize the network's longevity.

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2.5 The Significance of CH Selection:

To further expand the operational lifespan of the system, the meticulous and judicious selection of CHs becomes paramount. The choice of CHs performs a pivotal function in Determining the overall energy-saving measures and longevity of network. Therefore, it is crucial to exercise precision and deliberation in this process.

III. PROPOSED REINFORCEMENT LEARNING FOR CLUSTER'S GENERATION

The utilization of Reinforcement Learning (RL) for the purpose of cluster generation is a central aspect of this study. RL operates as a learning mechanism that assigns positive values as rewards to desirable actions. Key components of the RL process include the 'environment model, agent, action, state, reward, policy, and value function'. RL adopts Decision-making using Markov Chain (MDP) framework to execute its approach, incorporating temporal difference techniques and a greedy selection strategy during the selection and mathematical modeling phases. Considering the circumstances of this research, an RL algorithm is engaged in to facilitate the clustering of "Sensor Node's" (SNs). In the Wireless Sensor's Network (WSN), the nodes serve as the learning agents for the RL-based clustering method. These learning agents meticulously analyze the energy levels of neighboring nodes, adhering to specific regulations in order to form clusters. Prior to the creation of clusters, each node's MDP is assessed, encompassing critical elements such as state, action, policy, and reward.

The learning agents employ the temporal difference approach to determine the action policy within the network environment. This approach leverages Q-values to determine the optimal action to be taken according to the most recent route cost information. The incentive-related parameter serves as a representation of the price of connecting to the next-hop node from the present node. The fundamental principle underpinning MDP involves the elements: S stands for set of states, T for transition function, A for actions, and R for reward function.

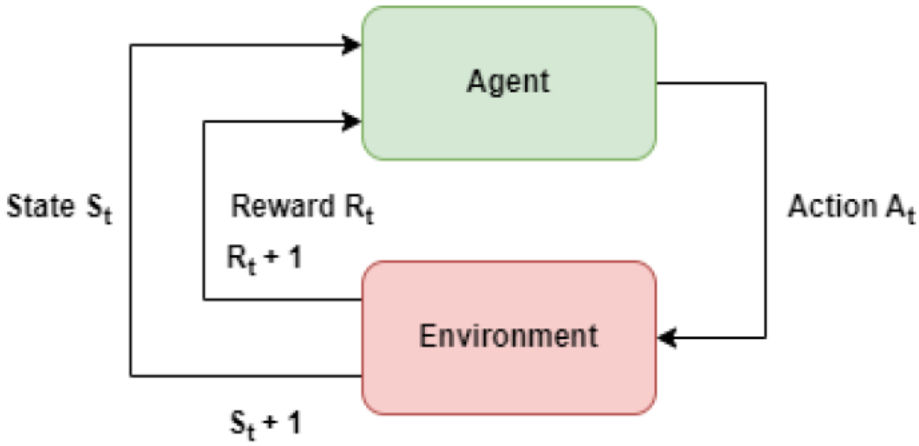

Figure 2 Reinforcement learning for the proposed approach

In Figure 2, the RL model for the proposed approach is depicted. Each Sensor Node (SN) integrates RL principles for clustering, with a primary focus on initially assessing route costs and conveying this knowledge to the Cluster Head (CH) according to the most up-to-date Q-value. The incentive-related parameter plays a pivotal role in illustrating the expense of the connection associated with the current node and its next-hop counterpart.

The learning agent's choice-making process involves the selection of all states 'S' displaying action 'A.' Using these selected actions, it calculates the amount of energy used Associated with Every group. Subsequently, a judicious choice is produced by assessing the prize 'R' value that was discovered using the predicted energy usage. 'S' to 'Si+1' (status) and 'A' to 'Ai+1' (activity) signs reflect the incremental progression of the situation as it is now and the action. The acquiring agent's ultimate goal aims to establish the best policy 'Q' through the accumulation of learning experiences, which in turn enhances the parameter for rewards. This ideal course of action 'Q' is subsequently engaged for the selection of the finest Cluster Head (CH). The connection between the state transition 'T' and reward 'R' in the MDP occurs in the moment, with the primary objective of the learning agent being the development of an effective policy, denoted as 'π.'

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Reinforcement Learning for Cluster Generation

The utilization of Reinforcement Learning (RL) for cluster generation is a central aspect of this study. RL operates as a learning mechanism that assigns positive values as rewards to desirable actions. Key components of the RL process include the environment model, agent, action, state, reward, policy, and value function. RL employs a Markov Decision Process (MDP) framework to execute its approach, incorporating temporal difference techniques and a greedy selection strategy during the selection and modeling phases.

IV. EXPERIEMENTAL SETUP

Within this segment, we delve into the DRLEER algorithm's suggested performance evaluation, focusing on key metrics say, throughput, and network lifespan and energy usage. The proposed algorithms leverage Reinforcement Learning (RL) techniques to maximize the selection of Cluster Heads (CH), with the overarching purpose of boosting network lifetime while lowering energy use.

Table 1 Simulation Parameters for DRLEER protocol

Parameter	Value
Field Dimensions	100 by 100
Number of Deployed Nodes	100–200
Cluster Head Selection Probability	< 0.1
Data Rate	256 kbps
Length of Packet (k)	< 4000 bits
Energy of Data Aggregation (EDA)	5 nJ
Transmission Energy (ETx)	50 nJ
Reception Energy (ERx)	50 nJ
Initial Energy per Node	0.5 Joules
Simulation Tool	MATLAB 2021ra
Maximum Number of Simulation Rounds	7000
Path Loss	0.13 pJ

The primary objectives of this article revolve around enhancing energy conservation and extending the operational the network's lifetime. Different approaches of defining a network lifespan appeared in the literature. In this study, we define network lifespan as the duration during which data transmission remains feasible and uninterrupted. To gauge the performance of the proposed protocol in achieving these goals, we conducted a comparative analysis against other clustering protocols, namely GEEC, DEEC, and E-DEEC, focusing on energy efficiency and network longevity.

To facilitate this comparison, we employed the following metrics:

i) Number of Active Devices per Round: This metric serves a dual purpose, not only evaluating the energy efficiency of the protocol but also providing insights into the network's longevity. It quantifies the count of devices actively participating in each communication round.
ii) Energy Consumption per Round: This metric quantifies the amount of energy expended during each communication round, offering a precise measure of the protocol's energy efficiency.
iii) Total Throughput: Total throughput is a critical performance indicator that quantifies the overall data transfer capacity of the network, shedding light on the protocol's ability to efficiently handle data traffic.
iv) End-to-End Delay: The length of time it takes for data to go from source to destination across a network is measured by end to end latency, offering insights into the protocol's effectiveness in minimizing communication delays and ensuring timely data delivery.
By systematically assessing these metrics, we can comprehensively evaluate and compare the proposed protocol's energy efficiency and its contribution to extending the network's operational lifespan when contrasted with other clustering protocols.

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V. RESULTS ANALYSIS

Within this segment, we delve into the DRLEER algorithm's suggested performance evaluation, focusing on key metrics say, throughput, and network lifespan and energy usage. The proposed algorithms leverage Reinforcement Learning (RL) techniques to maximize the selection of Cluster Heads (CH), with the overarching purpose of boosting network lifetime while lowering energy use.

Throughout the simulation procedure, we take into a network comprising a variable number of nodes (N=100, 200) distributed across an area measuring (A=100 x 100) square meters. To initiate the simulation, we meticulously account for various network node parameters, including energy consumption, transmission delay, collision rate, and the coordination of each node. Figure 3.4 provides a visual representation of the cluster formation within the network. For a comprehensive understanding of the simulation setup, Table 3.1 offers a detailed breakdown of specific simulation settings. This section will present the findings and insights obtained from the simulation experiments, shedding light on the performance gains accomplished by the DRLEER algorithm As for throughput, ‘energy efficiency’, and the extended operational lifespan of the network.

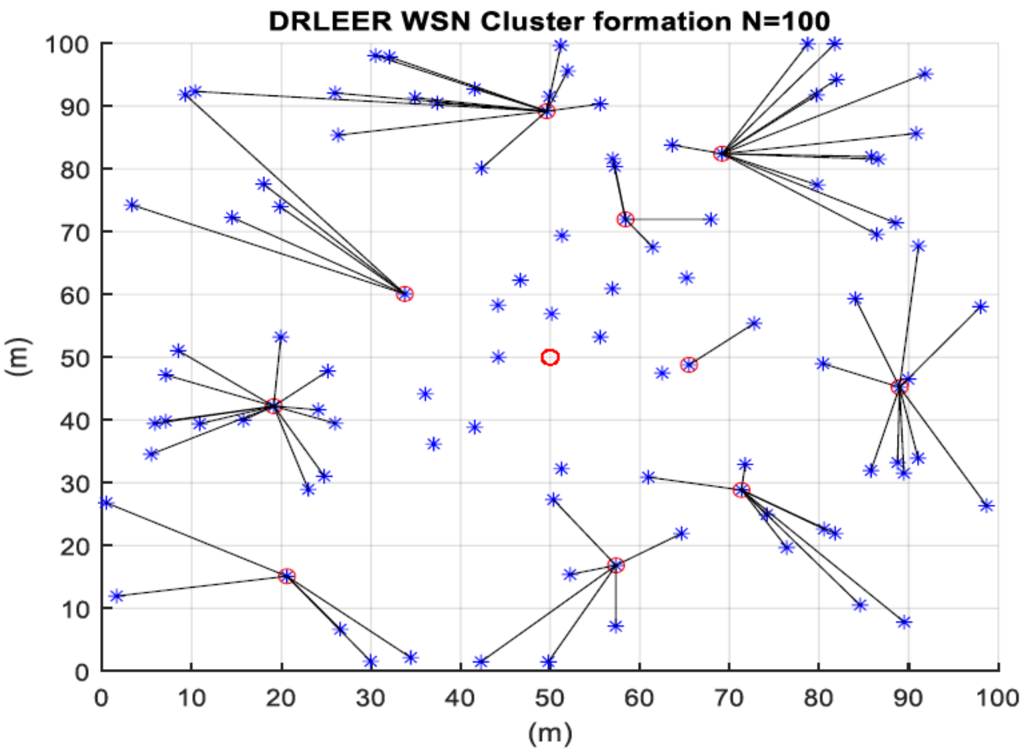

Figure 3 (a) WSN Cluster formation for N=100

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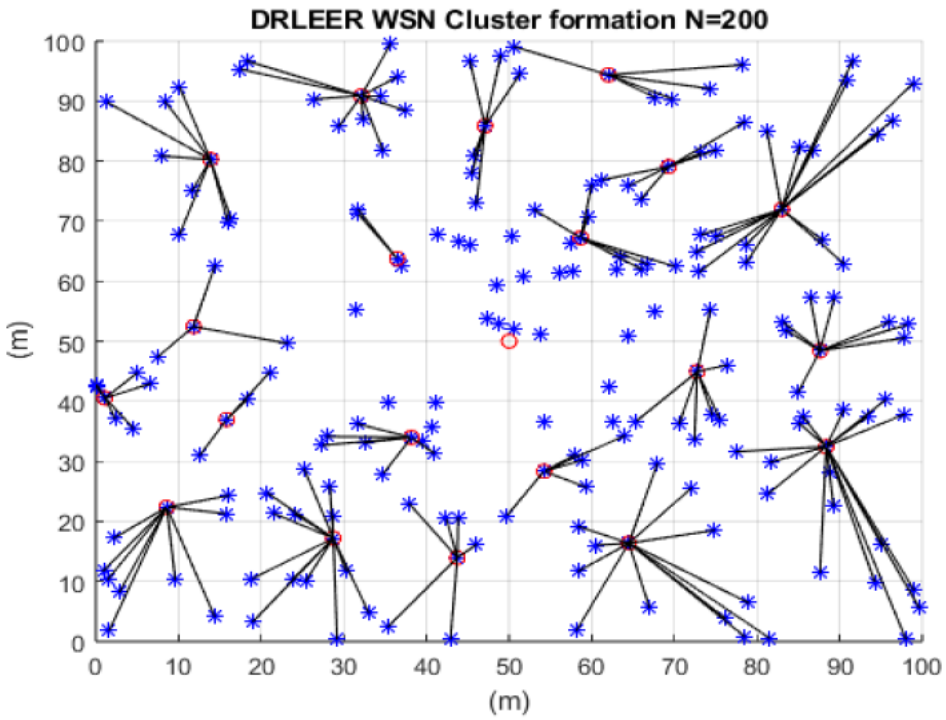

Figure 3 (b) WSN Cluster formation for N=200

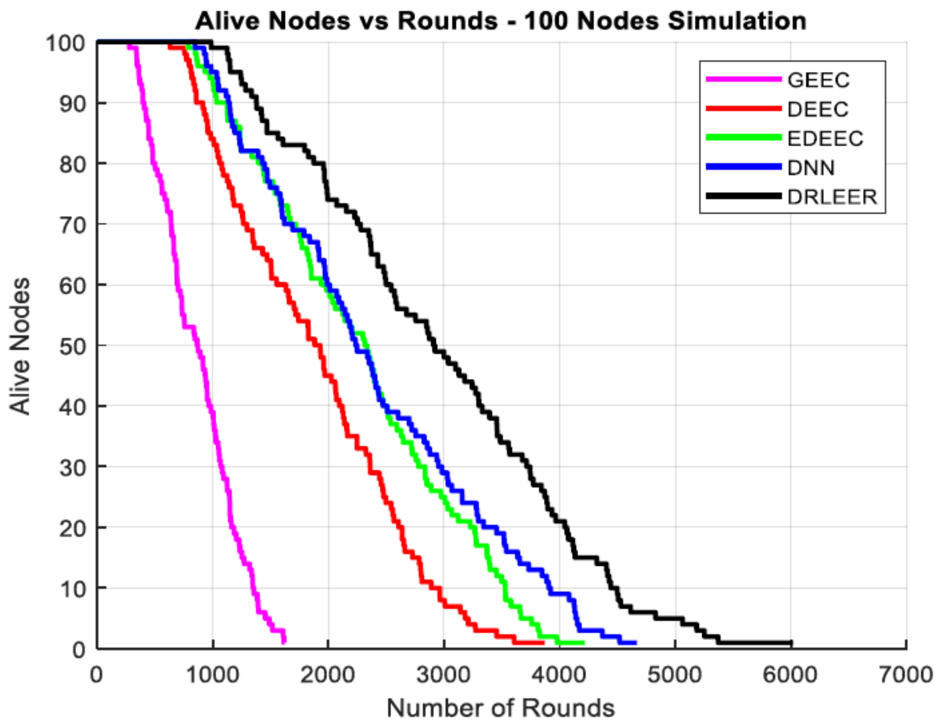

Figure 4 (a), the quantity of active sensor nodes compared to the total rounds (N = 100)

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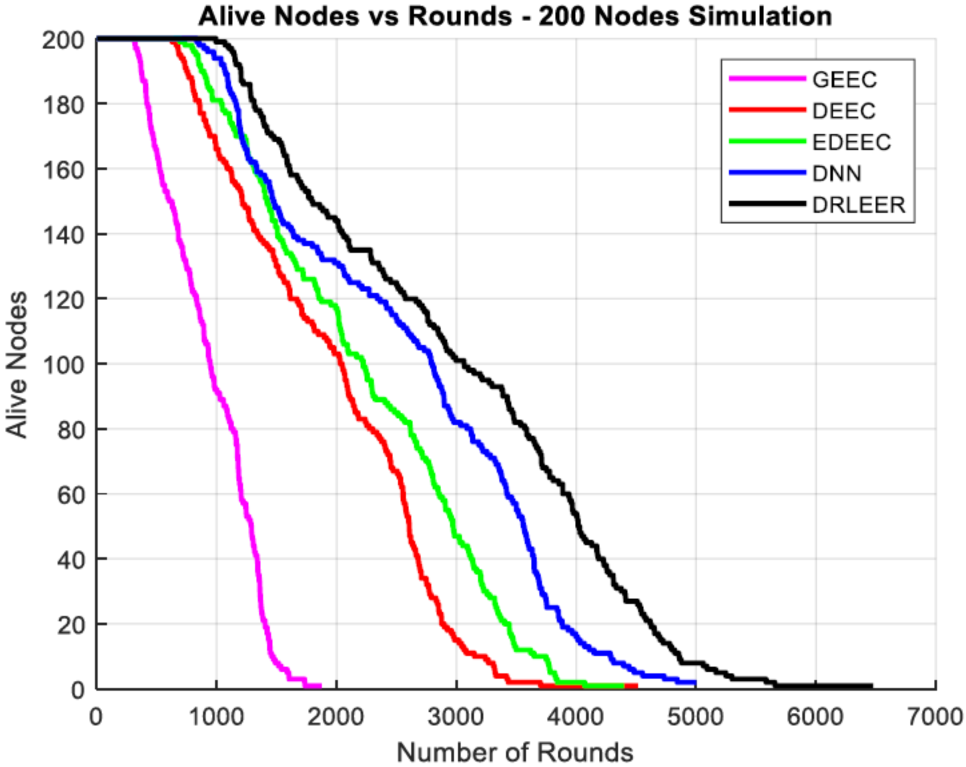

Figure 4 (b), Count of active sensor nodes vs total rounds (N=200)

In Figure 4(a) illustrates the results of network lifespan tests conducted with a network containing 100 sensor devices (N=100). The graph provides a visual representation of how the proposed DRLEER algorithm compares to existing clustering protocols, including GEEC, DEEC, E-DEEC, and DNN, in terms of extending network longevity. The y-axis likely represents the network lifespan or a related metric, while the x-axis may denote different simulation scenarios or time periods. In Figure 4(b), a similar network lifespan test is conducted, but this time with a network comprising 200 sensor devices (N=200). The graph showcases the performance of the DRLEER algorithm alongside the same set of clustering protocols as in Figure 3.5(a). The comparison highlights the algorithm's effectiveness in extending network lifespan in a larger network scenario. Our results show that the suggested approach performs better than the current ones. Particularly when it comes to extending network lifetimes.

In our quest to maximize network longevity, we considered two crucial factors: residual energy and hop count. This dual consideration is vital because excessive distances require a substantial amount of energy for data transmission. By taking into account both hop count and leftover energy, we sought to strike a balance that optimizes network lifespan, ensuring that data transmission remains feasible over extended periods. Figure 3.6(a) illustrates association between the quantity of dead sensor nodes along with the quantity of communication rounds in a network scenario where there are 100 sensor nodes (N=100). This graph provides insights into how the number of sensor nodes that have depleted their energy and become inactive (referred to as "dead" nodes) changes over a series of communication rounds. This figure 5 helps in understanding the network's energy depletion dynamics and its impact on node longevity.

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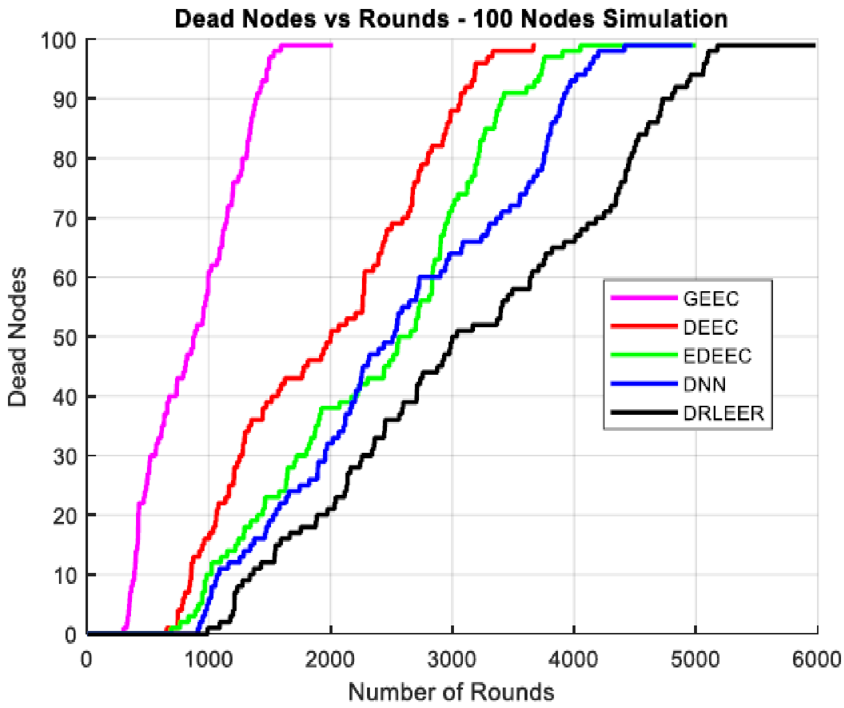

Figure 5 (a) Ratio of dead sensor nodes to rounds (N=100)

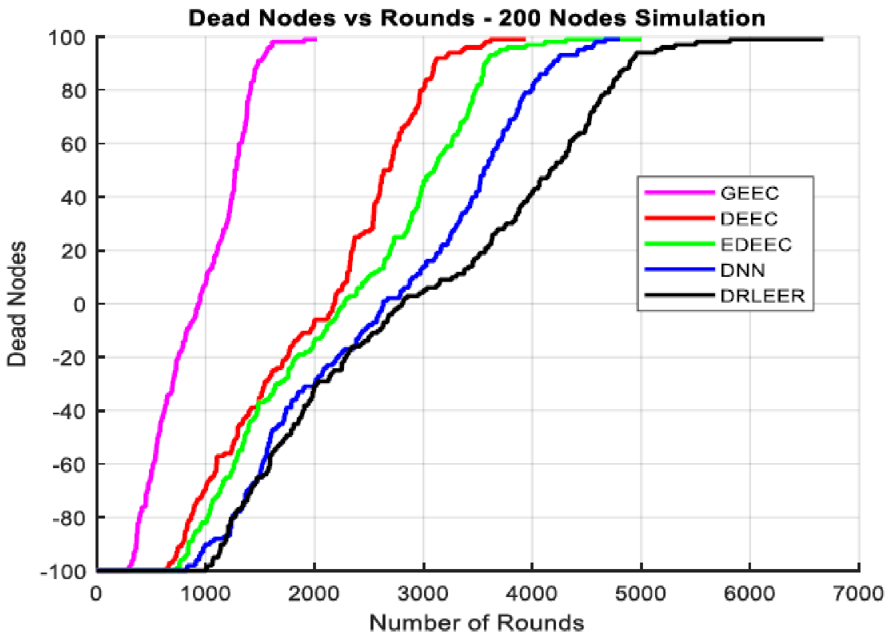

Figure 5 (b) Ratio of dead sensor nodes to rounds (N=200)

Figure 5 (b) provides a comparison evaluation of the quantity of dead sensor nodes in comparison to the quantity of communication rounds for two distinct network scenarios: one with 100 sensor nodes (N=100) and another with 200 sensor nodes (N=200). This graph provides valuable insights into the energy consumption and node longevity dynamics in networks of different scales. By comparing these two scenarios, the figure offers a perspective on how network size influences the exhaustion of energy supplies & resulting quantity of inactive sensor nodes over time.

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The assessment of Data packet transfer protocols average total latency is a fundamental aspect of network performance, typically quantified using a metric known as Network Delay. End-to-end delay characterizes the usual duration amid the original transmission of a packet from its source and its accomplishments reception at the intended place of arrival. When measuring this postponement, factors such as queuing and packet propagation delays are carefully taken into consideration.

The efficiency of the RL algorithm's clustering approach has led to a highly productive outcome for 'data's transfer', as indicated by the improved throughput. Furthermore, the suggested protocol demonstrates the ability to complete packet transfers at a higher rate without incurring data transmission losses, further underscoring its efficiency and efficacy in ensuring reliable and prompt data transmission.

Table 2 Comparative Performance Metrics of WSN Protocols

Protocols	Network Life time	Average "End – to - End delay"	"Average - Energy Consumption - Per Round"	Cumulative "Packets Delivery"
GEEC	1560	81ms	37.5	4.99*10^5
DEEC	3865	105ms	12	6.95*10^5
EDEEC	4330	80ms	5.5	10.97*10^5
DNN	4750	85ms	4.25	12.3*10^5
DRLEER Proposed	5866	55ms	2.75	14.2*10^5

The table 2 titled "Comparative Performance Metrics of WSN Protocols" offers a detailed evaluation of five different Wireless Sensor Network (WSN) protocols—GEEC, DEEC, EDEEC, DNN, and the proposed DRLEER—across several key performance metrics. These metrics include network lifetime, average energy usage per round and end-to-end delay, and cumulative packet delivery.

The data reveals that the proposed DRLEER protocol significantly beats the other protocols in performance, achieving the longest network lifetime of 5866 rounds, the lowest average energy consumption of 2.75 millijoules per round, and the shortest average end-to-end delay of 55 milliseconds. Additionally, DRLEER also excels in cumulative packet delivery, successfully transmitting 1.42 million packets, which is the highest among the protocols compared.

In contrast, the GEEC protocol exhibits the shortest network lifetime, the highest energy consumption per round, and the lowest cumulative packet delivery. This comprehensive comparison underscores the superior efficiency and performance of the DRLEER protocol, making it the most effective choice among the options evaluated.

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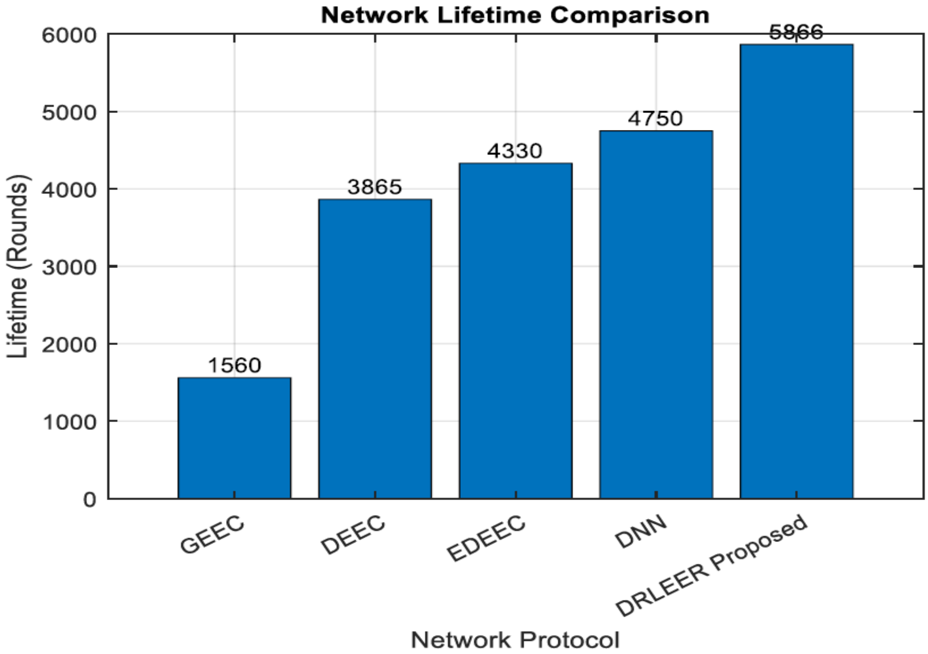

Figure 6 Network Lifetime Comparison

Figure 6 bar chart compares the network lifetime of various Wireless Sensor Network (WSN) protocols, including GEEC, DEEC, EDEEC, DNN, and the proposed DRLEER. The x-axis indicates different network methods, whereas the y-axis indicates the network lifetime measured in rounds. The figure shows that the proposed DRLEER protocol has the longest network lifetime of 5866 rounds, whereas the GEEC protocol has the shortest network lifetime of 1560 rounds.

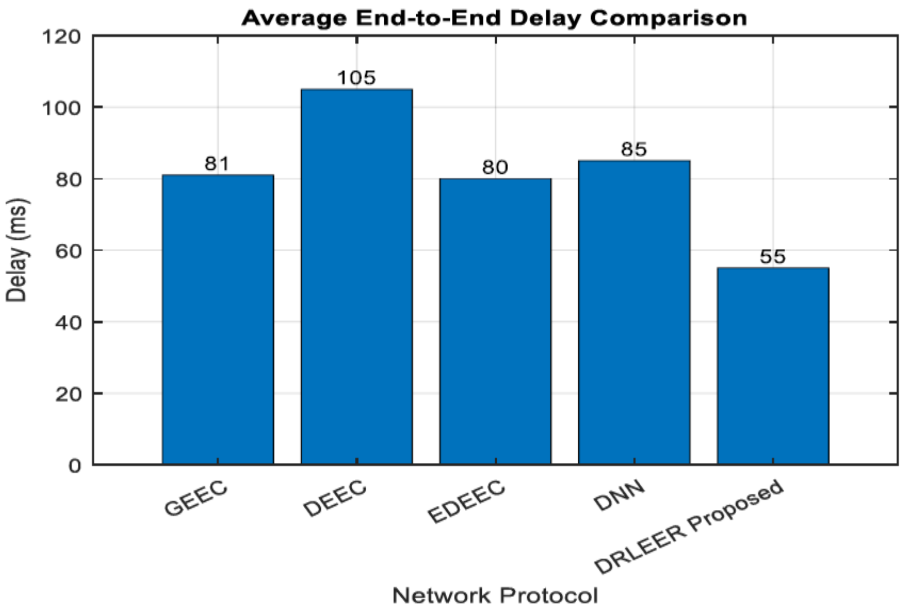

Figure 7 Average End-to-End Delay Comparison

Figure 7 bar chart displays the mean time between ends for each of the WSN protocols. The network protocols are shown on the x-axis, while the y-axis displays the average delay in milliseconds (ms). The proposed DRLEER protocol exhibits the lowest average "end-to-end delay" of 55 ms, indicating a more efficient data transmission, while DEEC has the highest delay at 105 ms.

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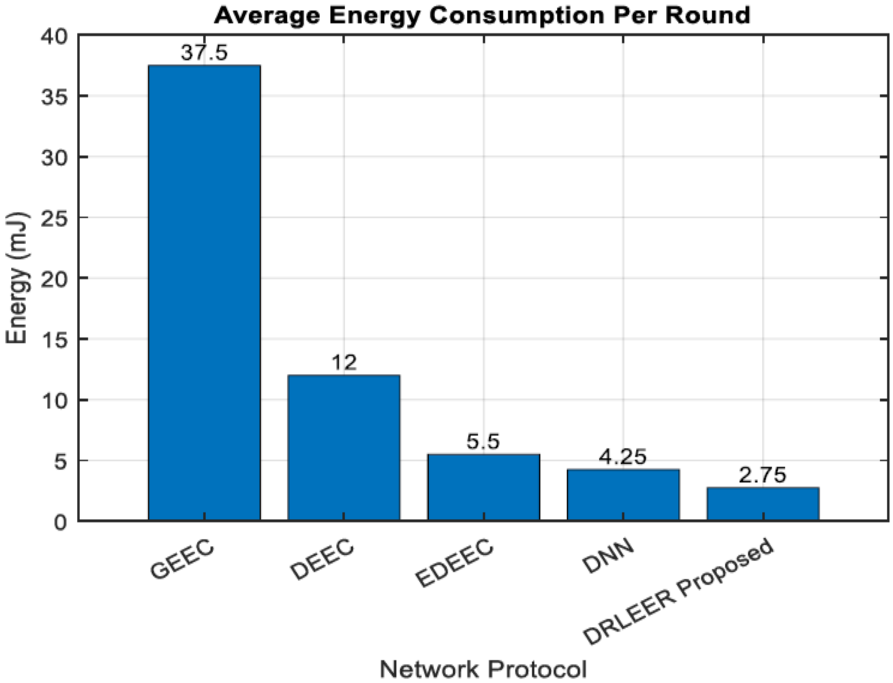

Figure 8 Average Energy Consumption Per Round

The average energy usage per round for each of the five WSN protocols is shown in figure 8. The millijoules (mJ) of energy usage are displayed on the y-axis, while the network protocols are represented on the x-axis. With an average consumption of 2.75 mJ each round, the suggested DRLEER protocol is the most energy-efficient, whereas GEEC is the least efficient, consuming 37.5 mJ every round.

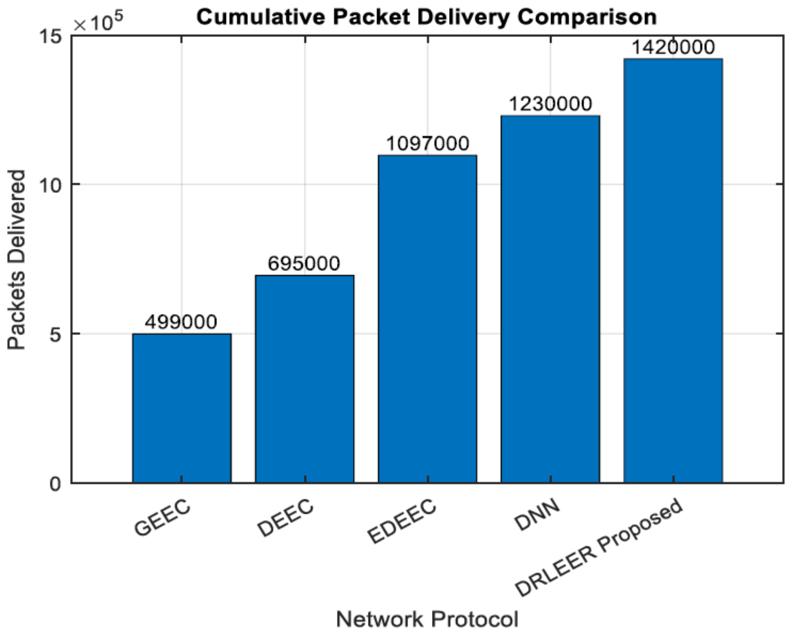

Figure 9 Cumulative Packet Delivery Comparison

Figure 9 chart compares the cumulative packet delivery across different WSN protocols. The network protocols are listed on the x-axis, while the number of delivered packets (in scientific notation) is shown on the y-axis. The proposed DRLEER protocol demonstrates the highest packet delivery rate, with a total of 1.42 million packets delivered, while GEEC delivers the least, with 499,000 packets.

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VI. CONCLUSION

In this work, we introduce DRLEER (Dynamic Reinforcement Learning-based Energy-efficient Routing), a routing protocol designed for the Internet of Things (IoT), which focuses on minimizing energy consumption and maximizing the operational lifespan of IoT networks. The development of DRLEER is structured around three key phases: network design and Cluster Head (CH) selection, cluster formation, and learning-driven data transmission. In the first phase, the initial Q-value for CH selection is calculated by considering hop count and initial energy levels, enabling the identification of the most effective CHs for data routing. The second phase involves CHs inviting devices within their broadcast range, while devices farther from the base station join the nearest cluster. This clustering process optimizes the network's structure. The final phase leverages Reinforcement Learning to make energy-efficient routing decisions based on hop count and the remaining energy levels of the devices, with an energy threshold set to control CH replacement and ensure the network's continued effectiveness. Simulation results demonstrate that DRLEER significantly outperforms other protocols in terms of energy consumption and network lifespan. Specifically, DRLEER achieves a network lifetime of 5866, a reduced average end-to-end delay of 55 ms, and an average energy consumption of 2.75 per round, along with a cumulative packet delivery of 14.2 × 10^5 packets. These results illustrate the protocol's superior performance in both energy efficiency and data transmission. The low-power Reinforcement Learning method used in DRLEER further accelerates the process while conserving energy. Future work will focus on exploring additional parameters to further optimize the routing system's efficacy.

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