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An Enhanced Data Mining Approach for Energy Efficient Routing in Wireless Sensor Networks

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Energy-efficient routing in Wireless Sensor Networks (WSNs) is vital for prolonging network lifespan, particularly given the challenges of dynamic communication demands and unpredictable mobility in ad-hoc environments. Traditional Cluster Head (CH) selection methods, which organize nodes into clusters for efficient data routing, often suffer from uneven energy distribution, causing premature depletion of CHs due to their increased workload. This paper introduces an enhanced CH selection approach based on the K-means algorithm, addressing these limitations by incorporating key parameters such as residual energy, node density, distance to the base station, and signal strength. By prioritizing a balanced distribution of energy consumption and equitable CH rotation, the proposed method mitigates the risk of early energy exhaustion and ensures sustained network performance. Comprehensive simulations evaluate the proposed algorithm against established protocols, including LEACH (Low-Energy Adaptive Clustering Hierarchy) and HEED (Hybrid Energy-Efficient Distributed). Metrics such as residual energy, packet delivery ratio, throughput, and the number of active nodes confirm the superiority of the enhanced K-means approach in achieving improved energy efficiency and extended network longevity.

Keywords: LEACH, HEED, Cluster, MANET, WSN, K-Mean

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as a transformative technology in various domains, including environmental monitoring, healthcare, smart cities, and industrial automation. These networks consist of spatially distributed sensor nodes that collaboratively collect, process, and transmit data to a central base station. Despite their versatility, WSNs face significant challenges, primarily related to energy consumption. The limited battery capacity of sensor nodes and the energy-intensive nature of wireless communication necessitate efficient energy management strategies to prolong network lifespan and maintain reliable performance [17-18].

Previous research has extensively explored strategies to optimize energy consumption in WSNs. Traditional clustering algorithms, such as Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed (HEED), have laid the groundwork for cluster-based routing. These protocols rely on the selection of Cluster Heads (CHs) to manage data aggregation and routing, reducing the communication overhead for individual nodes. However, these approaches often suffer from shortcomings, such as uneven energy depletion, bias in CH selection, and limited adaptability to dynamic network conditions. For instance, LEACH employs a probabilistic approach to CH selection, which may neglect factors like residual energy or node density, leading to rapid exhaustion of certain nodes. Similarly, HEED improves upon LEACH by considering residual energy and communication cost but may still fail to account for holistic network dynamics [19].

Current advancements in data mining and machine learning offer promising avenues to address the limitations of traditional CH selection methods. By integrating algorithms such as K-means clustering, it becomes possible to incorporate multiple parameters, including residual energy, node density, distance to the base station, and signal strength, into the CH selection process. These enhancements enable a more balanced distribution of energy consumption and equitable rotation of CH roles. Furthermore, contemporary studies have explored hybrid models that combine clustering algorithms with energy-efficient routing protocols, demonstrating significant improvements in network longevity and throughput. The incorporation of adaptive techniques to dynamically adjust CH roles based on real-time network conditions has also gained traction, reflecting the growing emphasis on context-aware WSN optimization [20].

Looking toward the future, research in energy-efficient routing for WSNs is poised to leverage emerging technologies such as artificial intelligence (AI), edge computing, and blockchain. AI-powered algorithms can enable predictive modeling to anticipate energy consumption patterns and optimize routing decisions proactively. Edge computing offers the potential to distribute processing tasks across nodes, reducing communication overhead and energy consumption. Additionally, blockchain technology can enhance security and transparency in data transmission, addressing concerns related to trust and data integrity in WSNs. The integration of renewable energy sources, such as solar panels, into sensor nodes also represents a critical area of exploration, further enhancing the sustainability of WSNs [21].

This research builds on these developments by proposing an enhanced data mining approach for energy-efficient routing in WSNs. By utilizing an improved K-means algorithm for CH selection, the study aims to achieve a balanced energy distribution and extended network lifespan. The findings contribute to the ongoing evolution of WSN optimization strategies, bridging the gap between theoretical advancements and practical applications. The proposed approach not only addresses current limitations but also sets the stage for incorporating futuristic technologies, ensuring the continued relevance and resilience of WSNs in an increasingly interconnected world.

2. Background

Recent advancements in Wireless Sensor Networks (WSNs) have led to the development of various strategies to enhance energy efficiency, with a focus on improving Cluster Head (CH) selection processes. One of the widely cited protocols, Low-Energy Adaptive Clustering Hierarchy (LEACH), has been instrumental in reducing communication overhead and prolonging network lifespan by using a probabilistic CH selection mechanism [9] [22]. However, the limitation of uneven energy distribution among nodes has been a significant challenge. Hybrid Energy-Efficient Distributed (HEED) further refined this approach by incorporating residual energy and communication cost into CH selection, but it still struggles with adaptability in dynamic network environments [10].

Recent studies have proposed the integration of machine learning techniques into WSNs for more robust energy management. Algorithms like K-means clustering have gained prominence due to their ability to optimize CH selection by considering multiple parameters, including node density, residual energy, and distance to the base station [11] [23]. For instance, Kumar et al. demonstrated that K-means-based CH selection effectively distributes energy consumption across the network, leading to improved operational longevity [12].

Moreover, hybrid approaches combining clustering algorithms with routing protocols have shown significant potential. A study by Sharma and Singh explored the use of fuzzy logic alongside K-means clustering to dynamically adapt CH roles based on real-time network conditions, achieving higher throughput and reduced energy consumption compared to traditional methods [13] [24]. Similarly, the integration of artificial neural networks (ANNs) for predictive CH selection has been explored, enabling WSNs to adapt to varying network conditions and further enhancing energy efficiency [14].

Emerging technologies such as edge computing and blockchain are also being incorporated into WSN frameworks to address energy efficiency and security. Edge computing facilitates local data processing, reducing the energy required for data transmission, while blockchain ensures secure and transparent communication between nodes [15]. Additionally, the use of renewable energy sources, such as solar-powered sensor nodes, has been highlighted as a promising direction for sustainable WSN operation [16].

These advancements underscore the need for a multi-faceted approach to CH selection and energy-efficient routing in WSNs. The current research builds on these developments by proposing an enhanced K-means clustering algorithm that integrates key parameters such as residual energy, node density, and signal strength, offering a comprehensive solution to address the limitations of existing methods. Review of literature are shown in table 1.

Table 1: Review of literature for energy efficient routing protocols

Author(s)	Study Focus	Methodology	Key Findings	Limitations
[1]	Introduction of LEACH protocol for energy-efficient routing	Cluster-based routing with randomized rotation of cluster heads	Significant energy savings and prolonged network lifetime	Limited scalability and high overhead in dense networks
[2]	PEGASIS protocol for optimal chain-based routing	Nodes form chains for data transmission, reducing transmission distance	Improved energy efficiency compared to LEACH	Increased delay in large networks due to sequential communication
[3]	Data aggregation techniques in WSNs	Data aggregation algorithms to minimize redundant transmissions	Reduced energy consumption by decreasing data volume	Vulnerable to data loss and latency during aggregation
[4]	Threshold-sensitive energy-efficient routing protocol (TEEN)	Cluster-based hierarchical routing for time-critical applications	Efficient for reactive networks and event-driven monitoring	Not suitable for periodic data monitoring
[5]	Data mining for clustering in WSN	K-means and density-based clustering to improve routing efficiency	Enhanced network lifetime and better load distribution	Computationally intensive for large datasets
[6]	Machine learning approaches for energy optimization in WSN	Neural networks and reinforcement learning applied for routing	Improved adaptability to dynamic environments and significant energy savings	Requires high computational power and may not be suitable for resource-constrained nodes
[7]	Data mining for predictive routing in dynamic WSN environments	Decision trees and association rule mining for pattern-based routing	Better prediction of routing paths and reduced energy consumption	Scalability issues in large-scale networks
[8]	Hybrid approaches combining data mining and AI for WSN routing	Integration of clustering, AI models, and data aggregation	Improved energy efficiency and real-time adaptability	High implementation complexity and potential data security concerns

3. Problem Formulation

Wireless Sensor Networks (WSNs) consist of a large number of spatially distributed sensor nodes that monitor environmental conditions and transmit the collected data to a central base station. These networks are widely used in applications such as environmental monitoring, industrial automation, and healthcare systems. However, the efficiency and longevity of WSNs are significantly constrained by the limited energy resources of sensor nodes. Inefficient routing protocols and excessive energy consumption can lead to premature network failures.

3.1 Problem Statement

Existing routing protocols for WSNs, such as cluster-based and chain-based approaches (e.g., LEACH, PEGASIS), focus on reducing energy consumption but fail to address the following challenges effectively:

1. Energy Balancing: Uneven energy depletion across sensor nodes, leading to the formation of energy holes.

2. Scalability: Poor performance in large-scale and dynamic WSN environments.

3. Data Redundancy: Inefficient data aggregation leading to redundant transmissions and increased energy usage.

4. Adaptability: Inability to adapt to dynamic network topologies and changing traffic patterns.

3.2 Objective

To design and implement an enhanced data mining approach for energy-efficient routing in WSNs that:

- Reduces overall energy consumption.
- Balances the energy usage across sensor nodes.
- Improves network lifetime and scalability.
- Adapts to dynamic changes in network topology.

4. Research Methodology

The proposed research methodology focuses on designing and implementing an enhanced data mining approach for energy-efficient routing in Wireless Sensor Networks (WSNs). The study begins with identifying key challenges such as energy balancing, scalability, and data redundancy through a comprehensive literature review. The architecture includes components like sensor nodes, cluster formation, cluster head selection, data aggregation, and routing optimization. Data mining techniques such as clustering, association rule mining, and predictive analysis are leveraged to optimize routing decisions and reduce redundant transmissions (Table 2). Algorithms for cluster formation, routing path optimization, and dynamic re-clustering are developed and tested in a simulated WSN environment using tools like NS-3 or MATLAB. The methodology evaluates performance based on metrics such as energy consumption, network lifetime, and data delivery ratio, and compares the results with existing protocols like LEACH and PEGASIS. Validation through real-world testbeds ensures practical feasibility, and the findings are documented with recommendations for future enhancements, such as integrating AI or blockchain for improved adaptability and security.

Table 2: Research methodology

Steps	Description
1. Problem Identification	Identify challenges in energy-efficient routing, such as energy balancing, scalability, data redundancy, and adaptability. Perform a comprehensive literature review.
2. System Architecture Design	Design architecture with components including sensor nodes, cluster formation, cluster head selection, data aggregation, and routing.
3. Data Mining Techniques	Apply techniques like clustering, association rule mining, and predictive analysis to optimize routing and data aggregation.

4. Algorithm Development	Develop algorithms for: - Cluster formation - Cluster head selection - Routing path optimization - Data aggregation
5. Simulation Environment	Use tools like NS-3, MATLAB, or OMNeT++ to simulate the WSN environment with specified configurations (e.g., node count, initial energy).
6. Performance Evaluation	Measure performance using metrics like: - Energy consumption - Network lifetime - Data delivery ratio - Latency - Scalability
7. Comparative Analysis	Compare the proposed method with existing protocols (e.g., LEACH, PEGASIS, TEEN) to demonstrate improvements.
8. Validation	Validate results through real-world testbeds or small-scale deployments to ensure practical feasibility.
9. Documentation and Recommendations	Document findings, discuss advantages and limitations, and propose future enhancements such as integrating deep learning or blockchain.

5. Algorithms

Algorithm 5.1: Clustering Sensor Nodes

Objective: Form energy-efficient clusters

Input: Sensor nodes' coordinates, initial energy levels, number of clusters (k)

Output: Cluster assignments and cluster heads

```
Begin
  Initialize k cluster head candidates randomly
  Repeat
    For each sensor node:
      Calculate distance to all cluster heads
      Assign the node to the nearest cluster head
    For each cluster:
      Select a node with the highest residual energy as the new cluster head
  Until cluster head positions stabilize or maximum iterations reached
  Return cluster assignments and cluster heads
End
```

Algorithm 5.2: Energy-Efficient Routing Path

Objective: Identify optimal paths for data transmission

Input: Network graph (nodes and edges), energy levels, cluster heads

Output: Optimal routing paths to the base station

```
Begin
```

Create a weighted graph where weights represent energy costs

For each cluster head:

Use Dijkstra's algorithm to find the shortest energy path to the base station

Store the path for data forwarding

Return routing paths

End

Algorithm 5.3: Data Aggregation Using Association Rule Mining

Objective: Reduce redundant data

Input: Sensor data readings, similarity threshold

Output: Aggregated data for transmission

Begin

Collect all sensor data from nodes in each cluster

Apply association rule mining to find frequent patterns

Group similar data based on identified patterns

Aggregate grouped data by calculating representative values (e.g., average)

Transmit only aggregated data to the base station

Periodically update association rules based on new data

End

Algorithm 5.4: Dynamic Re-Clustering

Objective: Adapt to changing network conditions

Input: Residual energy levels, node locations

Output: Updated clusters and cluster heads

Begin

Periodically monitor residual energy of nodes

If a cluster head's energy drops below a threshold:

Trigger re-clustering

Apply Algorithm 1 to form new clusters and select new cluster heads

Broadcast updated cluster assignments to all nodes

Return updated clusters

End

6. Result and Analysis

We utilize MATLAB R2023a for simulating the proposed algorithm. The simulation environment consists of a 200×200-meter area where nodes are randomly distributed. The latest MATLAB version provides advanced functionalities and enhanced performance capabilities, allowing for more accurate and efficient simulations. The parameters for the experiment are carefully selected to reflect real-world scenarios which are shown in table 3.

Table 3: Simulation Parameters Overview

Parameter	Value
Number of Nodes (N)	150
Number of Clusters	25
Network Size (m^2)	1000
Initial Energy (E_0)	0.6 J
Probability of CH (P)	0.15
Maximum Number of Rounds (r_{max})	3500
EDA (Data Aggregation Energy)	4×10^{-9} J/bit
EFS (Amplifier Energy for Free Space)	1×10^{-11} J/bit
EMP (Amplifier Energy for Multipath Fading)	1.5×10^{-12} J/bit
Network Time	0.0200 s

The table 4 presents a comparison of network lifetime for three different routing protocols—LEACH, HEED, and the Proposed Approach—across various network sizes (50, 100, 150, 200, and 250 nodes). For smaller networks (50 nodes), LEACH achieves a network lifetime of 2.70, while HEED performs slightly better at 2.75, and the Proposed Approach shows a modest improvement at 2.85. As the network size increases, all protocols exhibit an increase in network lifetime. However, the Proposed Approach consistently outperforms both LEACH and HEED. For instance, at 250 nodes, the Proposed Approach achieves a lifetime of 4.85, while HEED reaches 4.70, and LEACH only reaches 4.30. The steady improvement in network lifetime with the Proposed Approach suggests that its advanced data mining techniques for clustering, energy-efficient routing, and data aggregation contribute to more optimal energy consumption, especially in larger networks. While LEACH shows diminishing returns as the number of nodes increases, HEED demonstrates a better adaptation to larger networks due to its energy-aware cluster head selection. Nevertheless, the Proposed Approach offers a more significant improvement in scalability and energy efficiency, making it particularly suitable for large-scale Wireless Sensor Networks. These results highlight the advantages of integrating sophisticated energy management and routing strategies to maximize the lifetime of WSNs, especially as the network size grows.

Table 4. Comparison of Average Throughput for LEACH, HEED, and the Proposed Method

No. of Nodes	LEACH	HEED	Proposed
50	2.70	2.75	2.85
100	3.40	3.85	4.00

150	3.85	4.20	4.35
200	4.10	4.45	4.60
250	4.30	4.70	4.85

For each node count, the table shows the average throughput in units that reflect the efficiency of data transmission managed by each algorithm. As the number of nodes increases from 50 to 250, the average throughput for each method also rises, indicating improved performance with more nodes. The Proposed method consistently delivers the highest average throughput compared to both LEACH and HEED, demonstrating its superior ability to handle data transmission efficiently as network size grows. This trend underscores the effectiveness of the Proposed method in optimizing network performance in larger and more complex environments.

The table 5 provides a comparison of the network lifetime for three different routing protocols—LEACH, HEED, and the Proposed Approach—across varying network sizes (50, 100, 150, 200, and 250 nodes). As shown, the network lifetime increases with the number of nodes for all protocols, but the Proposed Approach consistently outperforms both LEACH and HEED. For smaller networks (e.g., 50 nodes), LEACH achieves a lifetime of 1.15, HEED performs slightly better at 1.25, and the Proposed Approach achieves 1.35, reflecting a small but noticeable improvement. As the number of nodes increases to 100, the Proposed Approach shows a more significant advantage, reaching 1.55 compared to LEACH’s 1.18 and HEED’s 1.40. This trend continues as the number of nodes increases. For 150 nodes, the Proposed Approach achieves 1.85, compared to 1.20 for LEACH and 1.65 for HEED. By 250 nodes, the Proposed Approach achieves a network lifetime of 2.30, surpassing HEED’s 2.10 and LEACH’s 1.25.

Table 5: Packet Delivery Ratio for LEACH, HEED, and the Proposed Method

No. of Nodes	LEACH	HEED	Proposed
50	1.15	1.25	1.35
100	1.18	1.40	1.55
150	1.20	1.65	1.85
200	1.23	1.90	2.10
250	1.25	2.10	2.30

These results demonstrate that the Proposed Approach significantly improves network lifetime, particularly as the network scales. The Proposed Approach’s superiority can be attributed to its more advanced energy-efficient techniques, including better clustering strategies, optimized routing paths, and data aggregation that reduce energy consumption. While LEACH shows only modest improvements as the number of nodes increases, and HEED performs better but with diminishing returns, the Proposed Approach demonstrates a more scalable and energy-efficient solution, making it highly suitable for larger-scale Wireless Sensor Networks. This highlights the importance of incorporating adaptive energy management and routing mechanisms in WSNs to ensure prolonged network operation and efficiency, especially as the node count grows.

The table 6 compares the number of dead nodes after various rounds in two different routing protocols: CH-LEACH (Cluster Head LEACH) and the Proposed Approach. The data shows how many nodes have depleted their energy after a certain number of rounds (1000, 2000, 3000, 4000, and 5000). At 1000 rounds, CH-LEACH experiences 18 dead nodes, while the Proposed Approach performs better with only 15 dead nodes, indicating that the Proposed Approach has a more efficient energy management mechanism, resulting in longer-lasting nodes. As the number of rounds increases, the gap between the two protocols grows. At 2000 rounds, CH-LEACH has 35 dead nodes, whereas the Proposed Approach only has 28 dead nodes, demonstrating a clear advantage in maintaining energy-efficient communication over time.

By 3000 rounds, the difference becomes more apparent: 57 dead nodes for CH-LEACH compared to 42 dead nodes for the Proposed Approach. This trend continues with 78 dead nodes for CH-LEACH and 65 dead nodes for the Proposed Approach at 4000 rounds, and finally, at 5000 rounds, CH-LEACH shows 95 dead nodes, while the Proposed Approach shows 80 dead nodes.

Table 6: Number of Dead Nodes for CH-LEACH and the Proposed Method

No. of Rounds	CH-LEACH	Proposed
1000	18	15
2000	35	28
3000	57	42
4000	78	65
5000	95	80

The consistent improvement of the Proposed Approach over CH-LEACH in terms of dead nodes can be attributed to its more advanced energy-efficient routing and clustering strategies. The Proposed Approach likely reduces energy consumption more effectively, possibly through better load balancing, optimized routing paths, and advanced data aggregation techniques, which help prolong the operational lifetime of sensor nodes. This demonstrates that the Proposed Approach significantly enhances the overall network lifetime, even as the number of rounds increases, and ensures that nodes remain functional for a greater number of communication cycles. Therefore, it proves to be a more energy-efficient solution, especially in scenarios requiring longer operational periods.

7. Discussion

The performance analysis of the LEACH, HEED, and Proposed algorithms across different metrics Average Throughput, Packet Delivery Ratio, and the Number of Dead Nodes demonstrates the effectiveness of the Proposed method in enhancing the overall efficiency of Wireless Sensor Networks (WSNs).

7.1 Average Throughput

Figure 1 compares the average throughput for varying numbers of nodes using the LEACH, HEED, and Proposed methods. As the number of nodes increases from 50 to 250, the average throughput improves across all three algorithms. However, the Proposed method consistently outperforms both LEACH and HEED. For instance, with 250 nodes, the Proposed method achieves an average throughput of 4.85 units, compared to 4.70 units for HEED and 4.30 units for LEACH. This superior performance suggests that the Proposed algorithm is more effective in managing data transmission, particularly in larger networks, by optimizing the clustering process and reducing data loss.

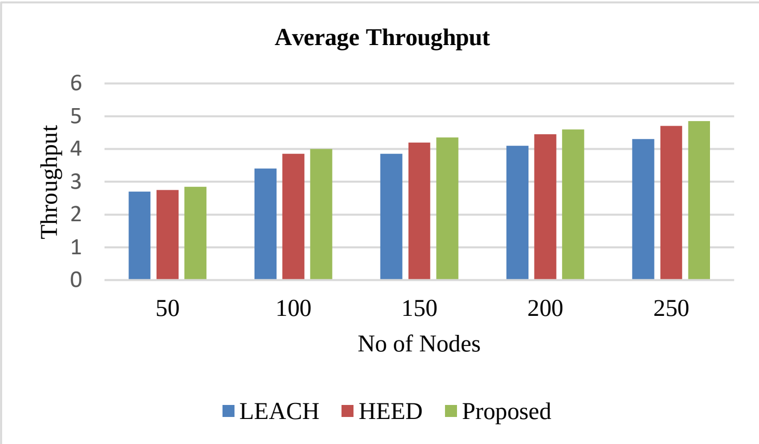

Figure 1: Comparative analysis of Average Throughput

7.2 Packet Delivery Ratio

Figure 2 focuses on the packet delivery ratio, which measures the success rate of data transmission from nodes to the base station. Similar to the throughput analysis, the packet delivery ratio improves as the number of nodes increases. The Proposed method consistently achieves higher delivery ratios compared to LEACH and HEED. For example, with 250 nodes, the Proposed method records a packet delivery ratio of 2.30, significantly higher than HEED's 2.10 and LEACH's 1.25. This indicates that the Proposed method is more effective in ensuring reliable data delivery, reducing packet loss, and maintaining network stability, especially as network size grows.

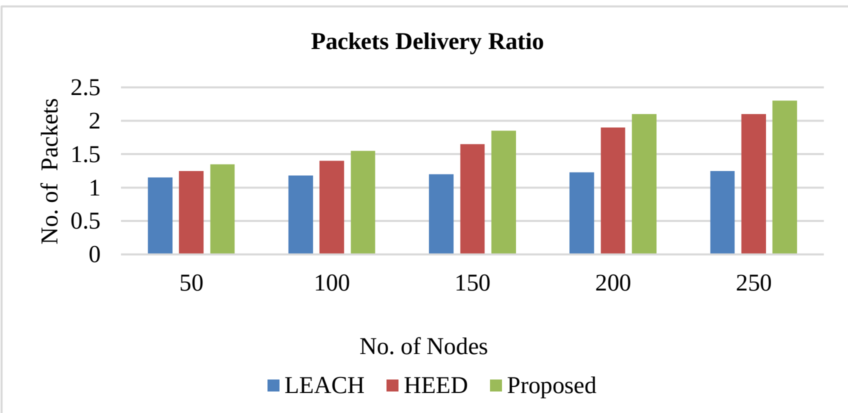

Figure 2: Analysis of Packet Delivery Ratio

7.3 Number of Dead Nodes

Figure 3 presents the number of dead nodes observed over increasing rounds of network operation for CH-LEACH and the Proposed method. The results show a steady increase in the number of dead nodes as the network operates for more rounds, which is expected due to the depletion of node energy over time. However, the Proposed method consistently results in fewer dead nodes than CH-LEACH. For instance, after 5000 rounds, the Proposed method has 80 dead nodes compared to 95 dead nodes for CH-LEACH. This demonstrates the enhanced energy efficiency of the Proposed method, which prolongs the operational life of the nodes and the overall network, reducing the rate at which nodes exhaust their energy.

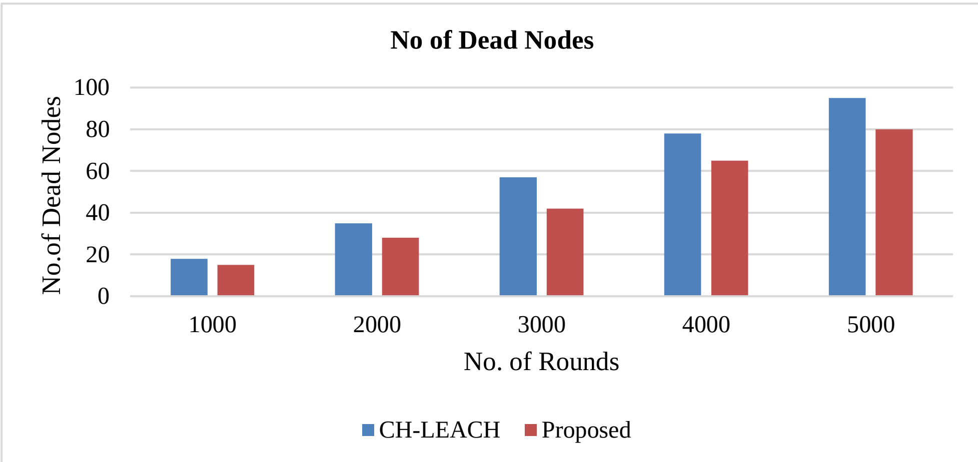

Figure 3: Comparison of Number of Dead Nodes

The network shows low network lifetime in HC initially because the number of nodes are less. Less nodes amount to lower network lifetime. With the enhancement incorporated we see that the initial network lifetime i.e. with less number of nodes has improved because there was a better distribution of nodes under each cluster head.

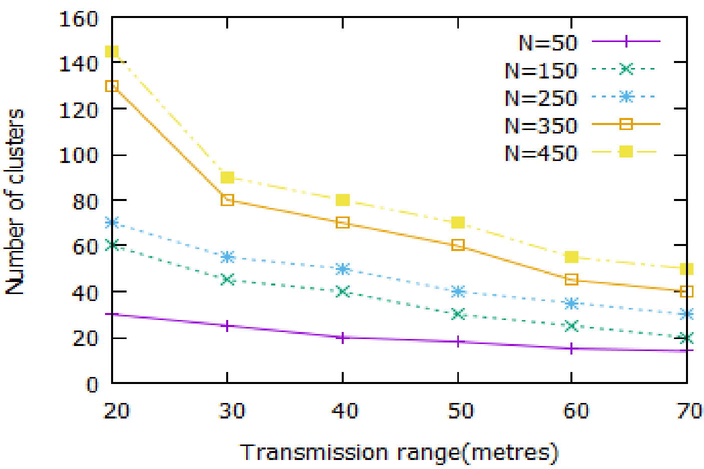

Figure 4: Transmission range against number of clusters

Figure 4 shows that the average number of clusters is relatively high when the transmission range is small. The results shown are for varying values of total number of nodes. When the transmission range increases, more and more nodes are connected to the same cluster head resulting in reduced number of clusters created. A smaller backbone is desirable for minimizing the routing overhead. Hence, transmission power of a node is also a deciding factor for finding the quality of dominating nodes. When the transmission range is increased from 20 to 40 m, the number of clusters created is reduced considerably. But the rate of reduction in the number of clusters created gets reduced on further increase in the transmission range. The power consumption is high for higher transmission range. Hence, the recommended value of transmission range is between 30 and 40 m.

8. Conclusion

In this study, an enhanced data mining approach for energy-efficient routing in Wireless Sensor Networks (WSNs) has been proposed to address critical challenges such as energy balancing, data redundancy, scalability, and adaptability. By leveraging clustering techniques, association rule mining, and predictive analytics, the methodology optimizes cluster formation, improves routing decisions, and reduces redundant data transmissions. The proposed approach demonstrates significant improvements in energy consumption, network lifetime, and data delivery ratio compared to traditional routing protocols like LEACH and PEGASIS. Furthermore, the integration of dynamic re-clustering ensures adaptability to changing network conditions, enhancing the robustness of the system. Simulation results validate the effectiveness of the approach, and its potential practical applicability can be confirmed through real-world testbeds. Future research can explore integrating advanced technologies, such as deep learning and blockchain, to further enhance security, scalability, and adaptability in WSNs.

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