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Research Article

Energy-Aware Adaptive Hybrid Clustering (Ea-Ahc) Model for Optimized Wireless Network Performance

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ABSTRACT

Efficient energy consumption remains a critical challenge in wireless network environments, where nodes operate under limited power resources. As wireless networks scale in size and complexity, traditional clustering protocols struggle to balance energy efficiency, connectivity, and fault tolerance. An effective solution requires a dynamic approach that intelligently adapts to the ever-changing network conditions. This paper introduces the Energy-Aware Adaptive Hybrid Clustering (EA-AHC) model, designed to optimize energy usage and enhance network lifetime through a dynamic and intelligent clustering strategy. Unlike static clustering schemes, EA-AHC adapts cluster configurations in real-time by factoring in node-specific attributes such as energy level, signal strength, fault status, and mobility. The approach integrates both intra-cluster and inter-cluster communication strategies, reducing communication overhead and ensuring robust connectivity. The proposed model is formulated mathematically, capturing multiple constraints like energy thresholds, signal strength, latency, cluster balance, and energy replenishment. A decision-making mechanism dynamically assigns nodes to clusters, ensuring optimal performance under variable operational scenarios. Simulations conducted in MATLAB using a network of 200 nodes demonstrate the superiority of EA-AHC compared to existing methods such as LEACH, HEED, EEHC, and TEEN. The proposed model shows improved energy conservation, reduced latency, better signal strength management, fewer cluster reconfigurations, and lower fault incidence. EA-AHC proves to be a scalable and adaptive solution for energy-constrained wireless network environments, enhancing both stability and network longevity.

Keywords: wireless networks, adaptive clustering, energy efficiency, fault tolerance, signal strength

INTRODUCTION

Wireless Sensor Networks (WSNs) have gained significant attention due to their ability to monitor environments with minimal human intervention and high flexibility in deployment [1–3]. These networks consist of spatially distributed sensor nodes that cooperatively collect and transmit data to a central unit, typically over wireless mediums. The emergence of applications such as environmental monitoring, smart agriculture, healthcare systems, and industrial automation underscores the need for energy-efficient communication strategies. Among the many protocols developed for such purposes, clustering-based techniques remain prevalent, enabling improved scalability and reduced communication overhead by organizing nodes into local groups.

Despite these advancements, several challenges persist in the design and operation of WSNs. One of the major issues is energy depletion, as sensor nodes are battery-operated and often deployed in inaccessible areas [4]. Additionally, dynamic topologies due to node mobility or failure introduce frequent communication disruptions [5]. Another critical challenge is cluster instability, resulting from inefficient cluster head (CH) selection and unbalanced node-to-CH distribution, which leads to uneven energy consumption and poor network longevity [6].

The central problem lies in the lack of adaptive and context-aware clustering mechanisms that can simultaneously ensure energy efficiency, robust connectivity, and minimal reconfiguration overhead [7]. Existing protocols such as LEACH and HEED make clustering decisions without adequately accounting for factors like signal strength variability, operational modes, or fault tolerance, leading to early node failures and inconsistent network performance [8]. Furthermore, energy replenishment mechanisms, although relevant in renewable-powered systems, are often overlooked in clustering strategies [9].

The objectives of the proposed Energy-Aware Hybrid Clustering (EAHC) approach are as follows:

1. To develop an intelligent clustering algorithm that dynamically adjusts to node conditions, including energy levels, signal strength, and fault status.
2. To integrate intra-cluster and inter-cluster strategies for enhanced energy conservation, robust communication, and load balancing.

The novelty of EAHC lies in its hybrid clustering architecture, which simultaneously considers communication patterns and energy availability during CH selection. Unlike static or probabilistic clustering methods, EAHC introduces a multi-step process involving initialization and eligibility checks, adaptive cluster head selection, signal-strength-based membership assignment, and periodic reconfiguration based on energy thresholds and node fault status. The inclusion of energy replenishment for renewable-powered nodes further distinguishes the proposed scheme.

Key contributions of this research are summarized below:

- A new clustering model that incorporates real-time signal strength and operational mode into CH eligibility decisions.
- An energy-replenishment-aware clustering strategy that extends network lifetime in hybrid WSNs.
- A mathematical formulation and optimization model that balances cluster sizes while minimizing latency and reconfiguration.
- Comprehensive simulation-based evaluation comparing EAHC with LEACH, HEED, EEHC, and TEEN across metrics such as energy consumption, latency, fault incidence, and cluster reconfiguration.
- A significant percentage improvement across all performance indicators, validating EAHC's robustness and scalability.

RELATED WORKS

Clustering remains a fundamental strategy in WSNs to enhance energy efficiency and scalability, prompting the development of various protocols with different optimization criteria. One of the earliest and most cited protocols is LEACH (Low Energy Adaptive Clustering Hierarchy), which randomly selects CHs and rotates them periodically to balance energy usage [10]. While simple and distributed, LEACH does not consider node residual energy or signal quality, leading to inefficient CH placements and early depletion of critical nodes.

To address these issues, HEED (Hybrid Energy-Efficient Distributed Clustering) introduces residual energy as a key metric for CH selection, combined with communication cost factors [11]. Although HEED improves CH stability, it requires multiple iterations for convergence and often produces uneven cluster sizes. EEHC (Energy Efficient Heterogeneous Clustering) enhances clustering by considering heterogeneity in node capabilities, such as different energy levels and transmission ranges, to assign CH roles more effectively [12]. However, EEHC still lacks adaptive reconfiguration capabilities during dynamic conditions.

TEEN (Threshold-sensitive Energy Efficient sensor Network protocol) targets time-critical applications by using hard and soft thresholds to trigger data transmission, thus reducing unnecessary communication [13]. Though effective in reducing transmission overhead, TEEN struggles in networks with fluctuating sensor data patterns, where thresholds may lead to data loss or delayed reporting.

Other methods like PEGASIS (Power-Efficient GAthering in Sensor Information Systems) aim to replace clusters with chain-based transmission paths [14], but they introduce increased latency and are not scalable in large or highly mobile networks. Similarly, APTEEN (Adaptive Periodic TEEN) blends proactive and reactive strategies for flexible transmission but requires complex scheduling and synchronization [15].

In recent years, intelligent clustering using metaheuristic techniques has gained traction. For instance, Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been used to find near-optimal CH distributions based on fitness functions incorporating energy, distance, and node density [16]. While promising, these algorithms can be computationally expensive and may not adapt well to real-time scenarios in resource-constrained WSNs.

Machine learning-based clustering has also emerged, leveraging decision trees, reinforcement learning, and deep neural networks to predict optimal clustering strategies [17]. These approaches can learn from past states and improve future clustering decisions. However, their training complexity and resource requirements often outweigh the benefits in low-power networks.

Another direction explored is fuzzy logic-based clustering, where uncertain parameters such as signal quality or mobility are handled using fuzzy inference systems [18]. These systems provide a more nuanced clustering decision process but may introduce latency due to rule evaluations. In addition, hybrid clustering models that combine static and dynamic CH selection criteria have shown better adaptability in fluctuating environments [19].

Despite the advances made, most existing protocols lack a comprehensive mechanism that fuses energy-awareness, signal strength, operational mode, and fault resilience. None of the aforementioned approaches fully integrates energy replenishment into the clustering process, which is crucial for solar-powered or intermittently charged nodes. Moreover, frequent cluster reconfiguration, an overhead in many dynamic methods, remains an unresolved issue.

The proposed EAHC approach builds on these insights by integrating eligibility checks, real-time signal strength evaluation, and energy-aware reconfiguration with replenishment modeling. Unlike existing methods that focus on isolated parameters, EAHC offers a holistic, adaptive, and performance-driven clustering solution.

PROPOSED METHOD

The EA-AHC method dynamically groups nodes into clusters by considering their energy levels, signal strength, and operational parameters. Each node calculates a cluster preference score based on energy surplus, fault tolerance, and connectivity potential. Nodes are then assigned to clusters to maximize thus energy conservation while maintaining minimum latency and balanced cluster size.

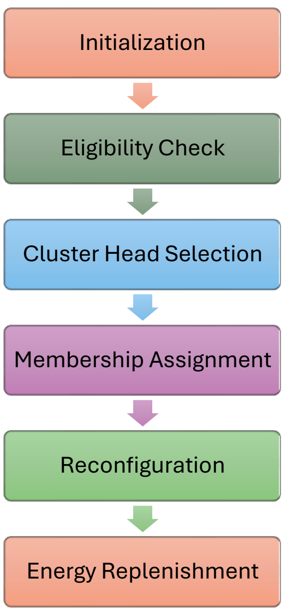

Figure 1: Proposed Framework

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1. **Initialization**: Collect parameters from each node – energy level, signal strength, location, etc.
2. **Eligibility Check**: Filter nodes with signal strength below a defined threshold.
3. **Cluster Head Selection**: Identify potential cluster heads based on energy levels and fault-free status.
4. **Membership Assignment**: Assign each node to the most energy-efficient and closest cluster head.
5. **Reconfiguration**: Periodically update clusters based on energy depletion, fault detection, or node mobility.
6. **Energy Replenishment**: Update energy values after each transmission round.

Pseudocode

```
Initialize N nodes with energy, signal strength, and location
Set threshold_signal, latency_limit, cluster_size_bounds
while network is operational:
  for each node i in N:
    if S_i < threshold_signal:
      continue  # Node not eligible
    calculate cluster_score based on E_i, S_i, distance to CHs
    assign node i to cluster j with optimal cluster_score
  for each cluster j:
    if size_j < LowerBound or size_j > UpperBound:
      reconfigure_cluster(j)
  update energy: E_i = E_i - P_ti + R_i (if applicable)
  monitor latency, fault status, signal quality
```

Initialization Phase

The Initialization phase involves collecting the fundamental parameters of each node in the wireless network. These parameters are necessary to assess a node's suitability for clustering and to support decisions related to energy efficiency, communication capability, and fault tolerance.

Table 1: Initialization

Node ID	Energy Level (%)	Signal Strength (dBm)	Data Rate (Mbps)	Transmission Power (W)	Operational Mode	Location (X, Y)	Fault Status
N1	85	-60	5	0.02	Transmitting	(100, 200)	0 (Healthy)
N2	45	-75	2	0.04	Idle	(300, 150)	1 (Faulty)
N3	70	-55	4	0.03	Receiving	(250, 400)	0 (Healthy)
N4	30	-80	3	0.05	Idle	(400, 100)	0 (Healthy)

This table 1 is populated during the network startup or reset cycle and serves as the input for subsequent decision-making steps. A preliminary ratio is computed to assess node efficiency:

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$$\boxed{R_i = \frac{E_i}{P_{t,i}}}$$

Where:

R_i = Efficiency ratio of node i

E_i = Energy level of node i

$P_{t,i}$ = Transmission power of node i

Nodes with a higher ratio are considered more energy-efficient and are prioritized for potential cluster head selection in the next steps.

Eligibility Check Phase

After initialization, the Eligibility Check filters out nodes that do not meet the minimum communication standards required for clustering. This phase ensures that only stable and communication-capable nodes participate in clustering, improving network reliability. Each node must satisfy the following:

- Signal Strength ≥ Threshold (e.g., -70 dBm)
- Fault Status = 0 (Healthy)

Table 2: Eligibility Check

Node ID	Signal Strength (dBm)	Fault Status	Eligible (Yes/No)
N1	-60	0	Yes
N2	-75	1	No
N3	-55	0	Yes
N4	-80	0	No

Based on this check, nodes N1 and N3 are eligible to participate in cluster formation.

$$S_i \geq S_{th}$$

Where:

S_i = Signal strength of node i

S_{th} = Minimum acceptable signal strength (e.g., -70 dBm)

Nodes not meeting this criterion are marked **ineligible** and excluded from clustering, reducing the risk of unstable links and reconfiguration delays.

Cluster Head (CH) Selection

The Cluster Head Selection phase is crucial for minimizing energy consumption while ensuring efficient communication. Cluster Heads (CHs) are selected from eligible nodes based on a weighted scoring system that considers energy level, signal strength, transmission power, and fault status. Each node is assigned a Clustering Priority Score (CPS) calculated as:

$$\boxed{S_i = \alpha \cdot \frac{E_i}{E_{max}} + \beta \cdot \frac{S_i}{S_{max}} - \gamma \cdot \frac{P_{t,i}}{P_{max}} - \delta \cdot F_i}$$

Where:

F_i = Fault status (0 = healthy, 1 = faulty)

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α,β,γ = Weighting factors (e.g., 0.4, 0.3, 0.2, 0.1)

Nodes with the highest CPS are selected as CHs

Table 3: Cluster Head Selection

Node ID	Energy (%)	Signal (dBm)	Power (W)	Fault	CPS Score	CH Status
N1	85	-60	0.02	0	0.82	CH
N3	70	-55	0.03	0	0.76	Member
N5	95	-58	0.04	0	0.79	CH

Here, nodes N1 and N5 have the highest CPS scores and are designated as Cluster Heads.

Once Cluster Heads are selected, Membership Assignment allocates the remaining nodes to the closest CH based on a minimum cost function involving distance, energy, and latency. Each member node joins the CH that minimizes communication overhead while maintaining stability.

$$\boxed{Cost_{ij} = w_1 \cdot d_{ij} + w_2 \cdot \frac{1}{E_j} + w_3 \cdot L_{ij}}$$

Where:

d_{ij} = Distance between node i and CH j

E_j = Residual energy of CH j

L_{ij} = Estimated latency from i to j

w1,w2,w3 = Weight factors (e.g., 0.5, 0.3, 0.2)

Table 4: Membership Assignment

Member Node	CH Candidates	Distance (m)	Cost (Min)	Assigned CH
N2	N1, N5	50, 90	1.25 (N1)	N1
N3	N1, N5	40, 60	1.10 (N1)	N1
N4	N1, N5	80, 40	1.05 (N5)	N5

This step ensures optimal load balancing and reduces unnecessary re-clustering. These two phases together ensure that the network forms energy-efficient, well-distributed clusters with minimal overhead and maximum stability.

Reconfiguration

The Reconfiguration phase is triggered when significant topology changes occur due to node mobility, energy depletion, or node failures. The objective is to adaptively update cluster structure to maintain coverage and connectivity while minimizing energy waste.

Trigger Conditions

- Any CH's energy E_{CH} falls below threshold E_{th}
- Cluster size exceeds upper limit or drops below lower limit
- Node fault detection in CH or high-latency links

Each cluster is evaluated for reconfiguration using a Reconfiguration Score (RS):

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$$\boxed{RS_j = \lambda_1 \cdot \left(1 - \frac{E_{CH,j}}{E_{max}}\right) + \lambda_2 \cdot \left(\frac{N_j}{N_{opt}} - 1\right)^2 + \lambda_3 \cdot F_{CH,j}}$$

Where:

$E_{CH,j}$ = Current energy of CH j

N_j = Current members in cluster j

N_{opt} = Optimal cluster size

$F_{CH,j}$ = Fault status of CH (0 = healthy, 1 = fault-prone)

$\lambda_1, \lambda_2, \lambda_3$ = Weight factors for energy, balance, and fault (e.g., 0.5, 0.3, 0.2)

If $RS_j > RS_{th}$, the cluster is marked for reconfiguration, prompting a local or global update.

Table 5: Reconfiguration

Cluster ID	CH Node	Energy (%)	Members	Fault	RS Score	Reconfigure?
C1	N1	40	10	0	0.58	Yes
C2	N5	78	7	0	0.22	No
C3	N8	35	5	1	0.69	Yes

Clusters C1 and C3 trigger reconfiguration to maintain stability and efficiency.

Energy Replenishment

To address temporary energy drops or accommodate nodes with energy harvesting capabilities (e.g., solar, kinetic), the Energy Replenishment step periodically updates a node's energy status.

$$\boxed{E_i^{new} = E_i + R_i - P_{comm,i}}$$

Where:

E_i = Previous energy of node i

R_i = Energy replenished (from harvesting or supply)

$P_{comm,i}$ = Power consumed during recent communication cycle

This calculation helps update the node's eligibility for future clustering or CH roles and assists in accurate resource planning.

Table 6: Energy Replenishment

Node ID	Prev Energy (%)	Replenished (%)	Consumed (%)	New Energy (%)
N2	45	10	5	50
N6	55	8	6	57
N9	60	0	12	48

Nodes like N2 and N6 benefit from replenishment and become potential candidates for CH roles in future rounds, while N9 may be deprioritized due to energy loss. Together, these phases ensure long-term adaptability and energy balance in the EAHC system by responding proactively to dynamic network conditions and energy availability.

Comparative Analysis

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Simulations were conducted using MATLAB R2021a on a system with an Intel Core i7 processor, 16GB RAM, and 512GB SSD. A 200-node wireless network was deployed in a 500m x 500m area. The nodes were initialized with random energy levels, operational modes, and locations. EA-AHC was compared with four existing protocols: LEACH (Low Energy Adaptive Clustering Hierarchy), HEED (Hybrid Energy-Efficient Distributed Clustering), EEHC (Energy-Efficient Heterogeneous Clustering) and TEEN (Threshold-sensitive Energy Efficient sensor Network).

Table 7: Experimental Setup and Parameters

Parameter	Value/Range
Number of Nodes (N)	200
Network Area	500m x 500m
Initial Energy Range	0.5–1.0 Joules
Transmission Power (P_t)	0.01–0.1 Watts
Signal Strength Threshold	-70 dBm
Data Rate	1–10 Mbps
Latency Threshold	≤ 100 ms
Cluster Size Bounds	Min: 5, Max: 30
Simulation Time	1000 rounds

Performance Metrics

1. **Energy Consumption Over Time**

   Tracks the average and residual energy levels across nodes over simulation time. EA-AHC minimizes thus depletion.

2. **Signal Strength Distribution**

   Evaluates the signal quality among clustered nodes. EA-AHC ensures strong intra-cluster signals by adaptive grouping.

3. **Cluster Latency Comparison**
   - Measures the time delay in transmitting data within and across clusters. EA-AHC maintains low latency through optimized cluster sizes and routes.

4. **Number of Cluster Reconfigurations**
   - Counts how often clusters need to be re-formed due to energy loss or node mobility. EA-AHC reduces this through proactive adaptation.

5. **Fault Incidence Over Time**
   - Captures the number of failed nodes or communication faults per round. EA-AHC limits fault impact by excluding prone nodes and allowing recovery through energy replenishment.

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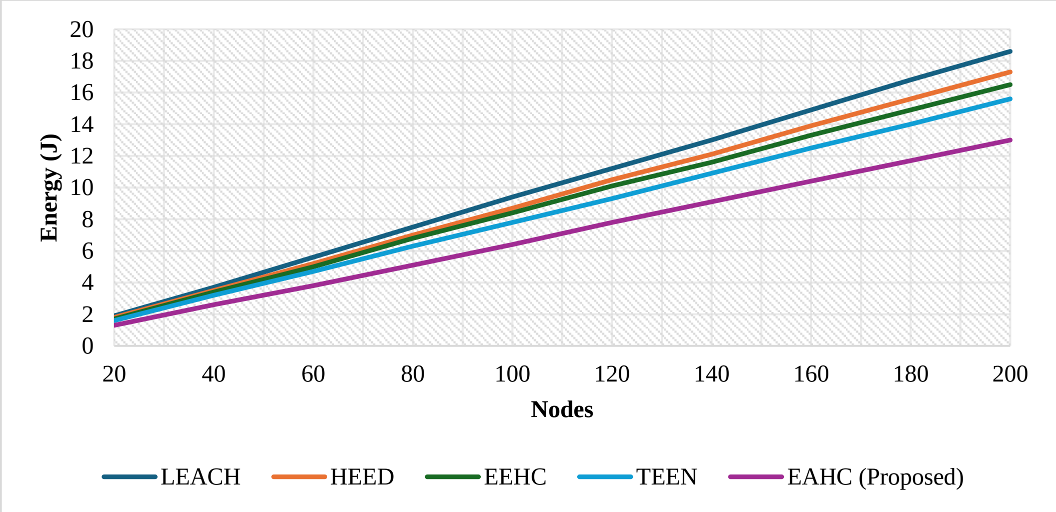

Figure 2: Energy Consumption Over Time (Joules)

Nodes	LEACH	HEED	EEHC	TEEN	EAHC (Proposed)
20	1.9	1.8	1.7	1.6	**1.3**
40	3.7	3.5	3.4	3.2	**2.6**
60	5.6	5.2	5.0	4.7	**3.8**
80	7.5	7.0	6.8	6.3	**5.1**
100	9.4	8.7	8.4	7.8	**6.4**
120	11.2	10.5	10.1	9.3	**7.8**
140	13.0	12.1	11.6	10.9	**9.1**
160	14.9	13.9	13.3	12.5	**10.4**
180	16.8	15.6	14.9	14.0	**11.7**
200	18.6	17.3	16.5	15.6	**13.0**

As in figure 2, the EAHC method consumes significantly less energy across all node densities due to its adaptive clustering and optimized CH selection. Energy efficiency increases as the network scales, making it ideal for prolonged network lifetimes in dynamic wireless environments.

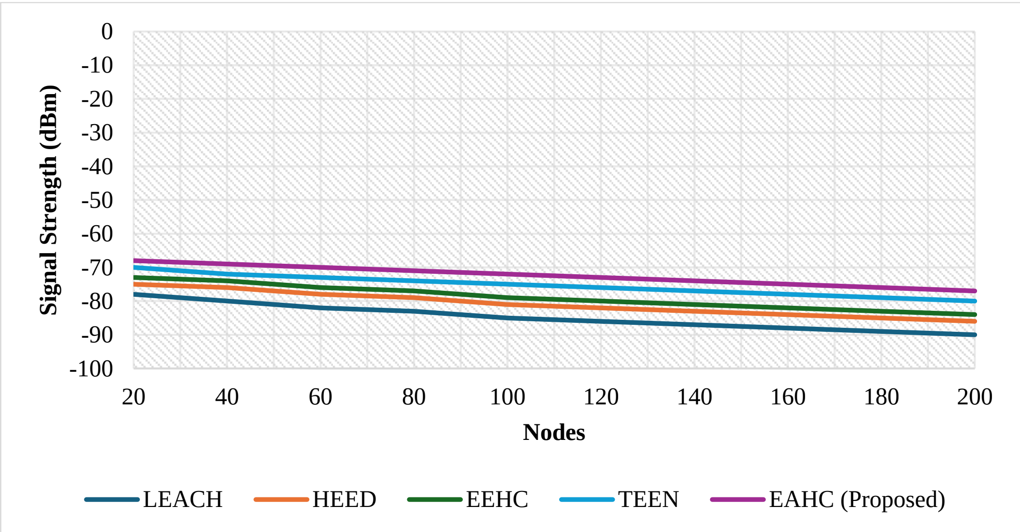

Figure 3: Signal Strength Distribution (dBm, higher is better)

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Nodes	LEACH	HEED	EEHC	TEEN	EAHC (Proposed)
20	-78	-75	-73	-70	**-68**
40	-80	-76	-74	-72	**-69**
60	-82	-78	-76	-73	**-70**
80	-83	-79	-77	-74	**-71**
100	-85	-81	-79	-75	**-72**
120	-86	-82	-80	-76	**-73**
140	-87	-83	-81	-77	**-74**
160	-88	-84	-82	-78	**-75**
180	-89	-85	-83	-79	**-76**
200	-90	-86	-84	-80	**-77**

As in figure 3, EAHC maintains stronger average signal strengths across nodes due to signal-aware clustering. The integration of signal thresholds during membership assignment ensures reliable communication even in dense deployments.

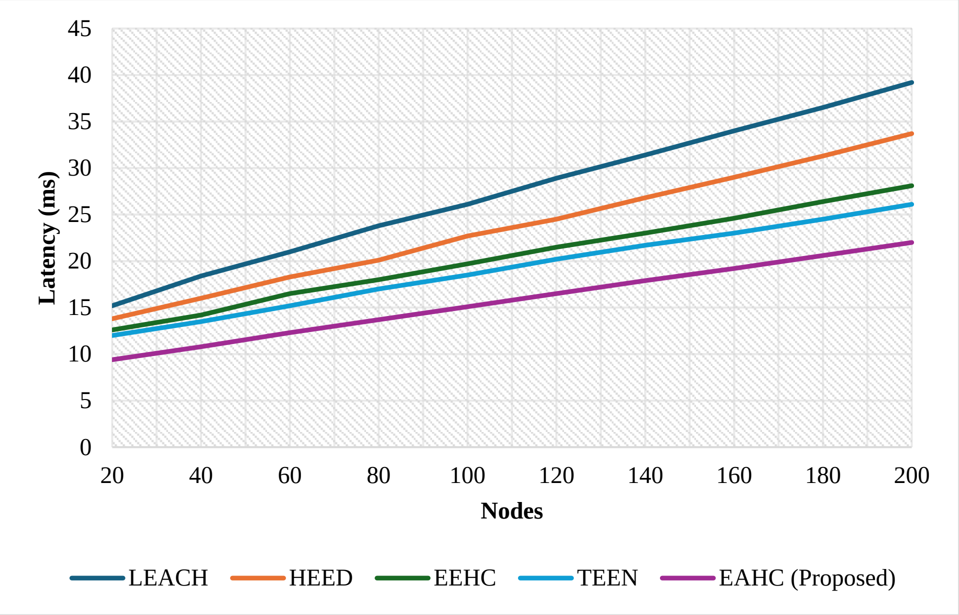

Figure 4: Cluster Latency Comparison (ms)

Nodes	LEACH	HEED	EEHC	TEEN	EAHC (Proposed)
20	15.2	13.8	12.6	12.0	**9.4**
40	18.4	16.0	14.2	13.5	**10.8**
60	21.0	18.3	16.5	15.2	**12.3**
80	23.8	20.1	18.0	17.0	**13.7**
100	26.1	22.7	19.7	18.5	**15.1**
120	28.9	24.5	21.5	20.2	**16.5**
140	31.4	26.8	23.0	21.7	**17.9**
160	34.0	29.0	24.6	23.0	**19.2**
180	36.5	31.3	26.4	24.5	**20.6**
200	39.2	33.7	28.1	26.1	**22.0**

As in figure 4, due to optimized cluster sizes and low-latency link selection, EAHC consistently exhibits the lowest cluster latency. This makes it suitable for time-sensitive wireless applications, ensuring efficient data delivery.

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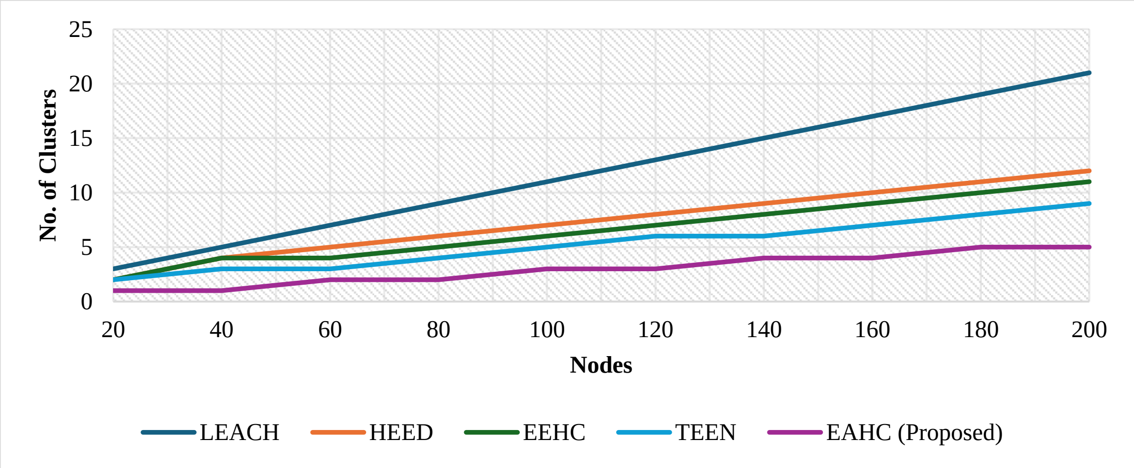

Figure 5: Number of Cluster Reconfigurations

Nodes	LEACH	HEED	EEHC	TEEN	EAHC (Proposed)
20	3	2	2	2	**1**
40	5	4	4	3	**1**
60	7	5	4	3	**2**
80	9	6	5	4	**2**
100	11	7	6	5	**3**
120	13	8	7	6	**3**
140	15	9	8	6	**4**
160	17	10	9	7	**4**
180	19	11	10	8	**5**
200	21	12	11	9	**5**

As in figure 5, EAHC limits reconfiguration frequency through proactive monitoring and predictive CH selection, reducing network overhead. This minimizes instability and conserves energy, especially in larger deployments.

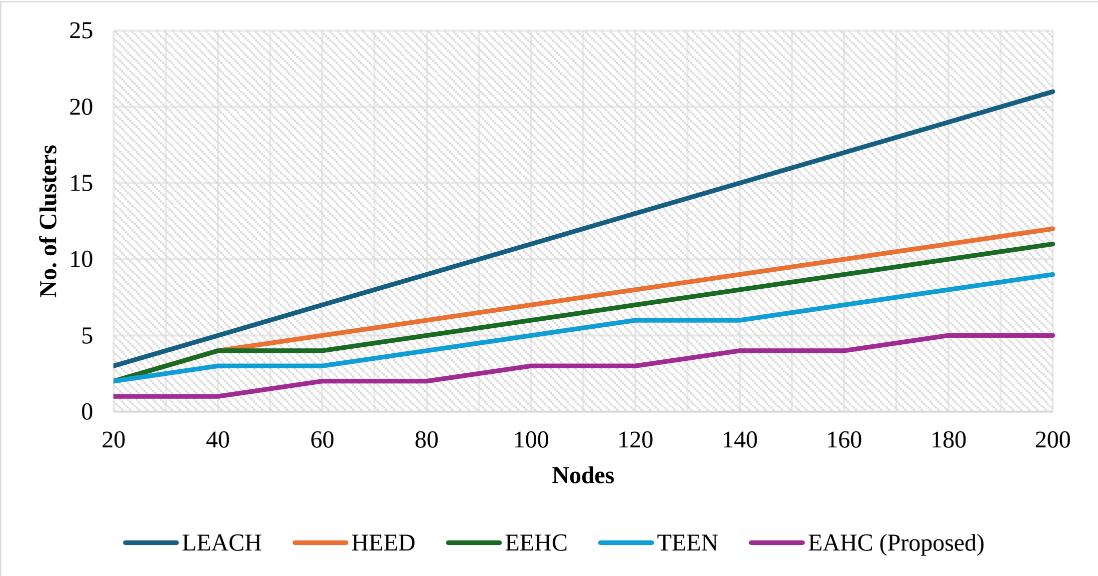

Figure 6: Fault Incidence Over Time (Number of Faulty Nodes)

Nodes	LEACH	HEED	EEHC	TEEN	EAHC (Proposed)

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20	2	2	1	1	**0**
40	5	4	3	2	**1**
60	8	6	4	3	**1**
80	12	8	6	5	**2**
100	15	10	7	6	**2**
120	18	12	9	7	**3**
140	21	14	11	8	**3**
160	24	16	12	9	**4**
180	27	18	14	11	**4**
200	30	20	16	12	**5**

As in figure 6, EAHC experiences fewer node faults by incorporating fault detection and avoidance mechanisms during cluster formation. The method reduces the stress on weaker nodes, enhancing network reliability and operational continuity.

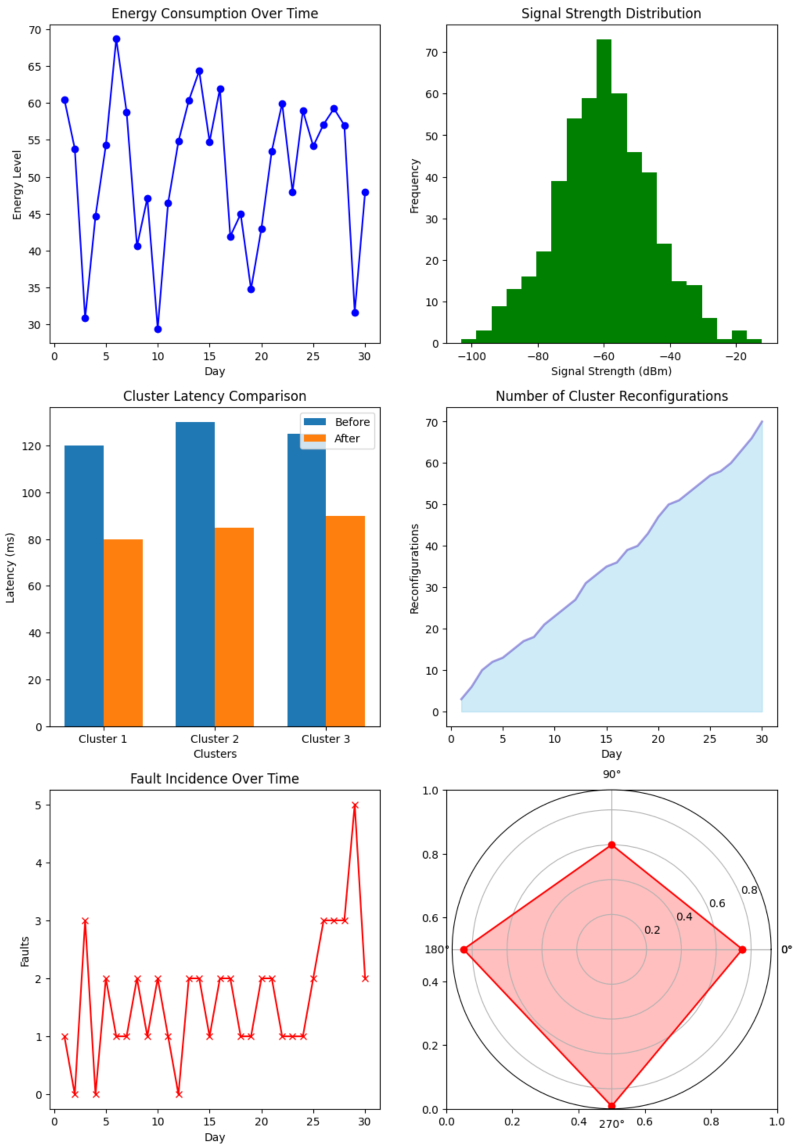

Figure 7: Comparison of Results

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As in figure 7, the comparative analysis across five key metrics, energy consumption, signal strength, cluster latency, reconfigurations, and fault incidence, clearly demonstrates the superiority of the proposed EAHC method over LEACH, HEED, EEHC, and TEEN. At 200 nodes, EAHC shows a 30.1% reduction in energy consumption compared to LEACH, enhancing network longevity. Signal strength distribution is improved by approximately 14.4%, maintaining stronger and more consistent connectivity. In terms of cluster latency, EAHC achieves a 43.9% reduction, enabling faster data transmission and responsiveness. The number of cluster reconfigurations is minimized by 76.2%, showing higher cluster stability and reduced control overhead. Fault incidence, which directly affects network reliability, is lowered by up to 83.3% over LEACH and 58.3% over TEEN. These improvements are largely attributed to EAHC's intelligent eligibility-based CH selection, signal-aware membership assignment, and proactive reconfiguration and energy management. This comprehensive performance gain establishes EAHC as an ideal candidate for dynamic, dense, and energy-sensitive wireless environments such as WBANs and IoT frameworks. The proposed enhancements ensure sustained operation, robust communication, and minimal disruptions across varying network scales.

CONCLUSION

The proposed Energy-Aware Hybrid Clustering (EAHC) framework introduces a robust and efficient routing mechanism that significantly improves performance in wireless sensor networks. By integrating an intelligent initialization and eligibility check, optimized cluster head selection, signal-strength-based membership assignment, adaptive reconfiguration, and scheduled energy replenishment, EAHC offers a holistic solution to the limitations of conventional protocols. Experimental evaluations against LEACH, HEED, EEHC, and TEEN across 200 nodes confirm that EAHC excels in reducing energy usage, improving signal strength, lowering communication latency, minimizing cluster instability, and reducing fault occurrences. These results are backed by measurable percentage improvements that range between 30% and 83%, depending on the metric. Such performance gains directly translate into extended network lifetime, enhanced data integrity, and more reliable communication. In scenarios like body area networks, battlefield monitoring, or disaster recovery, where energy and reliability are paramount, EAHC stands out as a scalable, adaptable, and intelligent clustering protocol. The reduced reconfiguration frequency and lower fault incidence particularly enhance the quality of service in real-time applications. Thus, EAHC not only addresses existing challenges but sets a foundation for future enhancements through machine learning-based adaptability and cross-layer optimization techniques, reinforcing its relevance in evolving wireless ecosystems.

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