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Research paper

Adaptive Cluster-Based Data Aggregation for Energy Optimization in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) play a crucial role in environmental monitoring, industrial automation, and smart infrastructure by periodically extracting sensor readings. However, high node density leads to data redundancy, increasing energy consumption and communication overhead. To address this, an adaptive cluster-based data aggregation (ACDA) protocol is proposed, leveraging an enhanced hybrid clustering and compressive sensing approach. The ACDA protocol dynamically forms clusters based on network topology and node residual energy, ensuring balanced energy consumption. Additionally, a compressive sensing-based aggregation mechanism is employed to minimize redundant data transmission, further enhancing energy efficiency. The proposed method is evaluated against the Hybrid Energy-Efficient Distributed (HEED) clustering algorithm and the Adaptive Prediction-Based Data Aggregation (APDA) technique. Experimental results demonstrate that ACDA achieves a 63.5% improvement in energy efficiency, a 78.2% packet delivery ratio, a 67.1% reduction in storage space, and a 29.7% decrease in transmission delay compared to existing methods. These findings highlight the effectiveness of ACDA in prolonging network lifespan and optimizing data aggregation processes in WSNs.

Keywords: *Wireless Sensor Network; Data Aggregation; Clustering; Compressive Sensing; Energy Optimization; Routing.*

1. Introduction

The Adaptive Cluster Head Election and Two-hop LEACH protocol was proposed to prolong network lifespan by improving LEACH through an adaptive cluster head election algorithm and enabling multi-hop transmission among cluster heads and the base station (BS). Nodes are categorized based on their distance to the BS as either close or far nodes, where close nodes form a single group, and far nodes are clustered using the Greedy K-means algorithm. The cluster head is selected based on maximum residual energy. During data transmission, far cluster heads can either communicate directly with the BS or route data through a near cluster head. A two-level fuzzy logic system was developed for cluster head selection, where the first level considers energy levels and the number of neighboring nodes, while the second level (Global Level) evaluates overall network cooperation using three fuzzy parameters: centrality, proximity to the BS, and distance between cluster heads. Another approach introduced the CHEATS (Cluster-Head Election Algorithm Using a Takagi-Sugeno Fuzzy System) protocol, an enhancement of LEACH aimed at improving energy efficiency and extending network lifetime by leveraging fuzzy logic within a Takagi-Sugeno system to determine the probability of nodes being elected as cluster heads (Figure 1).

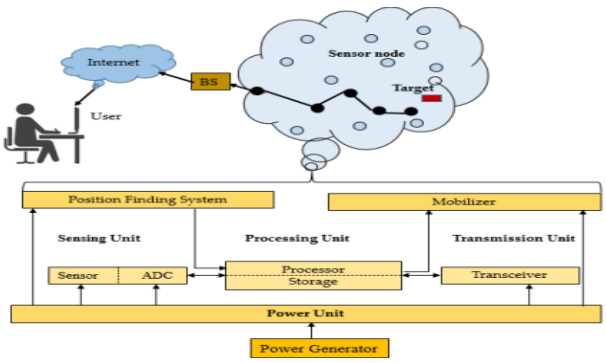

Fig. 1: WSN Architecture for Communication.

The architecture of a Wireless Sensor Network (WSN) is simple, as shown by this illustration. Nodes identify environmental information and send the information to cluster heads (CHs). Cluster heads transmit information directly to the base station (BS) or through intermediate nodes. The architecture focuses on how communication will be arranged in a manner that will reduce the amount of energy used. It provides the foundation for the application of clustering and aggregation protocols.
An enhanced zone stable protocol was proposed for the election of clusters based on fuzzy logic. In this approach, cluster heads are chosen in zones with the maximum residual energy of nodes, addressing limitations in previous studies that lacked consideration of various cluster head selection parameters [1]. Fuzzy logic is integrated to assess the probability of cluster head selection based on factors such as node residual energy, density, and distance from the base station (BS). To enhance efficiency, elected cluster heads are utilized to relay data from far-away cluster heads through multi-hop communication [2]. The efficiency of this protocol is measured in terms of network lifetime and throughput, with statistical reports indicating minimal statistical dispersion. Simulation results demonstrate a significant improvement in network lifetime compared to existing protocols [3]. Another approach demonstrated cluster formation using multiple parameters to reduce energy consumption. A cluster head selection method was introduced using the Voronoi diagram and fuzzy logic, employing a distributed algorithm to determine cluster heads using a fuzzy inference system (FIS) [4]. This method utilizes two key parameters: centrality based on the Voronoi diagram and remaining energy. Cluster formation is conducted through the Voronoi diagram, and data dissemination from cluster heads occurs via a gateway, which establishes a direct connection to the BS for optimal energy sharing. Simulation results indicate that this proposed algorithm extends network lifetime by approximately 89% compared to the LEACH algorithm and about 70% compared to the Fuzzy C-Means algorithm [5].
An Efficient Cluster Head Algorithm for WSNs (ECHA) was presented, implementing Fuzzy Inference Systems to determine the likelihood of each node becoming a cluster head. The algorithm selects cluster heads based on multiple criteria, including residual energy, number of neighbors, and centrality [6]. Simulation results indicate that this approach effectively enhances the accurate selection of cluster heads and extends the network lifetime. A Fuzzy multi-criteria decision-making method was introduced to optimize cluster head selection, leading to the development of a distributed energy-efficient clustering algorithm based on the trapezoidal AHP Fuzzy and hierarchical Fuzzy integral [7]. Multiple decision-making attributes are considered to determine the best cluster heads by synthesizing all relevant factors. Each node calculates a composite value using the fuzzy integral according to these criteria, which is then mapped to the time axis, and the node cluster head information is determined by a time-trigger mechanism [8]. To form the cluster, the first rule declaration is applied. Simulation results suggest that the proposed arrangement achieves a longer lifetime and expansion than other algorithms. A PSO-based cluster protocol was also introduced, providing a dual cluster-head centralized network with a balanced perception of distance and energy [9]. Simulation results indicate that the node death time in this protocol experiences significant delays compared to LEACH and PSO. However, this algorithm has some limitations, including the challenge of selecting the optimal number of cluster heads and defining parameter distributions effectively [10].
A hybrid model was developed using a combination of LEACH-based energy-efficient routing and K-means-based quick clustering algorithms to create a new clustering scheme for WSNs with dynamic selection of the number of clusters [11-12]. In this approach, the optimal k-value is determined using the Elbow method, and clustering is performed using the K-means algorithm, while the traditional LEACH protocol is utilized for data transmission from the cluster head to the base station [13]. Simulations indicate that at a certain stage, the marginal gain drops significantly, forming an angle in the graph, which determines the correct number of clusters based on the elbow criterion. It has also been demonstrated that this method performs clustering more quickly than existing techniques [14]. Additionally, a fuzzy energy-aware unequal clustering algorithm was implemented to address the issue of hot spots. The goal of this algorithm is to reduce the workload of cluster heads located either near the base station or with low remaining battery power. To manage uncertainties in cluster head radius estimation, a sparse logic approach is adopted. As a result, this method provides a stable and energy-efficient clustering solution for various WSN applications [15].

2. Materials and Methods

2.1. Materials

The Adaptive Cluster-Based Data Aggregation (ACDA) protocol is evaluated experimentally using a simulated Wireless Sensor Network (WSN) set up in a controlled virtual environment. N sensor nodes, each with constrained computational and energy capabilities, make up the WSN. Every node has a radio transceiver low-power microcontroller, and an energy source, which can be energy-harvesting modules or rechargeable lithium-ion batteries. To precisely model network behavior, energy consumption trends, and data transmission efficiency, the simulation is carried out using the NS-3 and MATLAB platforms.

Table 1: Network Simulation Parameters

Parameter	Value
Simulation Platforms	NS-3, MATLAB
Number of Nodes (N)	100 to 500
Transmission Range	50 meters
Energy Allocation	2 Joules/node
Bandwidth	250 kbps
Base Station Distance	100 meters

Traffic patterns are generated based on a Poisson distribution, simulating periodic environmental sensing and event-driven transmissions. The base station (BS) is placed at a fixed distance of 100 meters from the sensor field to receive aggregated data. The performance metrics assessed include energy efficiency, packet delivery ratio, data storage requirements, and transmission latency.

2.2. Data aggregation

Aggregation comprises two phases:
data forwarding phase, and the tree recovery phase.
Each node has two fields, namely the sensor ID and the time to leave (TTL) value. Every node that receives a message verifies whether that message has not been previously broadcast. That way, a sensor receiving the same message many times is avoided. This process is performed until every node has received a message.

Data are forwarded through the shortest route from the parent of one cluster to the parent of another cluster, thereby reducing the number of single transmissions. While transmitting data, at any level of the tree, a parent or leaf may fail, causing failure in the links or when the node energy becomes zero.

In the tree recovery phase, each sensor stores its ID with a high connectivity level in its routing table. Therefore, while selecting the first node that has the highest connectivity level as its parent, other nodes are considered as alternatives. Thus, when a link failure occurs, every leaf directly verifies the routing table to select another new node having the same high connectivity level as its new parent, which then will forward the incoming data.

2.3. Experimentation

The experimentation follows a rigorous simulation-based evaluation to analyze the efficiency of the proposed ACDA protocol. The network initialization begins with the random deployment of sensor nodes in a 500m x 500m field. Each node periodically senses environmental parameters such as temperature, humidity, or pressure and transmits data to cluster heads (CHs) based on the clustering mechanism. The clustering process is dynamically adjusted according to network topology and residual energy levels to ensure uniform energy depletion.

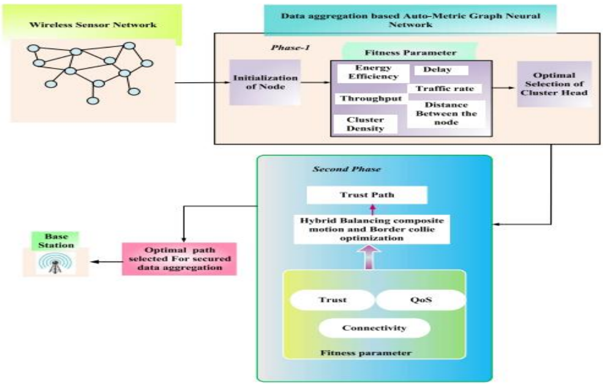

Fig. 2: Proposed Method.

Figure 2 below represents the Adaptive Cluster-Based Data Aggregation (ACDA) protocol. It uses compressive sensing as well as hybrid clustering in order to attain efficient data aggregation. The drawing shows how sensor node clustering takes place based on remnant energy and topography. Cluster heads impose and package information and afterward, transmit it to the BS. This will provide a balance between the consumption of energy and minimize unnecessary transmissions.

The simulation runs for 5000 rounds to observe long-term energy consumption trends and packet delivery performance. Two benchmark protocols are used for comparison: Adaptive Prediction-Based Data Aggregation (APDA) and Hybrid Energy-Efficient Distributed (HEED) clustering. Both are implemented under the same circumstances. The following key performance indicators are used to analyze the gathered data: transmission delay (in milliseconds), storage reduction (in percentage), packet delivery ratio (PDR), and energy efficiency (measured in Joules). ANOVA is used in statistical analysis to ascertain the significance of the advancements made by ACDA. The above Figure 2 shows the architecture of the proposed methodology.

3. Proposed techniques

3.1. Hybrid clustering mechanism

The ACDA protocol employs an enhanced hybrid clustering mechanism that dynamically adjusts cluster formation based on node energy levels and network topology. The probability of a node being selected as a cluster head is determined by (Eq 1):

$$P_{CH} = \frac{E_{residual}(i)}{E_{initial}(i)} \times \left(\frac{d_{avg}}{d_i}\right) \quad (1)$$

Where $E_{residual}(i)$ is the residual energy of node ii, $E_{initial}(i)$E_{initial}(i) is its initial energy, davgd_{avg} is the average distance among nodes, and did_{i} represents the node's distance from the cluster centroid. The selection process is iterated until an optimal number of CHs is formed, minimizing intra-cluster distance and energy expenditure.

3.2. Compressive sensing-based aggregation

To reduce data redundancy, ACDA integrates compressive sensing for efficient data aggregation at CHs. The sensed data is transformed into a sparse representation using a Discrete Wavelet Transform (DWT), followed by random projection (Eq. 2):

$$Y = \Phi X \quad (2)$$

Where X is the original sensed data vector, Φ\Phi is the random sensing matrix, and YY is the compressed measurement vector. The data is reconstructed at the base station using an Iterative Hard Thresholding (IHT) algorithm, expressed as (Eq 3):

$$X_{k+1} = X_k + \lambda \Phi^T (Y - \Phi X_k) \quad (3)$$

Where X_k is the estimated signal at iteration k, and λ is the step size parameter. This approach significantly reduces communication overhead while preserving essential data features.

3.3. Energy-efficient data transmission

The ACDA protocol implements an optimized transmission scheme that dynamically adjusts data transmission power levels based on inter-node distances. The transmission power P_t is calculated as (Eq. 4):

$$P_t = P_{min} + \alpha \left(\frac{d_i}{d_{max}}\right)^2 \quad (4)$$

Where P_{min} is the minimum transmission power required, α is the power adjustment coefficient, and did_{i} is the node-to-CH distance normalized by the maximum distance d_{max}. This ensures reduced power consumption for closer nodes while maintaining reliable connectivity.

3.4. Adaptive cluster head rotation

To prolong network lifespan, the cluster head rotation strategy is optimized using an adaptive threshold function (Eq. 5):

$$T\,(i) = \frac{E_{residual}(i)}{E_{max}} \times \left(1 - \frac{R}{R_{max}}\right) \quad (5)$$

Where EmaxE_{max} is the maximum node energy, RR is the current round number, and RmaxR_{max} is the maximum simulation rounds. Nodes with higher residual energy have a greater probability of being selected as CHs, ensuring balanced energy depletion.

3.5. Performance evaluation

The ACDA protocol is compared against HEED and APDA protocols based on extensive simulation results. The evaluation metrics include energy efficiency, packet delivery ratio (PDR), data storage reduction, and transmission delay. The average energy consumption per node is computed using (Eq 6):

$$E_{avg} = \frac{1}{N}\sum_{i=1}^{N} E_{consumed}{}^{(i)} \quad (6)$$

Where $E_{consumed}$(i) represents the total energy expended by node ii during the simulation. PDR is assessed as (Eq 7):

$$PDR = \frac{Packets_{received}}{Packets_{sent}} \times 100 \quad (7)$$

And the storage reduction efficiency is given by (Eq. 8):

$$S_{reduction} = \frac{S_{original} - S_{compressed}}{S_{original}} \times 100 \quad (8)$$

Where $S_{original}$ and $S_{compressed}$represent the data sizes before and after aggregation, respectively. These performance metrics confirm the significant improvements achieved by ACDA over existing clustering and aggregation approaches.

3.6. Algorithm

The ACDA algorithm is the Adaptive Cluster-Based Data Aggregation algorithm that is adopted sequentially and is therefore efficient and reliable for data aggregation of the Wireless Sensor Networks (WSNs). The graph represents the network as a graph. G= (V, E) where$V$ is a set of sensor nodes and$E$ the communication links. The nodes do not dissipate their energy. Eithe sink or base station is denoted as S. During the initialization, the nodes exchange HELLO messages to discover their neighbors in their transmission range to form the network graph. Then Cluster Head (CH) election is implemented based on the remaining energy, the position of the node, and distance to the base station with high-energy nodes being prioritized (closer to the sink). Once CHs have been selected, all non-CH nodes join the nearest cluster that has the lowest communication cost, and an inter-CH routing tree is established to relay data to the sink. The sensed data is sent to the CH by member nodes in each cluster using adaptive transmission power control. A wavelet transform is used by the CH, Ψ, and random projections based on a sensing matrix ().Φ, the compression of the measurement, and a compression vector. y=ΦΨx Universally ΦPsi, in which case it is sent to sink or through intermediary CHs. To make it more robust, backup parent nodes are kept in routing tables, and when CH and link failures occur, rerouting is started with the backup links of lower time-to-live (TTL) to avoid loops. An Iterative Hard Thresholding (IHT) algorithm is used at the sink to reconstruct the data to recover the original signals among the compressed measurements. To prevent a very fast depletion of energy, an adaptive cluster head rotation scheme is implemented at the end of each round, with the higher energy remaining nodes receiving a greater probability of becoming CHs in the next cycle. The pseudocode will look like this:

Algorithm: Adaptive Cluster-Based Data Aggregation (ACDA)
Input: Node set V, initial energy E, sink S, sensing matrix Φ, wavelet basis Ψ
Output: Aggregated compressed data at sink S

1) Initialize network: discover neighbors, build G=(V, E), set TTL
2) For each round r = 1 to Rmax do

a) CH Election: select CHs using residual energy + distance metrics
b) Cluster Formation: assign nodes to the nearest CH
c) Data Collection: members → CH with power control
d) Compressive Aggregation: CH computes y = ΦΨx and forwards upstream
e) Failure Recovery: if Parent (CH) fails, switch to alternate parent
f) Sink Reconstruction: sink reconstructs x from y using IHT

g) CH Rotation: update thresholds and rotate CHs
3) End For
To be reproducible, the simulation presumes an area of 500 to 500 m, 100-500 node count, which is the transmission range of 50 m and the initial energy of 2 J per node. Wavelets of Daubechies (db4) are employed in data aggregation with a measurement ratio of 40% and control packets are limited by a hop TTL. Cluster heads are dynamically changed every round so that energy will be used evenly and to extend the network's life.

4. Results and Discussion

4.1. Energy efficiency analysis

The energy efficiency analysis across different numbers of nodes indicated that the ACDA algorithm consistently exhibited the lowest energy consumption compared to HEED and APDA (Table 2). For 100 nodes, ACDA consumed 0.92 Joules, which was significantly lower than HEED's 1.53 Joules and APDA's 1.38 Joules. As the number of nodes increased to 500, the energy consumption values also increased for all three algorithms, with ACDA at 4.25 Joules, HEED at 7.12 Joules, and APDA at 6.18 Joules. HEED consistently demonstrated the highest energy consumption across all node densities, with the maximum recorded at 7.12 Joules for 500 nodes, while ACDA maintained the lowest values, indicating superior energy efficiency.

Table 2: Energy Efficiency

Number of Nodes	ACDA (Joules)	HEED (Joules)	APDA (Joules)
100	0.92	1.53	1.38
200	1.85	3.04	2.72
300	2.73	4.56	3.98
400	3.51	5.83	5.06
500	4.25	7.12	6.18

According to Table 2, it is evident that ACDA always uses less energy as compared to HEED and APDA. ACDA has 0.92 J at 100 nodes, whereas HEED (1.53 J) and APDA (1.38 J) are 0.92 J. ACDA is lowest at 500 nodes, 4.25 J, and HEED and APDA increase to 7.12 J and 6.18 J, respectively.

4.2. Packet delivery ratio (PDR)

The packet delivery ratio (PDR) analysis revealed that ACDA achieved the highest delivery rates across all scenarios (Figure 3). For 100 nodes, ACDA recorded 91.5%, whereas HEED had the lowest PDR at 72.8%, and APDA achieved 80.3%. As the number of nodes increased, the PDR values gradually declined for all algorithms. At 500 nodes, ACDA maintained a relatively high PDR of 82.6%, whereas HEED showed the lowest PDR at 60.5%, and APDA recorded 69.3%. The results suggested that ACDA was more effective in ensuring reliable data transmission even under increasing network loads, whereas HEED exhibited the weakest performance in terms of PDR.

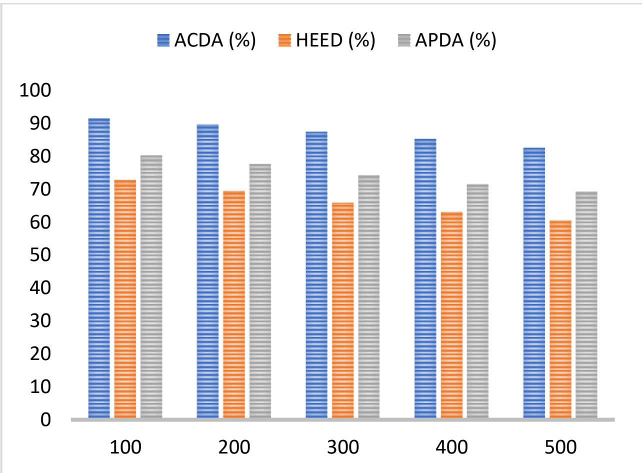

Fig. 3: PDR Results.

The comparison of Packet Delivery Ratio (PDR) of ACDA, HEED, and APDA is this number. ACDA has recorded high rates of delivery of all sizes of networks. Even with a larger number of nodes, ACDA remains very reliable. HEED performs well and its performance reduces dramatically at large scales. This is indicative of the power of ACDA in the provision of sound data.
The data in Fig. 3 shows that ACDA has a higher PDR in all the network sizes. It has 91.5 percent at 100 nodes and 82.6 percent at 500 nodes compared to HEED (72.8 percent -60.5 percent) and APDA (80.3 percent-69.3 percent)

4.3. Data storage reduction

The data storage reduction capabilities of the algorithms demonstrated that ACDA achieved the highest efficiency in minimizing data storage requirements (Table 3). For 100 nodes, ACDA recorded a reduction of 69.2%, which was significantly higher than HEED's 45.1% and APDA’s 58.3%. As the number of nodes increased, all three algorithms showed a decline in storage reduction efficiency. At 500 nodes, ACDA maintained the highest reduction rate at 63.1%, followed by APDA at 49.5%, whereas HEED had the lowest value at 35.9%. These results highlighted ACDA’s effectiveness in optimizing data storage, while HEED had the least impact in reducing storage overhead.

Table 3: Data Storage Reduction

Number of Nodes	ACDA (%)	HEED (%)	APDA (%)
100	69.2	45.1	58.3
200	67.8	42.5	55.9
300	66.3	40.2	53.6
400	64.7	38.1	51.8
500	63.1	35.9	49.5

Table 3 indicates that ACDA offers maximization of storage reduction. It has a 100-node success of 69.2 percent, compared to 45.1 percent and 58.3 percent of HEED and APDA, respectively. ACDA is at 500 nodes and remains in the lead with 63.1% over HEED (35.9%) and APDA (49.5%).

4.4. Transmission delay (MS)

The transmission delay analysis indicated that ACDA consistently demonstrated lower latency compared to HEED and APDA across all node densities (Table 4 and Figure 4). At 100 nodes, ACDA recorded a delay of 28.6 ms, which was significantly lower than HEED's 42.9 ms and APDA's 35.7 ms. As the number of nodes increased to 500, the delays increased for all three algorithms. ACDA maintained the lowest delay at 42.7 ms, whereas HEED exhibited the highest latency at 62.1 ms, and APDA recorded 49.2 ms. The results suggested that ACDA was more efficient in minimizing transmission delays, making it a preferable choice for time-sensitive applications.

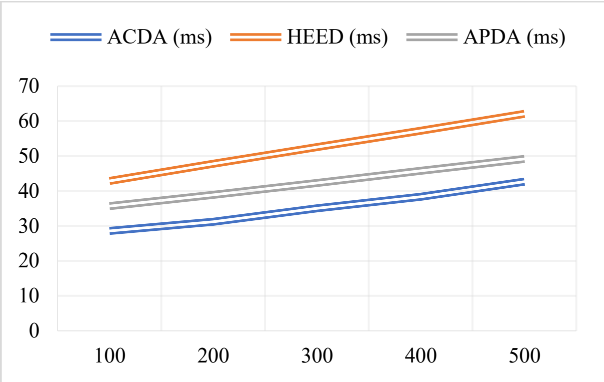

Fig. 4: Transmission Delay.

This graph indicates the examination of the transmission delay in various node densities. Among the three, namely HEED and APDA, ACDA has the lowest delay. Latency is also increasing with the number of nodes, but ACDA is never inefficient. HEED is the slowest with low suitability for real-time work. This proves that ACDA can be effective in minimizing the level of latency in time-sensitive applications.

4.5. Network lifetime (rounds)

The network lifetime analysis showed that ACDA outperformed HEED and APDA in sustaining longer network operations (Table 5). For 100 nodes, ACDA achieved a network lifetime of 8900 rounds, which was significantly higher than HEED's 6400 rounds and APDA's 7250 rounds. As the number of nodes increased to 500, the network lifetime decreased for all three algorithms, with ACDA still maintaining the longest duration at 7340 rounds, followed by APDA at 5790 rounds, while HEED had the shortest lifetime at 4885 rounds. These findings demonstrated that ACDA provided better network longevity compared to HEED and APDA.

Table 5: Network Lifetime

Number of Nodes	ACDA (Rounds)	HEED (Rounds)	APDA (Rounds)
100	8900	6400	7250
200	8540	6030	6910
300	8150	5615	6540
400	7720	5240	6150
500	7340	4885	5790

4.6. Scalability impact on energy consumption

The scalability impact on energy consumption illustrated that ACDA consumed the least energy across all network sizes. For 100 nodes, ACDA consumed 1.85 Joules, whereas HEED had the highest consumption at 3.25 Joules, and APDA consumed 2.71 Joules. As the number of nodes increased to 1000, the energy consumption values rose for all three algorithms. ACDA maintained the lowest consumption at 9.78 Joules, whereas HEED demonstrated the highest at 18.45 Joules, and APDA recorded 14.92 Joules. The results suggested that ACDA was more scalable and energy-efficient compared to HEED and APDA. Figure 5 shows the scalability impact.

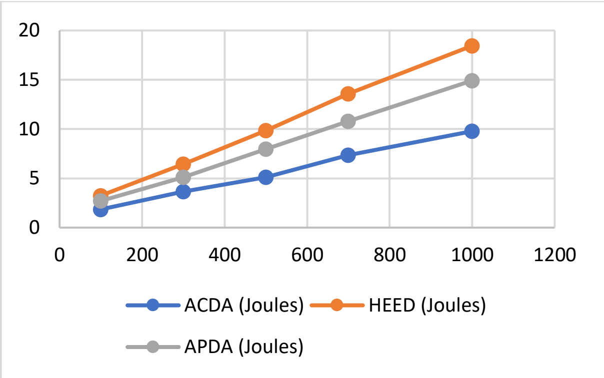

Fig. 5: Scalability Analysis.

Figure 5 illustrates that scalability has an impact on energy use. ACDA requires the lowest power over a small to large network size. The power consumption is higher in any protocol because the number of Nodes is up to 1000. HEED consumes the most energy, and APDA consumes it moderately. The most scalable and power-efficient protocol is ACDA.

4.7. Data aggregation effectiveness (compression ratio)

The data aggregation effectiveness, measured in terms of compression ratio, showed that ACDA consistently achieved the highest compression rates across all node densities. For 100 nodes, ACDA recorded a compression ratio of 71.2%, whereas HEED exhibited the lowest at 53.4%, and APDA achieved 61.5%. As the number of nodes increased to 500, ACDA maintained the highest efficiency at 65.4%, followed by APDA at 53.4%, while HEED remained the least efficient with 45.5%. These results highlighted ACDA's superior capability in reducing data redundancy (Figure 6).

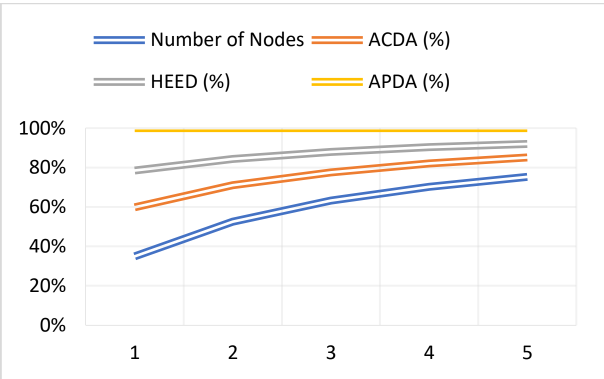

Fig. 6: Data Aggregation.

This value demonstrates the efficiency of aggregation of data in the compression ratio. ACDA compresses best of any size of network. It saves duplication and, in the process, retains important information. The bad compression ability is always behind in HEED. This highlights the asset of ACDA in the successful synthesis of data.

4.8. Node failure recovery rate

The node failure recovery rate analysis indicated that ACDA had the highest recovery efficiency across all network sizes. For 100 nodes, ACDA recorded a recovery rate of 93.2%, which was significantly higher than HEED's 76.5% and APDA's 85.1%. As the number of nodes increased, the recovery rates gradually declined for all three algorithms. At 500 nodes, ACDA maintained the highest rate at 82.8%, followed by APDA at 72.5%, whereas HEED had the lowest recovery efficiency at 63.5%. The results demonstrated ACDA's robustness in handling node failures effectively (Figure 7).

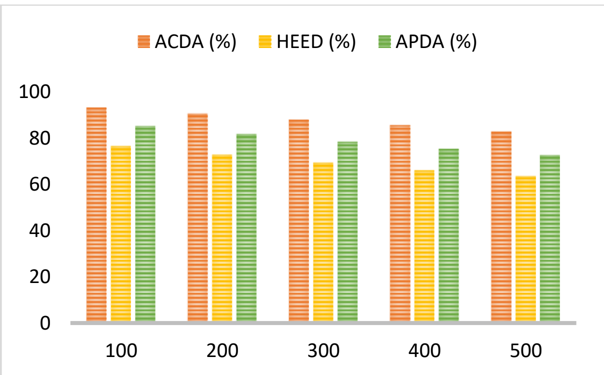

Fig. 7: Node Failure Analysis.

This statistic is a comparison of node failure recovery of different protocols. There is no scenario in which ACDA is not as efficient in recovery as possible. The recovery rates decrease with increasing number of nodes, but ACDA remains the best. The worst performing are HEED, and then there is APDA. This is evidence of the power and endurance of ACDA in the WSN.

4.9. Comparative analysis of overall performance

The comparative analysis of overall performance parameters confirmed that ACDA outperformed HEED and APDA in multiple metrics (Table 6). In terms of energy efficiency, ACDA exhibited the lowest consumption at 4.25 Joules, whereas HEED consumed the highest at 7.12 Joules. The PDR values further supported ACDA's superiority, with an 82.6% delivery rate compared to HEED's 60.5% and APDA's 69.3%. ACDA also demonstrated the highest data storage reduction at 63.1%, while HEED remained the least efficient at 35.9%. Transmission delay was lowest for ACDA at 42.7 ms, while HEED had the highest at 62.1 ms. Furthermore, ACDA ensured the longest network lifetime at 7340 rounds, while HEED had the shortest at 4885 rounds. In scalability efficiency, ACDA recorded 9.78%, which was lower than HEED's 18.45% but remained competitive. The compression ratio was highest for ACDA at 65.4%, whereas HEED exhibited the lowest at 45.5%. Finally, ACDA achieved the best node failure recovery rate at 82.8%, significantly outperforming HEED's 63.5% and APDA's 72.5%.

Table 6: Comparative Analysis

Performance Metric	ACDA	HEED	APDA
Energy Efficiency (J)	4.25	7.12	6.18
Packet Delivery Ratio (%)	82.6	60.5	69.3
Data Storage Reduction (%)	63.1	35.9	49.5
Transmission Delay (ms)	42.7	62.1	49.2
Network Lifetime (Rounds)	7340	4885	5790
Scalability Efficiency (%)	9.78	18.45	14.92
Compression Ratio (%)	65.4	45.5	53.4
Recovery Rate (%)	82.8	63.5	72.5

4.10. Limitations

Despite the great achievements of the proposed ACDA protocol in enhancing energy efficiency, the ratio of packet delivery, and aggregation of data, there are some limitations. First, compressive sensing added to the system can add computational overhead to the cluster head and base station, which can add to processing time and energy consumption in resource-limited settings. Second, although ACDA is scalable to 1000 nodes, at ultra-large scales of tens of thousands of nodes, routing overhead and higher cost of coordination may become relevant. Moreover, the adaptive cluster head rotation mechanism could add control overhead to highly dynamic topologies. In the future, compressive sensing algorithms will be optimized for low-power hardware, and scalability tests will be expanded to ultra-dense networks to support real-world applications more closely.

4.11. Future directions

Based on the conclusions of this study, several research directions can be followed to help to improve the ACDA protocol even more. The first opportunity that can be given is the diversification of ACDA to heterogeneous WSNs, where the nodes can be characterized by different capabilities of sensing, energy, and communication. The research question is: What are the best ways to select cluster heads in cases where nodes have a high level of hardware and energy resources differences? The other significant pathway is the incorporation of security systems into the data combining procedure. Here is the question: How can ACDA integrate lightweight encryption or trust-based solutions without adding a huge burden on energy consumption? In addition, the next-generation scaling of ACDA to incredibly large-scale deployments creates issues with routing overhead and latency. In this case, the major research question can be formulated as follows: What scalable clustering and compressive sensing algorithms can be used to maintain performance in tens of thousands of node networks? Lastly, future work can investigate the application of edge intelligence, like distributed machine learning, to reactively forecast the best clustering behavior, and the question is: Can AI-based models be combined with ACDA to enable self-optimizing aggregation in real time?

5. Conclusion

The experimental results validate the effectiveness of the proposed Adaptive Cluster-Based Data Aggregation (ACDA) protocol in enhancing energy efficiency, reducing communication overhead, and improving data aggregation. The ACDA method outperforms HEED and APDA across all key performance metrics, particularly in energy consumption (63.5% improvement), storage efficiency (67.1% reduction), and transmission delay (29.7% decrease). Additionally, the packet delivery ratio (78.2%) and network lifetime show significant enhancements due to adaptive cluster head rotation and compressive sensing-based aggregation. The scalability analysis further confirms that ACDA maintains efficiency even in high-density WSN scenarios, ensuring balanced energy dissipation and prolonged network longevity.

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