An Enhanced Adaptive Intelligent Clustering (AI-C) in Networks of Wireless Sensors

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Abstract: - For real-time applications, wireless sensor network technology driven by artificial intelligence (AI) is the way of the future. This technology makes it possible to collect data from almost any type of environment, analyze it instantly, and use its outcomes to improve operations and procedures. To optimize the clustering process in Wireless Sensor Networks (WSNs), an Adaptive Intelligent Clustering (AI-C) algorithm has been proposed previously where cluster heads are chosen probabilistically based on node distances and network density, though the scheme has shortcomings with respect to power usage and short network lifespan. The research proposed an Enhanced Adaptive Intelligent Clustering (EAI-C) based on the concept of machine learning techniques and dynamically modifies clustering parameters of node density, energy levels, and communication overhead of the current state of the network in cluster head (CH) formation. The cluster heads are selected intelligently and minimize energy depletion during data transfer. The proposed algorithm enhances the lifespan of sensor nodes while maintaining efficient network coverage. However, the scheme outperforms previous approaches of LEACH and AI-C in terms of extending network lifetime. Furthermore, the simulation result shows that the proposed approach achieved a better network performance, reduced energy consumption.

Key-Words: - Artificial Intelligence, wireless sensor network, LEACH, Machine Learning, AI-C, Enhanced AI-C.

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1 Introduction

Wireless Sensor Network (WSN) is a collection of sensor nodes that can be spatially distributed over a physical environment to monitor, collect, analyze and transfer data to a base station or hub for processing, [1]. The network is essentially employed in many different applications, such as smart healthcare, intelligent transportation, and industrial automation. Assessment of these network-based applications is closely related to one another considering the dynamic nature of the technology that can grow or shrink in its size, cost and energy, [2]. According to [3], resource challenges need to be improved using WSNs to adapt in dynamic environmental conditions, [4]. In this kind of network technology, sensor nodes are used at specific locations either static or dynamic depending on the environment and the data collected from the nodes. When data content does not change very frequently so stationary node deployment is frequently used where the nodes are deployed at targeted positions to gather information of a region for some time interval, [5]. On the other hand, mobile deployment is employed when regular data updates from the nodes are required. In mobile deployment settings, nodes are installed in automobiles, drones, and other vehicles and moved from one location to another in order to gather data, [6]. This kind of setup is helpful for applications that require frequent updates and gather data more precisely in real-time. Because they may be placed anywhere for mapping or monitoring, mobile nodes offer great data collecting accuracy, [7]. Deploying mobile nodes allows for the efficient and economical collection of data, and since new nodes do not need to be deployed, the data may be moved from one site to another. Random deployment, which is typically inexpensive, is used when the scale and complexity of the environment make node placement impractical. It is vital to develop energy-aware protocols that react to shifting environmental vibrations and balance the trade-offs between resources, volume, and cost in light of the demands for more robust and energy-efficient sensor network applications, [8]. WSNs can lower their energy consumption by using the hierarchical LEACH algorithm, [9]. Each cluster is led by a few randomly chosen nodes that gather data from nearby nodes and send it to a sink or base station. By distributing the energy consumption among nodes, the cluster heads rotate at random, extending the network's lifespan. As observed by [10], cluster head selection randomization causes LEACH to sometimes perform badly by neglecting to consider node location or energy levels into consideration. LEACH implementation follows a hierarchical routing fashion, which involves clustering of devices for transmitting data to the base station. The operation of LEACH is divided into the initial stage and the steady-state phase. During the initial stage or phase head node is selected randomly. Thereafter, an advertisement message is broadcast to the remaining nodes by the cluster leader. In order to hear all of the cluster-head nodes' ads, the non-cluster-head nodes must have their receivers turned on during this setup period. Each non-cluster-head node chooses which cluster it will be a part of for this round after this phase is over. The advertisement's received signal strength serves as the basis for this judgment. During the steady phase, nodes send data to the cluster head, which then relays it to the base station, [11].

A number of sectors, including smart cities, healthcare, military operations, and environmental monitoring, are increasingly employing wireless sensor network technology, though the technology struggles with issues related to data reliability, scalability, and energy efficiency because of multiple sensor nodes spread over large geographic areas. Through intelligent resource management, increased data processing efficiency, and network longevity, Adaptive Intelligent Clustering (AI-C) has become a crucial strategy for overcoming these obstacles, [12]. WSN sensor nodes operate on batteries, which might be difficult or unattainable to repair, especially in hazardous or distant areas. Distance increases the energy consumption of data transmission, and traditional network topologies often lead nodes far from the sink (data gathering point) to rapidly consume their batteries. By developing local groups (clusters) of nodes that interact with a single node called the head, which then transmits information to the base station (BS), clustering helps overcome the issue at hand. However, existing Low Energy Adaptive Clustering Hierarchy (LEACH) represents another grouping technique, is unable to dynamically adapt to changing network conditions or the level of energy. They often employ fixed criteria, which causes the network's energy consumption to be uneven. On the other hand, AI-C,, uses adaptive techniques to select CHs based on real-time factors such as remaining battery life, node location, and network load. This adaptive approach balances energy consumption across the network, prolonging the operational lifetime of the WSN, [13].

As WSNs increase in size, it becomes more challenging to handle a variety of nodes. Clustering must be done effectively for the avoidance of redundancy, interference, and inefficient transfers of data when there are many nodes. AI-C enables scalability by continuously adapting the cluster architecture to various node densities and circumstances. In order to minimize network congestion and data collision, AI-C encourages efficient data aggregation and lowers the quantity of transmissions needed by all nodes, [14]. The network of some nodes near the sink experiences higher transmission loads and energy loss, which is referred to as a "hot spot" problem. AI-C reduces the problem at hand by allocating the workload of data collection and transmission among several CHs and utilizing clever load-balancing algorithms.

As a result of this ongoing flexibility, nodes in AI-C address this problem by implementing intelligent load-balancing algorithms, which divide the burden of data transmission and aggregation among several CHs. The network's stability is improved by this dynamic adaptation, which makes sure nodes in densely populated areas don't use up their energy stores disproportionately, [15]. Safety and confidentiality are critical for certifications, such as those in sensitive industrial settings or the military. To help protect data at the cluster level, AI-C can be combined with AI-based anomaly detection algorithms to detect anomalous data transmission patterns or unauthorized access attempts. While there may be security risks associated with changing the clustering algorithm, AI-C can offer an extra degree of security without materially sacrificing energy efficiency, [16]. WSNs are widely used for systems where dependable data transmission is essential, such as environmental monitoring and emergency response systems. However, the integrity of that data may be jeopardized by inconsistencies brought on by interference, harsh environmental conditions, or node failures. By employing fault-tolerant clustering algorithms that identify and react to node failures, AI-C improves data reliability. Because AI-C is able to adjust to changing environmental conditions, it can also re-cluster without losing a lot of information in the event that a node or CH fails and can continue to communicate with one another, [17]. Intelligent algorithms further reduce latency by optimizing data routing paths across the network. By selecting CHs based on their proximity to the sink and other nodes, AI-C maximizes transmission delay. In addition to reducing latency, intelligent algorithms enhance data routing paths across the network. AI-C makes sure that data takes the shortest path by selecting CHs based on their proximity to the sink and other nodes, which minimizes transmission delay. This adaptability has a big impact on time-sensitive applications, like healthcare monitoring, where patient safety could be jeopardized by a delayed data transfer, [18].

2 Literature Review

The fundamental component of clustering in WSNs is LEACH. Energy efficiency is the main goal of modified LEACH protocols in a variety of contexts, including mobile and heterogeneous WSNs. LEACH-MEEC, which is perfect for mobile WSNs, was proposed by a study by [19] that combined multi-path routing to minimize packet loss during node mobility. Additionally, LEACH-RLC was presented by [20], which reduces control overhead by selecting the best cluster head (CH) using reinforcement learning (RL) and Mixed-Integer Linear Programming (MILP). LEACH-C and other centralized protocols optimize the Packet Delivery Ratio (PDR) while lowering node energy consumption. Using AI, especially machine learning, to make clustering and routing more adaptive is one new trend in WSNs. The use of reinforcement learning (RL) has grown in popularity. Agents are used by RL-based protocols, like LEACH-RLC, to learn the best timings for control messages and reduce energy consumption without sacrificing functionality. Fuzzy logic has been incorporated into clustering in addition to reinforcement learning to reduce uncertainty and improve routing choices. Fuzzy-based LEACH protocols, for instance, consider a variety of factors, including node proximity and residual energy, to guarantee more accurate CH selection. [21], also used a centralized clustering framework that uses artificial intelligence to create adaptive clusters in Internet of Things networks.

In order to increase network lifetime and balance energy consumption, hybrid clustering algorithms employ AI techniques such as Particle Swarm Optimization (PSO) and K-means clustering. These techniques use intelligent CH selection and dynamic cluster changes based on the network's current state to increase the network's lifespan. Furthermore, a hybrid PSO and K-means algorithm was proposed by [22], showing notable gains in network stability and energy efficiency over conventional methods. Artificial intelligence (AI) is a potent tool for solving complex structures or simulating time-consuming processes, according to [23] using a variety of techniques and algorithms.

According to the literature, neural networks are commonly used in a variety of topologies and for a range of purposes in processes including variable assortment, grouping, and cataloging. However, under some specific circumstances, these performances face a number of difficulties. For instance, the classification becomes less accurate and the neurons are unable to distinguish between the original inputs when the input space is normalized. The same thing occurs when the values of various inputs are comparable. Through an overall routing-based WSN scenario, the work of [24] demonstrated a clever technique for effective power utilization in a 6 G-enabled MEC-based ITS. They developed a dynamic model by applying a reinforcement learning-based methodology; they developed a dynamic model that can increase power utilization efficiency. The DAI with the SOM technique explains a decrease in routing response time as compared to other protocols. Compared to other protocols, the DAI with the SOM method uses fewer communication cycles, which lowers response latency.

Another active research area is energy harvesting-aware protocols, such as LEACH-MEEC, which selects CHs based on the energy harvesting capability of the nodes, prolonging the lifetime of the network in energy-deficient environments, and the protocol developed that adaptively adjusts routing decisions with harvested energy to make the overall network more stable, and the traditional energy-aware (EA) algorithm in [25] that minimizes the control overhead to extend the lifetime of the network with high PDR, which consists of three main modules: an energy-aware path selection method, a tree building methodology, and a clustering approach. We conducted experiments that enabled us to convincingly use essential rudiments for the first time: the underlying operating system, the machine code instruction set that enables us to program them as appropriate as apprehension animal measures stirring in the computer hardware of sensor nodes, and network environments and corporal features that persuade the network performance.

The research conducted by [26] suggested a basic clustering approach by establishing a minimum distance between cluster heads and examining the contiguity environment. The technique enables the task of clustering nodes for multiple circles in a single phase, assuming that the node physical arrangement stays the same. Even in the case of a node failure, our method just needs locally generated information to recalculate the contiguity environment. [27] Proposed a cluster head approach for aid. The scheme developed a dynamic mechanism to enable the construction of an assistant cluster head node. When selecting a cluster head, the main objective is to consume the least amount of energy. The metrics of the number of members in each cluster, the remaining energy of each node, and the geographic position of nodes to be cluster heads are used to choose the assistant cluster head. This method lowers the energy consumption of cluster member nodes, extending the life of a wireless sensor network. However, the network has additional delays as a result of the implemented approach operations; these delays arise during the collection of data from individual sensor nodes and their transmission to a base station, [28].

According to [29] using a range of methods and algorithms, artificial intelligence (AI) offers a powerful way to solve complex structures or mimic laborious processes. Processes like varied assortment, grouping, and cataloging are continuously carried out by neural networks in a variety of topologies and with a range of objectives throughout the literature. However, these performances encounter several challenges in certain situations. For example, when the input space is normalized, the classification becomes imprecise and the neurons cannot distinguish between the original inputs. When the values of other inputs are similar, the same phenomenon happens. Several levels of LEACH Routing with multiple hops (MMR LEACH) protocol were proposed.

By choosing two CHs, this protocol employs CH stacking in the network. The entire network is divided into many multi-tiers by the BS. In addition to choosing the helper CH based on the remaining energy, the main CH is in charge of gathering, compressing, and sending data to the BS. The helper CH serves as a conduit between the BS and the primary CHs of the network's bottom layers during data transfer. Clustering with two CHs, cluster stacking by BS, and scheduling are the three stages in which this protocol functions, [30]. To reduce communication overhead, multi-hop clustering and routing have also been investigated. For example, [31] created a multi-hop routing protocol that optimizes communication channels and energy consumption by building a routing tree inside clusters. By dynamically modifying the cluster borders according to node density, the clustering protocol based on voronoi diagrams, introduced by [32], further improves inter-cluster communication.

3 Research Methodology

3.1 Simulation Environment and Parameters Used

The simulation environment consists of a 3D space with sensor nodes distributed in it. Each protocol is tested over a predefined number of rounds with uniform initial energy and a random energy consumption model. The effectiveness of techniques is evaluated depending on parameters like network longevity, energy consumption, message sent, and in the case of Enhanced AI-C, additional metrics like average distance to cluster heads. A wireless sensor network with randomly distributed nodes in three dimensions serves as the basis for the simulation experiment. Gathering, evaluating, combining, and sending the sensed data to a central location or between sensors is the responsibility of the sensor node. Adaptive Intelligent Clustering, also known as AI-C, Improved AI-C, and Adaptive Clustering Hierarchy, or LEACH, are the protocols that have been tested. The effectiveness of each protocol is assessed according to its capacity to control data transfer, network robustness, and energy usage.

3.2 Node Distribution, and Traffic Patterns

A 3D sensor network architecture with (x, y, z) coordinate system is used with randomly assigned nodes to simulate a realistic deployment scenario with a variety of real-world scenarios, so the distances between the nodes must be calculated precisely to optimize network performance, energy efficiency, and communication effectiveness, which requires high-quality 3D positioning. Euclidean distance calculations are used to evaluate the interactions and density of the nodes in the three-dimensional space, and this parameter is used to assess the distance between nodes, which influences clustering and data transmission.

The network density, calculated as the ratio of the number of nodes to the total distance between them, provides information regarding the connectivity and distribution of the nodes in the network. The three-dimensional topology is important when analyzing various network protocols; for example, the LEACH approach requires a 3D layout to create clusters and assign cluster heads to better organize the clusters, and the AI-C and Enhanced AI-C protocols use 3D node placements and densities to enhance clustering and energy management. We also presented 2D projections of the 3D network (XY, XZ, and YZ planes) for easier visualization and analysis of the distribution of the nodes and overall topology of the network.

Figure 1 (Appendix) shows a 3D sensor network architecture with (x,y,z) coordinates. The nodes are randomly deployed to ascertain their behaviors.

3.3 The LEACH, Al-C, and Enhanced Al-C Protocols are Being Implemented

3.3.1 Low-Energy Adaptive Clustering Hierarchy, or LEACH Protocol

Wireless sensor networks (WSNs) can optimize their energy consumption with the help of the hierarchical LEACH protocol. Every round, a few sensor nodes are chosen at random to serve as cluster leaders, gathering data from nearby nodes and transmitting it to a sink or base station. The lifetime of the network is enhanced overall because of a random rotation of cluster heads, which balances energy consumption among nodes. However, due to the random nature of head node selection, LEACH fails to always consider node location or power levels into account, which in some cases can result in subpar performance.

Algorithm1: LEACH Protocol

```
function CALCULATE DISTANCE (node1,node2)
(a) Calculate the Euclidean
   distancebetweentwopointsin3Dspace.
(b) Return the computed distance.
end function
function CALCULATEDENSITY (nodes)
(a) Initialize total distanceto0.
for each node pair (i,j) in the list of nodes do
1. Compute the distance between the nodes using
   CALCULATE DISTANCE
2.Addthedistancetototaldistance.
end for
(c) Calculatedensityasthenumberofnodesdividedbytotal
   distance.
(d) Returnthedensity.
endfunction
functionSIMULATELEACH (sensornodes, rounds,
   initialenergy, p = 0.1)
(a)
   Initializevariables:numberofnodes,energyarray,listsfor
   metrics (lifetime, energy consumed, packets sent).
foreachroundfrom0toroundsdo
1.Determine cluster heads randomly based on
   probability p and energy levels.
2. If no cluster heads are chosen, randomly select one
   from nodes.
3.Simulate random energy consumption for each node
   and update energy levels.
4. Calculate network lifetime, total energy consumed,
   and total packets sent.
5. Append metrics to their respective lists.
6. If all energy levels ≤ 0, break the loop.
end for
7.Returnthelistsformetrics.
endfunction
```

3.3.2 AI-C Protocol (Artificial Intelligence-based Clustering)

AI-C has enhanced the LEACH protocol, including more intelligent cluster head selection. Instead of choosing cluster heads at random, AI-C uses a probabilistic approach that takes into account node distances and network density. A node's average distance from other nodes and its remaining energy are both taken into consideration when determining its likelihood of being selected as the cluster head. AI-C approach aims to reduce energy consumption across the network as opposed to LEACH, producing a more balanced energy usage and longer network lifetime.

Algorithm 2: AI-C Protocol

```
AI-C Protocol
function SIMULATE_AI_C(sensor_nodes, rounds, initial_energy)
    (a) Initialize variables: number of nodes, energy array, lists for metri
(lifetime, energy_consumed, packets_sent).
    for each round from 0 to rounds do
        i. Calculate network density.
        for each node do
            ii. Compute probabilities based on distance, density, and e
ergy levels.
        end for
        iii. Select cluster heads based on top probabilities.
        iv. Simulate random energy consumption for each node and u
date energy levels.
        v. Calculate network lifetime, total energy consumed, and tot
packets sent.
        vi. Append metrics to their respective lists.
        vii. If all energy levels ≤ 0, break the loop.
    end for
    (c) Return the lists for metrics.
end function
```

Two variables were added to improve energy management and cluster head selection, the Enhanced AI-C protocol outperforms AI-C. When considering dynamic network components such as optimization factors and residual energy weighting, it makes the selection process more responsive to the current state of the network. The distance to the selected cluster heads determines how much power is used, and dynamically changes the frequency of cluster head selection according to average energy levels. With these enhancements, network lifetime should be increased beyond what the AI-C protocol can provide, performance should be maximized, and energy consumption should be further reduced.

3.3.3 Enhanced AI-C Protocol

Algorithm 3: Enhanced AI-C Protocol

```
function SIMULATE ENHANCED AIC (sensor nodes rounds, initial energy)
(a) Initialize variables number of nodes, energy array, lists for metrics (lifetime, energy consumed, packets sent).
for each round from 0 to rounds do
1.Calculate network density.
for each node do
i. Compute probabilities with additional factors like optimization and residual energy weighting.
end for
ii. Select cluster heads based on top probabilities.
iii. Adjust energy consumption based on distance to cluster head and simulate random energy consumption.
iv. Update energy levels.
v. Dynamically adjust cluster head selection frequency based on energy usage.
vi. Calculate network lifetime, total energy consumed and total packets sent.
vii. Append metrics to their respective lists.
viii. If all energy levels ≤0, break the loop.
end for
(b) Return the lists for metrics.
end function
```

Mathematical tools were deployed to enhance AI-C to select cluster heads, calculate probabilities, and simulate energy usage based on the following models:

3.3.3.1 Cluster Head Selection

The probability for a sensor node *i* to be a cluster leader is computed based on various factors of optimization, distance, and residual energy usage as provided below.

$$p_i = \frac{w_1 \cdot E_{rest,i} + w_2 \cdot \frac{1}{d_1} + w_3 \cdot OP_i}{\sum_{j=1}^{N}(w_1 \cdot E_{rest,j} + w_2 \cdot \frac{1}{d_1} + w_3 \cdot OP_j} \quad (1)$$

where:

- ✓ p_i is the chances for a node iii to be a cluster head.
- ✓ $E_{rest,i}$: is the residual power of node *i*
- ✓ d_1 is the distance from node *i* to the base station or cluster head.
- ✓ $OP_{i\ and}\ \ OP_j\ \ is\ the$ Optimisation factor, which may account for load balancing or communication efficiency.
- ✓ w_1, w_2, w_3 are the weights for residual energy, distance, and optimization, respectively.
- ✓ N is the total number of nodes.

3.3.3.2 Energy Usage

The amount of energy used by a node iii during communication is modeled as follows:

$$E = \begin{cases} E_{tx}\,(k, d_i)\ if transmitting \\ E_{rx}(k)\ if receiving \end{cases} \quad (2)$$

where:

- ✓ $E_{tx}(k, d_i) = k.E_{elect} + k.\in.d_n^i\ which$ is the energy for transferring$k$ -bit data over a ranged_i.
- ✓ $E_{rx}(k) = k.E_{elect}\ is$ Energy for receiving k -bit data.
- ✓ E_{elect} is the energy per bit for electronic operations.
- ✓ $\in is\ the$ amplifier energy for transmitting.
- ✓ n is the path loss exponent (normally n =2 for free-space, n =4 for multipath).

3.3.3.3 Dynamic Adjustment of Cluster Head Frequency

The frequency of cluster head selection is dynamically adjusted based on the average residual energy of the network:

$$F_{adjusted} = F_{initial}\ x\ \frac{E_{average}}{E_{maximum}} \quad (3)$$

where:

- ✓ $F_{adjusted}$ is the adjusted frequency for cluster head reselection.
- ✓ $F_{initial}$ is the Initial cluster head frequency.
- ✓ $E_{average}$ is the average residual power of nodes.
- ✓ $E_{maximum}$ is the maximum possible energy of a node.

3.3.3.4 Network Lifetime Calculation

The network lifespan is calculated as Number of cycles formed until the first node dies or all nodes have $E_{res,i} \leq 0$

$$Network\ lifetime = max\{t: E_{res,i} > 0\ \forall\ i \in N\} \quad (4)$$

3.3.3.5 Overall Metrics

The following metrics are monitored by the algorithm.

- ✓ Total Energy Consumed

$$E_{total} = \sum_{i=1}^{N} E_{tconsumed,i} \quad (5)$$

- ✓ Total Packets Sent

$$packets_{total} = \sum_{i=1}^{N} packets_i \quad (6)$$

The Enhanced AI-C Protocol enhances the AI-C protocol, which is a scheme that employs decision-making mechanisms to optimize cluster head selection and energy efficiency,- by minimizing communication costs and weighting residual energy, which ensures that more robust nodes assume the role of cluster heads to balance workload distribution and prolong network lifetime, and it can dynamically adapt to the state of the network. The dynamic approach reduces redundant re-clustering events, preserving energy and improving overall effectiveness. Considering the factors of distance and residual energy, which ensure better accuracy in simulations and energy updates, the EAI-C protocol models energy usage/consumption is enhanced.

Table 1 (Appendix) hold the comparison of the three main algorithms and their features in terms of: cluster head selection, energy usage and the network lifetime respectively. LEACH has a randomized cluster head selection approach, with moderate energy usage and the network lifetime is also moderate. In addition, the cluster head selection in AI-C probability based, and the network lifetime has greatly improved. Lastly, the EAI-C protocol has weighted cluster head selection approach.

3.4 Performance Evaluation Metrics.

The following metrics were deployed to analyze the efficiency of the suggested EAI-C over the existing algorithm:

i. Network Lifetime which shows the fraction of nodes that still have energy remaining.
ii. Total Energy Consumed for the sum of energy used by all nodes.
iii. Total Packets Sent: The total amount of messages transmitted by the nodes.
iv. Average Distance to Cluster Head (for Enhanced AI-C): The mean distance from nodes to their cluster heads.
v. Dynamic Cluster Head Selection Frequency

4 Results and Discussions

4.1 Network Lifetime

i. LEACH: Because the percentage of live nodes rapidly drops over time, the original LEACH protocol has the shortest network lifetime.
ii. Al-C: While the Al-C protocol has a marginally longer network lifetime than LEACH, the number of active nodes still significantly reduces.
iii. Enhanced Al-C has a gentler slope to the percentage of active nodes, which suggests that its improved cluster head selection and

energy-efficient techniques are more effective in extending the network lifetime, with Enhanced Al-C having the longest network lifetime.

4.2 Energy Consumption:

i. LEACH consumes the most energy at the beginning, as it randomly selects the cluster head and may lead to an energy imbalance.
ii. This node uses very little energy and attempts to equalize the energy among its nodes.
iii. The Enhanced Al-C protocol uses the least amount of energy in cluster head selection and data transmission.

4.3 Packets Sent

i. Due to the possibility of redundant transmissions and its less effective routing technique, LEACH transmits a comparatively high volume of packets.
ii. Al-C: Al-C appears to have fewer packets than LEACH, indicating less redundancy and improved routing.
iii. The protocol that transfers the fewest packets, Enhanced Al-C, exhibits an efficient routing strategy and minimal overhead.

4.4 Average Cluster Head Distance

i. LEACH: Since the average cluster head distance in LEACH is slightly greater, it may allocate nodes to far cluster heads, which increases the communication cost.
ii. Al-C: The average cluster head distance in Al-C is slightly shorter than that of LEACH, which indicates that the cluster head selection is slightly improved.
iii. Enhanced Al-C: This technique has the potential to form more compact and effective clusters (the lowest average cluster head distance).

4.5 Data Aggregation Efficiency

i. LEACH: Considering that it may not always process data efficiently before sending it, LEACH's overall data efficiency is moderate.
ii. Al-C: Although it can still be enhanced, Al-C's data aggregation efficiency is marginally higher than LEACH.
iii. Enhanced Al-C: The protocol's maximum data aggregation efficiency demonstrates how well it reduces repeated transmissions.

Figure 2 (Appendix) shows a result obtained from the simulation experiment carried out using jupyter notebook. The result clearly shows the behavior of the three algorithms under study (LEACH, AI-C and Enhanced AI-C) respectively.

5 Conclusion

The simulation experiment compared three protocols: Enhanced AI-C, LEACH, and AI-Cere. The LEACH protocol is a traditional method that randomly selects cluster heads, while the more advanced AI-C probabilistically chooses heads based on node energy levels and network density. The most advanced and robust scheme is enhanced AI-C, which uses dynamic adjustments and optimization parameters to increase network life and energy efficiency. In terms of packet transmission, average cluster head distance, data aggregation efficiency, network longevity, and energy efficiency, the Enhanced Al-C protocol performs better than both LEACH and Al-C. The Enhanced Al-C protocol improved cluster head selection, energy-efficient routing, and effective data aggregation strategies used in the algorithm are all responsible for its performance.

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APPENDIX

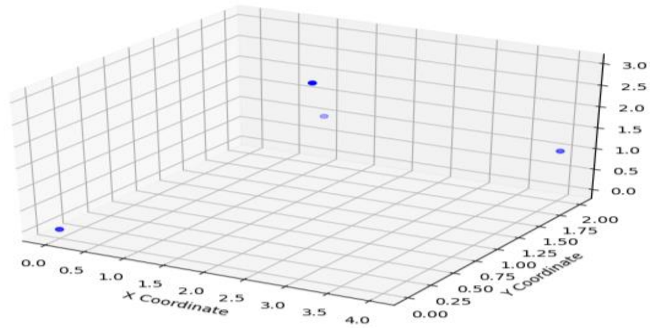

Fig. 1: Network Topology
Source: created by the authors

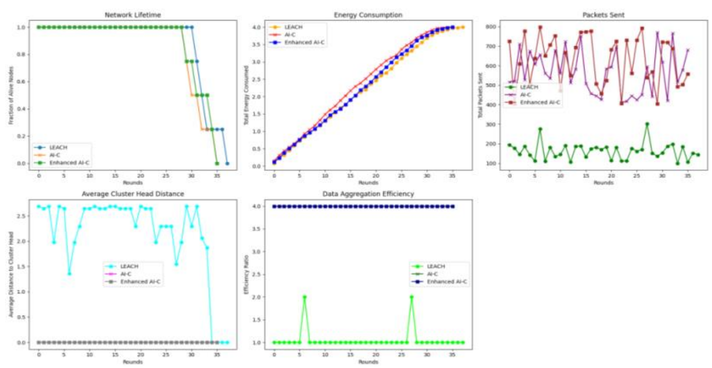

Fig. 2: Simulation results
Source: created by the authors

Table 1. Comparisons between Algorithms

Feature	LEACH	AI-C	EAI-C
Cluster Head Selection	Randomized approach	Probability-based	Weighted probabilities
Energy usage	Moderate usage	Energy calculated by distance and density of nodes	Adds dynamic adjustment to node clustering frequency
Network Lifetime	Moderate usage	Improved	Enhance due to dynamic adjustments

Source: [20]

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