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ARTICLE

Clustering in Sensor Networks Using Regional Hierarchical Optimization: A Hybrid LEACH-ACO-GA Approach

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ABSTRACT: This study introduces a hybrid routing protocol, Low Energy Adaptive Clustering Hierarchy—Ant Colony Optimization—Genetic Algorithm (LEACH-ACO-GA), for wireless sensor networks. It combines regional ant colony optimization for cluster head selection with inter-cluster routing based on a genetic algorithm. The proposed method reduces energy consumption from 6.9 J (LEACH Classic) to 5.6 J (LEACH-ACO-GA) and decreases latency from 460 to 390 ms, while maintaining a packet delivery ratio of 0.97. These values are averaged over 70 rounds based on 30 independent simulation runs conducted on networks with 50 and 200 nodes. The hybrid method extends network lifetime by up to 50% compared to traditional LEACH and improves performance robustness in dense network environments. The results indicate that two-level metaheuristic optimization is effective for scalable and energy-efficient wireless sensor networks in Internet of Things scenarios.

KEYWORDS: ACO; genetic algorithm; LEACH protocol; WSN; latency; energy consumption; expected transmission count

1 Introduction

Wireless sensor networks (WSNs) have become a fundamental component of modern monitoring and control systems, enabling diverse applications such as energy optimization and environmental observation [1]. Nevertheless, the deployment of these networks is strongly limited by inherent resource constraints, notably restricted energy reserves, limited bandwidth, and modest processing capabilities at the sensor node level [2]. Among these constraints, energy availability remains the most critical issue, as sensor nodes usually rely on finite power sources, including batteries or renewable solutions such as solar energy. This limitation directly affects network lifetime and reliability [3,4].

Limited node energy, unbalanced cluster formation, and communication latency remain persistent challenges in WSNs. Although LEACH-based hierarchical protocols exhibit good scalability, empirical studies indicate that maintaining energy efficiency becomes challenging in dense and dynamically evolving network topologies. Current hybrid LEACH-based methodologies, such as LEACH-GA or LEACH-ACO, generally implement optimization at a singular level, concentrating either on cluster-head (CH) selection or inter-cluster routing, rather than simultaneously addressing both dimensions. This constraint leads to unstable routing, premature node failure, and uneven depletion of energy resources between regions. To address these challenges, a hierarchical clustering protocol known as Low Energy Adaptive Clustering

Hierarchy (LEACH) was established to enhance energy efficiency via the periodic rotation of cluster leaders [5]. Notwithstanding its advantages, LEACH does have its limitations, particularly in its ability to provide scalability and flexibility in dynamic network topologies [6].

This study explores and compares the performance of various LEACH protocol variants for IoT networks, including LEACH Classic, LEACH-GA (Genetic Algorithm) [7], LEACH-ACO (Ant Colony Optimization) [8], and a LEACH Hybrid approach combining GA and ACO [9]. The analysis focuses on performance optimization across different network sizes (50 and 200 nodes), with particular attention to energy consumption, packet delivery ratio (PDR), and latency. The study analyzes how hybrid approaches improve the efficiency and reliability of wireless sensor networks by comparing the strengths and limitations of each strategy. Due to their dynamic nature and constrained resources, efficient routing and clustering remain essential for prolonging network lifetime and reducing energy consumption [10]. Combining meta-heuristic algorithms with natural and biological behaviors has led to the development of flexible and reliable approaches for solving NP-hard routing and clustering problems in large-scale networks [11]. Algorithms like Ant Colony Optimization (ACO) and Genetic Algorithms (GA) have proven to be effective in discovering energy-efficient solutions while operating within limited computational constraints [12,13].

In contrast to existing LEACH-GA and LEACH-ACO, the proposed regional hierarchical hybrid LEACH-ACO-GA model features a two-level optimization structure, rather than applying GA and ACO independently or sequentially at the global level. This architecture employs ACO locally in each region to identify the most energy-efficient cluster heads (CHs), while GA is utilized globally to optimize inter-cluster routing to the base station. This area segmentation improves scalability and reduces computational complexity in concentrated deployments. A weighted multi-objective cost function (Eq. (8)) simultaneously optimizes energy consumption, latency, and load balancing. The cooperative interaction between ACO and GA improves energy distribution, reduces latency, and extends network lifetime by mitigating premature convergence compared to traditional hybrid methods. Table 1 summarizes the structural differences between the proposed approach and existing LEACH-based hybrid variants. These findings underscore the efficacy of hybrid metaheuristic methodologies in tackling critical wireless sensor network difficulties, including energy depletion, uneven load distribution, and scalability limitations in dense networks [14]. The proposed hybrid model significantly improves energy efficiency, network robustness, and communication performance, resulting in extended network lifetime and reduced latency compared to the classic LEACH model. This research establishes a basis for subsequent investigation into intelligent hybrid optimization methods, emphasizing real-time adaptability, machine learning upgrades, and dynamic clustering tactics to enhance IoT network resilience and performance.

Table 1: Structural comparison of LEACH-based hybrid clustering approaches.

Approach	**Optimization Scope**	**Metaheuristic Role**	**Routing Strategy**	**Structural Characteristic**
LEACH-GA	Global	GA for CH selection	Direct or simplified	Single-stage optimization
LEACH-ACO	Global	ACO for CH selection	Implicit or direct	Single-stage optimization
GA–ACO Hybrid [8&23]	Global or sequential	GA and ACO	Global routing	Loosely coupled hybrid
Proposed LEACH–ACO–GA	Local + Global	ACO (local), GA (global)	Inter-cluster optimized	Regional hierarchical coupling

This work is arranged as follows: Section 2 presents related work, Section 3 describes the proposed method, Section 4 presents the dataset structure, Section 5 details the implementation, Section 6 presents the simulation results, Section 7 discusses the results, and Section 8 concludes the paper.

2 Related Work

The many uses of wireless sensor networks in fields as diverse as the Internet of Things (IoT), smart cities, and environmental monitoring have prompted extensive research into these networks. LEACH is one of the most widely adopted low energy routing protocols, and it has been continuously enhanced and extended over time [15].

Various studies have focused on optimizing cluster head (CH) selection, improving security mechanisms, and integrating bio-inspired optimization techniques for better energy management. Hussain et al. [15] investigated LEACH successors extensively, classifying them according to CH selection optimization, hybrid clustering, and energy harvesting techniques. Their analysis highlights that optimizing the CH selection process can significantly improve network longevity and reduce communication overhead.

Kalra et al. [16] created the Energy-Effective Scalable Routing Algorithm (EESRA), which is an improved version of LEACH that is better suited for cognitive radio networks (CRNs). Their method combines hierarchical clustering with multi-hop communication, which extends network lifetime and reduces energy consumption.

Hybrid optimization methods have also become more popular for routing in WSNs. Kumar et al. [17] developed the Whale-Ant Optimization Algorithm (WAOA) by combining whale optimization to select the best CH and ant colony optimization (ACO) to find the best route. Their results showed that they were more energy-efficient than MOORP and AZEBR, with longer network lifetimes and better energy balance.

Abose et al. [18] focused on energy-efficient clustering by introducing Improved Residual Energy LEACH (IMP-RES-EL) and Energy-Efficient LEACH (EEL). Their simulations showed a 36% improvement in network longevity and a 44% increase in aggregated data transmission compared to traditional LEACH implementations.

Murugesan et al. [19] enhanced the lifetime of the network through a Modified Ant Colony Optimization (M-ACO) algorithm, which ensures a better energy distribution and reduces the early depletion of nodes. Their experiments validated that M-ACO achieves more stable network performance and lower latency.

Wang et al. [20] improved node energy consumption using an enhanced ant colony optimization (ACO) method that modifies the state transition formula to avoid premature stagnation. Their research shows that selecting paths with higher residual energy can extend the lifetime of a network by 52%.

El Khediri et al. [21] proposed a hybrid metaheuristic approach that integrates Artificial Bee Colony (ABC) and ACO for WSN routing. Their method showed a 40% improvement in network lifetime and a significant reduction in energy consumption between sensor nodes.

Badole and Thakare [22] explored the application of Genetic Algorithms (GA) in optimizing cluster-based multicast routing in VANETs, achieving improvements of up to 23.2% in throughput and 22% in network longevity compared to traditional routing protocols.

Suresh and Prasad [23] proposed an energy-efficient and secure routing framework using LEACH for IoT-based WSNs. Their rank-based CH selection strategy improved communication quality while optimizing energy conservation.

Recently, certain hybrid approaches that mix deterministic clustering with machine learning have been created to make WSNs use even less energy. Qamar and Munir [24] proposed an LEACH-D–ANN framework that integrates deterministic clustering with artificial neural networks and Bayesian regularization. Their model improves cluster-head selection and energy-aware routing compared to conventional LEACH and other clustering protocols, resulting in lower energy consumption and extended network lifetime. In a related study, the same authors [25] proposed a hybrid LEACH-D combined with ANN to improve the stability of the energy distribution and delay initial node failure in dense networks. These deterministic clustering models that utilize artificial neural networks (ANNs) illustrate the promise of data-driven optimization in wireless sensor networks. The regional LEACH-ACO-GA protocol introduced in this paper adopts a dual-level metaheuristic optimization technique that simultaneously enhances cluster-head selection and inter-cluster routing, focusing on energy efficiency, latency reduction, and load balancing objectives. This distinction illustrates that our approach is complementary to LEACH-D–ANN methods and contributes a metaheuristic alternative that aligns with current research trends. Similarly, learning self-growth maps and multi-view clustering approaches focus on data-centric problems such as imbalanced streaming data and imprecision across heterogeneous feature representations, while dynamic 3D CAD model clustering methods rely on inertial or geometric feature encoders to group complex shapes. Although these works share the general concept of clustering, they operate at a different abstraction level and do not consider network-level constraints such as energy consumption, routing efficiency, latency, or cluster-head selection in wireless sensor networks. Consequently, direct quantitative comparison with the proposed energy-aware hierarchical routing framework is not applicable.

Recent optimization studies have also been reported in other application domains, such as automotive radar systems in spectrally crowded V2I environments and high-precision space target localization using multi-sensor association. Although these works employ advanced optimization techniques, they address domain-specific sensing and estimation problems and do not consider network-level constraints such as energy efficiency, clustering, routing, or network lifetime in wireless sensor networks.

In [26], the authors examined the application of metaheuristic optimization methodologies for routing updates in WSNs. To improve the resilience and efficiency of wireless sensor networks, future research should focus on lightweight cryptography, adaptive clustering in real-time, blockchain security, and hybrid routing algorithms based on artificial intelligence [27].

3 Proposed Method

The proposed methodology employs a hierarchical network architecture, segmented into many zones to enhance energy efficiency and scalability of the sensor network. In the proposed approach, the deployment area is spatially divided into a fixed number of regions using an equal-area grid-based partitioning strategy. The network field is segmented into rectangular regions of identical size, and sensor nodes are assigned to regions according to their geographical coordinates. All clustering and optimization operations are first performed locally within each region before global inter-cluster routing optimization is applied.

This hybrid methodology integrates two synergistic algorithms:

- Ant Colony Optimization (ACO) for the best selection of cluster heads (CHs), ensuring a balanced distribution of responsibilities and enhanced energy management [28,29].
- Genetic Algorithm (GA) for the efficient routing of data between Cluster Heads (CHs) and the Base Station (BS), aimed at minimizing communication expenses [30–32].

Initially, ACO dynamically identifies the ideal nodes as Cluster Heads (CHs). Subsequently, genetic algorithms are employed to determine the optimal communication pathways between the cluster heads and the base station.

At each round, ACO selects the cluster heads, and GA subsequently refines the solution, ensuring continuous joint optimization of clustering and inter-cluster communication. After the formation of clusters, the cluster heads communicate the gathered data to the base station via pathways optimized by genetic algorithms. An example of the resulting grid-based regional partitioning and the distribution of clusters generated by the hybrid LEACH-ACO-GA methodology is illustrated in Fig. 1. The proposed hybrid framework's synergy between ACO and GA is based on the complementary character of their search mechanisms. ACO efficiently identifies local optima for cluster-head (CH) placement by performing exploration through pheromone-guided probabilistic decisions. Through mutation and crossover operations, GA guarantees the global refinement and exploitation of CH to BS routes. Thus, the proposed architecture accomplishes a balance between global optimization, thereby preventing premature convergence, a limitation of numerous conventional hybrids. In this work, the genetic algorithm optimizes the selection of cluster heads, while the resulting inter-cluster communication cost is implicitly evaluated through distance- and latency-based metrics rather than explicit CH-BS path encoding. This design choice allows routing efficiency to be captured within the multi-objective optimization framework without increasing algorithmic complexity.

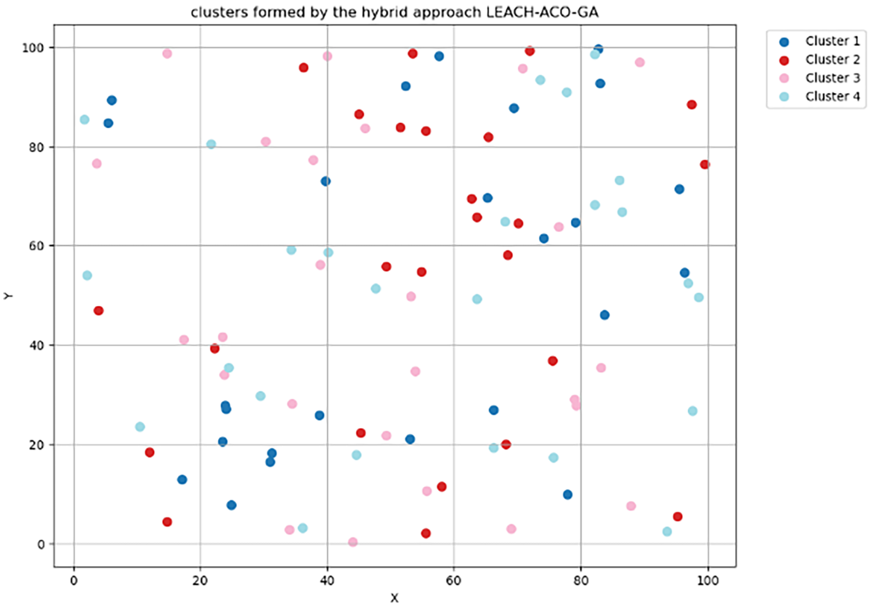

Figure 1: Spatial clustering obtained using the proposed LEACH–ACO–GA framework, illustrating the equal-area grid-based regional partitioning of the network field.

The objective function (Eq. (8)) incorporates normalized metrics of energy, latency, and average distance with adaptive weights w_1, w_2, w_3, and w_4.

3.1 Optimization Constraints

To optimize clustering, the network is divided into several regions, each grouping a certain number of nodes while respecting various constraints.

3.1.1 Energy Constraints

Each node has a limited energy capacity E_i, while cluster heads (CHs) consume more energy due to their additional functions. Eq. (1) represents the total residual energy of the network at a given round and serves as a as global indicator of network lifetime. The proposed protocol aims to preserve this residual energy over time by optimizing cluster head (CH) selection, reducing transmission distances, and adopting rotation mechanisms to balance the energy load.

$$E_{\text{res}} = \sum_{i=1}^{N} E_i \tag{1}$$

3.1.2 Distance Constraint

A node can only join a cluster whose cluster head (CH) is situated at a maximum acceptable distance d_{max}. To optimize energy consumption, the distance between the CH and its members must be reduced, which is expressed by

$$d_{intra} = \sum_{i=1}^{M} d(i, CH) \tag{2}$$

where

- d_{intra} represents the sum of the distances between each member node i and its CH.
- M is the total number of nodes in the cluster.
- $d(i, CH)$ is the distance between node i and its CH.

3.1.3 Connectivity Constraint

All cluster heads (CHs) must be connected to the base station (BS) either directly or via other CHs. A CH can only relay data if it has sufficient remaining power, i.e.:

$$E_{CH} > E_{\text{threshold}} \tag{3}$$

where:

- E_{CH} is the remaining energy of CH,
- $E_{threshold}$ is the minimum energy level required to relay data. and is set to 0.1 E_{init} (constant across rounds).

This constraint ensures network stability by preventing a depleted CH from becoming a point of failure while ensuring efficient transmission to the base station.

3.1.4 Load Constraint

A cluster head (CH) can only manage a maximum number of nodes, noted as N_{max}. The aim is to ensure a homogeneous distribution of clusters, respecting the relation:

$$\frac{N}{K} \approx N_{\text{average per cluster}} \tag{4}$$

where

- N is the total number of nodes in the network.

- K is the total number of clusters.
- $N_{\text{average per cluster}}$ represents the average number of nodes per cluster.

This constraint aims to avoid overloading the CHs by guaranteeing a balanced distribution of nodes within the network. The following Table 2 groups the constraints we have defined.

Table 2: Clustering constraints and formulations.

Constraint	Formula	Description
Minimum Energy Threshold	$E_i \geq E_{\min}$	Prevents weak nodes from becoming CHs
Maximum Distance to BS	$d(i, BS) \leq d_{\max}$	Reduces long-range transmissions to save energy
At Least One CH per Region	$\forall r, \quad \exists CH_r \in N_r$	Ensures complete network coverage
Minimization of CH-to-BS Distance (GA)	$\min \sum_{i=1}^{N_{CH}} d_{CH_i, BS}$	Reduces energy consumption for inter-cluster communication
ACO-based CH Selection	$\text{Score}i = \alpha \times \frac{1}{E_i} + \beta \times d(i, BS)$	Ensures optimal CH selection by balancing energy and distance
Load Constraint	$N_{CH} \leq N_{\max}, N_{\max} = \frac{N}{K}$	Balances cluster distribution to prevent CH overload

Note: ^{r} denotes the region.

3.2 *Define the Metrics*

Latency: the total latency of a sensor network is the time between a sensor sending a packet and the base station (BS) receiving it, measured in milliseconds.

$$\text{Latency}_{\text{Total}} = \sum_{i=1}^{N} \text{latency}_{\text{i}} \tag{5}$$

In this work, latency is considered an aggregate network-level metric that reflects transmission and routing delays within the clustering process during each simulation round. It is used to evaluate the impact of cluster-head selection and routing efficiency on packet delivery time. The queuing delay, the physical propagation delay, and the node processing delay are not explicitly modeled.

Where N is the total number of active nodes transmitting data.

A high latency can slow packet transmission, which is especially problematic for real-time applications.

Energy: sensor networks use energy to transmit data from sensors to their Cluster Head (CH), aggregate data at the CH, and send CH data to the base station.

$$E_{\text{cons}}^{(r)} = \sum_{i=1}^{N} \left(E_{\text{transmission},i}^{(r)} + E_{\text{reception},i}^{(r)} + E_{\text{aggregation},i}^{(r)} \right) \tag{6}$$

(Eqs. (1) and (6)) operate at different abstraction levels. Eq. (6) quantifies the energy consumed during each round, while Eq. (1) represents the total residual energy of the network used to assess network lifetime.

This metric quantifies the energy consumed per round and is expressed in joules (J),

where

- N is the total number of nodes,
- $E_{(\text{transmission},i)}$ represents the energy used to transmit sensor data to the CH,
- $E_{(\text{reception},i)}$ is the energy needed to receive packets at the CH level,
- $E_{(\text{aggregation},i)}$ is the energy consumed by the CH to process and send data.

High energy consumption reduces network lifespan and efficiency.

Packet Delivery Ratio (PDR): compares the number of successful packets to the total number of packets sent to determine packet transmission efficiency. If $PDR = 1.0$, no packets were lost, whereas a $PDR < 1.0$ indicates packet losses due to collisions, low connectivity, or interference.

$$PDR = \frac{\text{Packets successfully received}}{\text{Packets sent}} \tag{7}$$

In the simulation, packet reception is modeled probabilistically as a function of communication distance. For each transmitted packet, the reception outcome is determined according to a distance-dependent loss probability, which increases with the hop distance between the transmitting node and its cluster head and is bounded to avoid unrealistic loss values. The number of successfully received packets used in Eq. (7) is obtained by aggregating these probabilistic transmission outcomes over all nodes and rounds.

A high PDR ensures reliable communication and better service, whereas a low PDR causes data loss, which is critical for sensitive applications that need precise and fast data transmission.

3.3 Object Function

Multiple performance measures, including energy consumption, latency, load balance, and average distance, are aggregated into a single score using a weighted sum technique, where a lower score denotes improved performance by means of cost reduction across several dimensions.

$$\text{Score} = w_1 \cdot EC + w_2 \cdot LT + w_3 \cdot LB + w_4 \cdot \text{AvgDistance} \tag{8}$$

We use equal weights that are standardized in this work:

$$w_1 = w_2 = w_3 = w_4 = 0.25 \tag{9}$$

this ensures that no single criterion takes priority over optimization. This choice was made to maintain a neutral and fair compromise between the performance measures considered and to facilitate consistent comparison with other LEACH-based approaches. Preliminary observations with small variations in weightings showed no significant impact on the relative performance ranking of the evaluated protocols, indicating that the proposed optimization is not overly sensitive to moderate change in weighting.

4 Dataset Structure for Simulations

Metaheuristic algorithms like ACO, GA, and Hybrid LEACH-ACO-GA in WSNs require a well-defined dataset configuration. The following Table 3 organizes simulation parameters for network topology, energy models, communication settings, and optimization. These settings accurately assess clustering efficiency, energy use, and network performance.

Table 3: Simulation parameters.

Parameter	Description	Value Range
Number of Nodes (N)	Total number of sensor nodes in the network	$50 \leq N \leq 200$
Network Area (A)	Deployment area dimensions (square/rectangle)	100×100 m^2
Initial Energy (E_{init})	Initial energy per node	2.0 J
Packet Size (P_s)	Data packet size transmitted	4000 bits
Transmission Energy (E_{tx})	Energy per transmission	50×10^{-9} J/bit
Reception Energy (E_{rx})	Energy per reception	50×10^{-9} J/bit
Amplifier Energy (E_{fs}, E_{mp})	Free-space and multipath fading models	10^{-12} to 0.0013×10^{-12} J/bit/m^2
Threshold Distance (d_0)	Distance for switching between E_{fs} and E_{mp}	75 to 100 m
Base Station Position	Coordinates of the sink node (BS)	$(50, 150)$
Number of Clusters (K)	Number of cluster heads per round	5 (Fixed)
ACO Parameters (α, β, ρ)	Pheromone influence and evaporation rate	$\alpha = 1, \beta = 2, \rho = 0.5$, Num Ants = 20, Iterations = 50
GA Parameters	Population size, generations, mutation/crossover rates	Config 1: Pop = 70, Gen = 50, Mut = 0.1 Config 2: Pop = 30, Gen = 50, Mut = 0.1 Config 3: Pop = 50, Gen = 50, Mut = 0.1
Simulation Rounds (R)	Number of iterations for protocol execution	$50 \leq R \leq 200$

The number of clusters was fixed to k = 5 for all protocols to ensure a fair and consistent comparison under identical simulation conditions. This setting follows common practice in LEACH-based studies, and the investigation of adaptive cluster count selection is left for future work.

Experiment Environment

The Anaconda environment was employed to conduct all simulations in Python 3.11 using Jupyter Notebook. The experiments were conducted on a computer that was equiped with a Windows 10 (64 bit) operating system, 16 GB of RAM, and an Intel Core i7-8665U (1.9 GHz) CPU. Three GA configurations (population = 30–70, generations = 50, mutation = 0.1) were tested, and each protocol was evaluated for 50 to 200 cycles. In order to attain convergence stability, the ACO parameters ($\alpha = 1$, $\beta = 2$, $\rho = 0.5$, 20 ants, 50 iterations) were adjusted through pilot experiments. Clusters were arbitrarily initialized within a 100 * 100 m^2 region, and the base station was fixed at coordinates (50, 150) m.

5 Implementation of Algorithms

5.1 Algorithm 1: Cluster Head Selection Using Ant Colony Optimization (ACO)

In Algorithm 1, $\tau(i)$ denotes the pheromone intensity associated with node i, while the heuristic information $\eta(i)$ is computed from the node's residual energy and its distance from the base station.

Algorithm 1: Cluster head (CH) selection using ACO

```
Init: Place $N$ sensors, BS; set $(m, \rho, \alpha, \beta, Q)$, initialize $\tau(i) = \tau_0$
repeat
    ACO Clustering:
    for node $i$ do
        if $i$ meets energy/distance constraints then
            $P(i) = \frac{\tau(i)^{\alpha}\eta(i)^{\beta}}{\sum_j \tau(j)^{\alpha}\eta(j)^{\beta}}$
        end if
    end for
    Select CHs (≥1/region)
    for each CH $i$ do
        $\tau(i) \leftarrow (1-\rho)\tau(i) + \Delta\tau(i)$
    end for
    Assign non-CH nodes to the nearest CH
    sensors send to CHs; CHs aggregate & send to BS; update energy
    for each link $(i, j)$ do
        $\tau(i, j) \leftarrow (1-\rho)\tau(i, j) + \frac{Q}{\text{Score}}$
    end for
    compute metrics (energy, latency, balancing, and distance).
    Score = $w_1E + w_2L + w_3B + w_4D$
until Energy threshold or max rounds
```

This method (Algorithm 1) improves LEACH by using the Ant Colony Optimization (ACO) algorithm to choose Cluster Heads (CHs) and optimize routing operations in wireless sensor networks. Optimizing cluster head selection and data routing enhances energy efficiency and extends network lifetime. Wireless sensor networks increase energy efficiency and extend network lifespan. The procedure begins with sensor initialization and the configuration of ACO parameters, including pheromones, evaporation rate, and influencing factors. In each cycle, ACO assigns CHs based on numerous criteria. Selection is probabilistic based on pheromone concentration and residual energy. After clustering, sensors send data to their Cluster Head (CH), which forwards the aggregated data to the Base Station (BS) directly or via ACO-optimized multi-hop routing. After each transmission, the pheromones disperse to avoid biased learning and enhance the most efficient pathways based on energy consumption, latency, load balance, and the average distance between sensors and the cluster head. The technique continues until insufficient remaining energy or the maximum number of rounds is reached.

It is important to note that pheromone updates are applied exclusively during the cluster head selection phase within each region. Routing decisions between cluster heads and the base station are optimized independently by the genetic algorithm and are not influenced by ACO pheromone information.

5.2 Algorithm 2: Cluster Head Selection Using Genetic Algorithm (GA)

The evolutionary Algorithm 2 enhances the selection of Cluster Heads (CHs) to augment energy efficiency and communication inside a wireless sensor network. Following startup, during which sensors are randomly distributed and settings established, an initial population of solutions is created. Then, each solution is evaluated based on a bunch of criteria: distance between CH and BS, delay, load balancing, energy consumption, and average distance between the sensor and CH, which makes it easier to give a weighted score. The progression of the genetic algorithm happens through selection, crossover, and mutation, improving the solutions over several generations. then, each sensor connects to its nearest Cluster Head (CH), facilitating data transfer from the sensor to the CHs, and then to the base station, accompanied by an update on the energy expended. The method terminates when energy is inadequate or after reaching a predetermined maximum number of generations, and the optimal solution identified is returned for clustering purposes.

Algorithm 2: Cluster head selection using genetic algorithm (GA)

```
1: Initialization:
2: Deploy $N$ sensors at $(x_m, y_m)$; place the BS at $(BS_x, BS_y)$.
3: Set GA parameters: population size $pop\_size$, number of generations $num\_generations$, crossover
   probability $P_c$, mutation probability $P_m$, and weights $[w_1, w_2, w_3, w_4]$.
4: Generate Initial Population:
5: for $i = 1$ to $pop\_size$ do
6:     Generate solution $S_i$ with $k$ random Cluster Heads (CHs).
7:     Add $S_i$ to the population.
8: end for
9: Evaluation:
10: for each solution $S$ do
11:     Compute the fitness score:
        $\text{Score}(S) = w_1EC + w_2LT + w_3LB + w_4AvgDist$
12: end for
13: Genetic Evolution:
14: for $g = 1$ to $num\_generations$ do
15:     Select parents (roulette or tournament selection).
16:     Apply crossover and mutation with rates $P_c$ and $P_m$.
17:     Evaluate offspring and update fitness scores.
18:     Retain the best individuals for the next generation.
19: end for
20: Clustering: Assign each sensor to the nearest CH.
21: Data Transmission: Sensors send data to CHs; CHs aggregate and transmit to BS; update energy levels.
22: Stopping Criteria:
23: if energy is exhausted or $g = num\_generations$ then
24:     Output the best routing solution.
25: else
26:     Repeat from Step 4.
27: end if
```

5.3 *Algorithm 3: Cluster Head Selection Using Hybrid Algorithm (LEACH+ACO+GA)*

The approach (Algorithm 3) enhances sensor clustering and routing in a wireless sensor network by employing Ant Colony Optimization (ACO) for Cluster Head (CH) selection and a Genetic approach (GA) for route optimization. The process starts with initialization, the specification of network settings, the random deployment of sensors, and the placement of the base station (BS). The network is later divided into regions, with each sensor assigned to a certain region. Multiple constraints are imposed, including a minimum energy threshold, a maximum permissible distance to the base station, and the requirement of at least one cluster head per region.

Algorithm 3: Hierarchical cluster-based routing algorithm.

```
Initialization:
Set network parameters: $num\_nodes$, $(xm, ym)$, $E_{init}, E_{tx}, E_{rx}, E_{fs}, E_{mp}, d_0, packet\_size$.
Place the Base Station (BS) at coordinates $(\frac{xm}{2}, ym + 50)$.
for each sensor $i$ in $num\_nodes$ do
    Assign random $(x, y)$ coordinates within $(xm, ym)$.
    Initialize energy $E_i = E_{init}$.
    Set region index $i \leftarrow 0$.
end for
Assignment of Regions:
Divide the observed area into $num\_regions$.
for each sensor $i$ do
    Allocate a sensor $i$ to a region according to its coordinates.
end for
Establish Constraints:
for each sensor $i$ do
    if $E_i \leq threshold$ then
        Mark sensor $i$ as inactive.
    end if
    if $distance(i, BS) > max\_distance$ then
        Mark the sensor $i$ as unreachable.
    end if
end for
Ensure each region contains at least one candidate Cluster Head (CH).
Selection of Cluster Heads (CHs) via ACO:
for each region $r$ do
    Initialize pheromone levels.
    for $iter = 1$ to $num\_ants$ do
        for each sensor $i$ in region $r$ do
            Compute local score based on residual energy and proximity to BS.
        end for
        Select the optimal CH in region $r$.
        Update pheromone levels.
    end for
    if no valid CH is found then
        Select the sensor with highest energy as CH.
    end if
end for
Routing Optimization using Genetic Algorithm (GA):
Ensure each region has at least one CH.
Initialize inter-CH routes and CH–BS routes.
for $g = 1$ to $num\_generations$ do
```

(Continued)

Algorithm 3 (continued)

```
42:     Evaluate each solution using the multi-objective score:
          $Score(S) = w_1 EC + w_2 LT + w_3 LB + w_4 AvgDist$
43: end for
44: Output the most efficient path
```

ACO algorithm identifies cluster heads by systematically assessing energy levels and distance to the base station, while updating pheromones to strengthen optimal selections. If no genuine CH is identified, the sensor with the greatest energy is selected. The genetic algorithm subsequently enhances routing by developing a population of potential CH to BS pathways throughout several generations, assessing solutions based on distance, and employing crossover and mutation to improve the optimal routes. The method finishes by providing the ideal Cluster Head selection and the most effective routing strategy to reduce energy consumption and improve network performance. Fig. 2 shows the general procedure of the suggested approach.

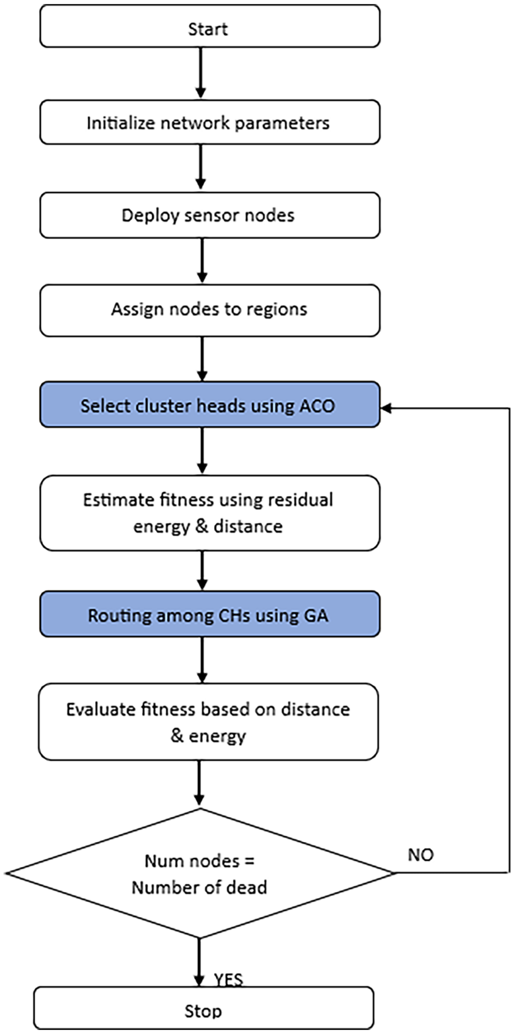

Figure 2: Flowchart of the proposed methodology.

6 Simulation and Result

In order to evaluate the effectiveness of the proposed clustering and routing methods, comprehensive simulations were performed to assess the influence of various LEACH-based protocols, including LEACH Classic, LEACH-GA, LEACH-ACO, and the hybrid LEACH-ACO-GA approach, on critical network performance indicators such as energy consumption, packet delivery rate (PDR), latency, and network longevity. The simulations were designed to accurately represent real wireless sensor networks, in which sensor nodes operate with limited energy resources and fluctuating communication constraints.

The performance analysis across various network sizes seeks to illustrate the advantages of hybrid methodologies in prolonging network longevity and enhancing overall efficiency. This section delineates the simulation structure, assessment measures, and outcomes analysis. All simulations were conducted under a static wireless sensor network assumption, which is consistent with the original LEACH design. This setting enables a controlled evaluation of the proposed clustering and routing strategies. Extending the proposed approach to dynamic scenarios involving node mobility or unexpected node failures is considered an important direction for future work.

A. Convergence of the Classic LEACH Algorithm

The development of a Low-Energy Adaptive Clustering Hierarchy (LEACH) score is shown in Fig. 3. The score represents how energy consumption and network delay are balanced. A gradual decrease is observed over iterations, indicating ideal cluster head selection and better load balancing to reduce energy consumption while maintaining effective communication. The generally consistent convergence of the protocol demonstrates its effectiveness in the network structure; however, some variations reflect the influence of random variables such as node energy distribution and communication distance. The method operates in cycles of cluster selection and leader node rotation, therefore equilibrating energy consumption across sensors. This figure highlights LEACH's effectiveness in extending network lifetime while suggesting possible improvements. Optimal cluster selection or integration with other enhancement methodologies, as illustrated in the following figures, can achieve these improvements.

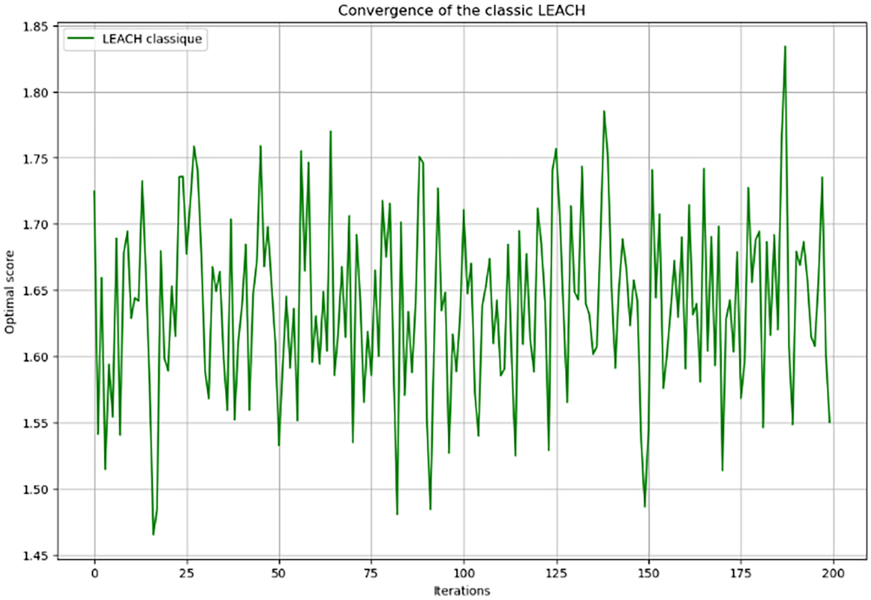

Figure 3: Convergence of the classic LEACH.

B. Convergence of the Genetic Algorithm

The evolution of the genetic algorithm (GA) through generations for three different configurations is depicted in Fig. 4. Each curve illustrates the progression of the optimal score achieved over the iterations, with a lower score indicating a more effective solution in terms of optimization.

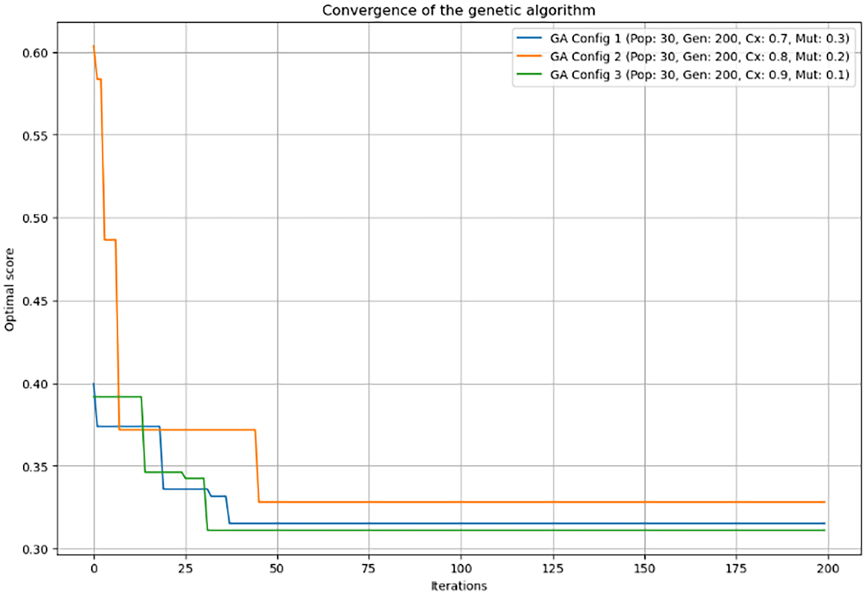

Figure 4: Convergence of genetic algorithm.

In all configurations, there is a consistent downward trend in scores, which means that the algorithm consistently identifies the best-performing options. The variations between the curves illustrate the influence of crossover (cx_prob) and mutation (mut_prob) factors on the velocity and stability of convergence. An increased crossover rate promotes rapid convergence toward an optimal solution, while a reduced mutation probability decreases genetic diversity and can lead to trapping in local optima. A greater mutation probability promotes the discovery of novel solutions, however may impede convergence to a stable solution.

This research underscores the significance of parameter selection in reconciling the utilization of known solutions with the investigation of novel alternatives to prevent local optima.

C. Convergence of the Ant Colony Optimisation (ACO) Algorithm

Figs. 5 and 6 illustrate the convergence behavior of the ACO algorithm under different configurations. Fig. 5 shows the evolution of the optimal score over iterations, while Fig. 6 presents the average convergence performance across configurations. This algorithm employs pheromones to explore the solution space and choose the optimal alternatives, inspired by ants. The algorithm's capacity to adapt to pheromones is shown by the curves' score increases.

The influence of parameters is very noticeable. Exploration-exploitation balance depends on pheromone evaporation rate (rho). A quick evaporation rate reduces pheromone concentration on a single solution, promoting exploration, whereas a lesser rate encourages exploitation of recognized solutions. Number of ants (num_ants) affects exploration quality, with more ants allowing more solutions to be investigated in parallel and boosting search resilience. Certain configurations converge quicker, emphasizing the significance of parameter selection in algorithm optimization. This graphic shows how pheromones affect collective learning and how exploration and exploitation lead to an ideal solution.

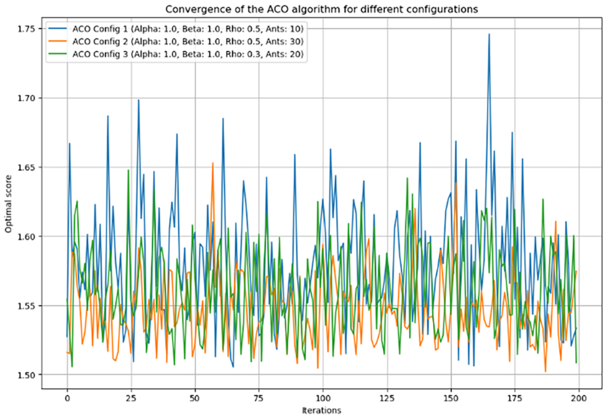

Figure 5: ACO algorithm convergence.

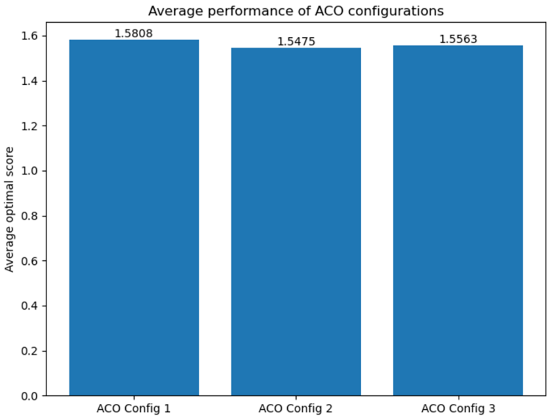

Figure 6: Average convergence of ACO algorithm.

D. Convergence of the Hybrid Approach (ACO-GA)

Fig. 7 shows how population size (pop_size), crossover rate (cx_prob), mutation rate (mut_prob), and ACO algorithm parameters (alpha, beta, rho, num_ants) affect optimization and the hybrid ACO-GA approach's convergence for different genetic algorithm configurations. All configurations improve in score, proving that ACO for cluster-head selection and GA for global optimization refine solutions. A bigger population (pop_size = 50) and high crossover rate (cx_prob = 0.9) accelerate convergence to an optimal solution, while a lower mutation (mut_prob = 0.1) reduces variability and stabilizes the solution rapidly. ACO works best with a balanced pheromone intensity (alpha = 1.0), a moderate distance impact (beta = 1.0), an optimal evaporation rate (rho = 0.3) in order to prevent losing accumulated information too quickly, and enough ants (num_ants = 30) to efficiently explore the solution space. Pop_size = 50, cx_prob = 0.9, mut_prob = 0.1, alpha = 1.0, beta =1.0, rho = 0.3, and num_ants = 30 appear to be the optimal combination for speedy and efficient convergence to an optimized solution.

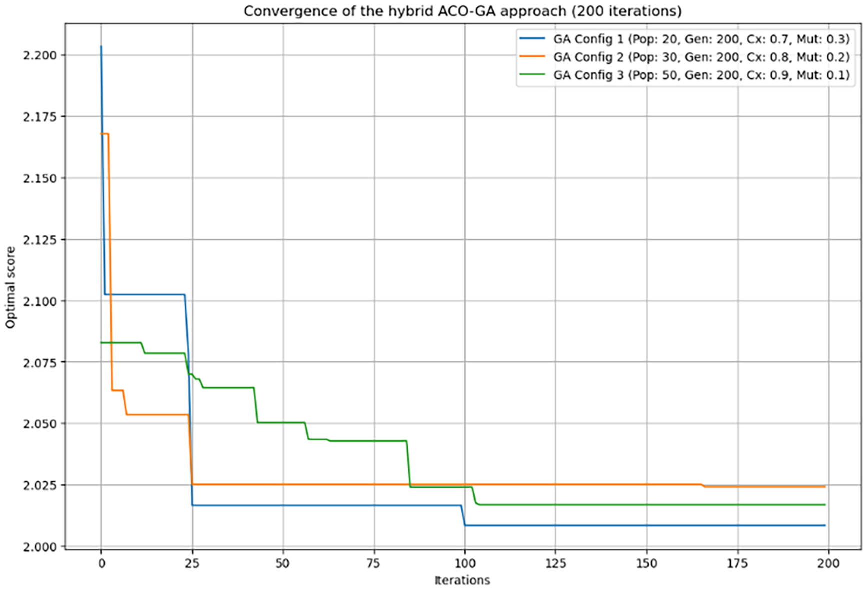

Figure 7: Convergence of the hybrid approach.

In this work, network lifetime is evaluated based on the evolution of the number of alive nodes over simulation rounds. In particular, the first node death (FND) is used as a primary reference point for lifetime comparison, and all protocols are assessed using the same criterion for consistency.

6.1 Simulation Results for 50 Nodes

The results of Figs. 8–14 confirm that, for a 50-node network, LEACH Hybrid (GA + ACO) consistently outperforms the other variants. It achieves the lowest energy consumption and preserves a higher number of active nodes over time, reflecting superior energy management. Classical LEACH exhibits the fastest degradation, whereas LEACH+GA and LEACH+ACO partially mitigate early node depletion. Latency remains more stable for GA- and ACO-based methods, with the hybrid protocol achieving the lowest and least fluctuating delay. At first, all protocols keep a high PDR, but LEACH drops it earlier as nodes go down. In contrast, the hybrid method sustains a stable delivery rate throughout the simulation. Overall, with 50 nodes, LEACH Hybrid proves to be the most resilient and efficient solution across energy, latency, and reliability metrics. All results are averaged over 30 independent simulation runs, and the error bars shown in the figures represent the standard deviation. Since the evaluated performance metrics evolve over simulation rounds and exhibit consistent trends across all independent runs, standard deviation was considered sufficient to assess result variability, and formal hypothesis testing was not applied, as the analysis focuses on long-term protocol behavior rather than point-wise statistical significance.

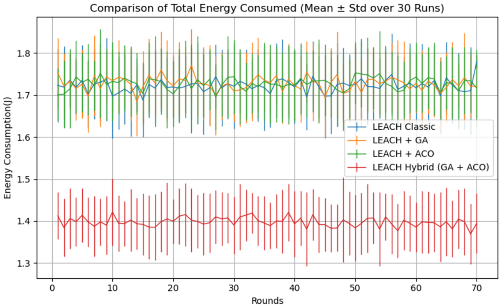

Figure 8: Comparison of energy consumption (50 nodes).

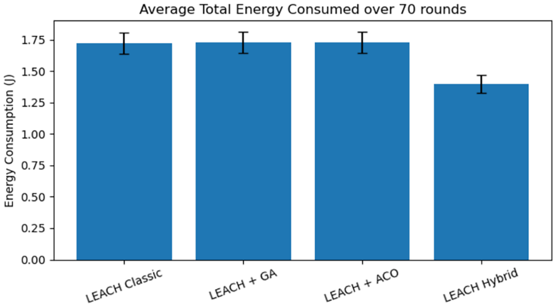

Figure 9: Average energy consumption over all rounds (50 nodes); error bars indicate standard deviation over 30 runs.

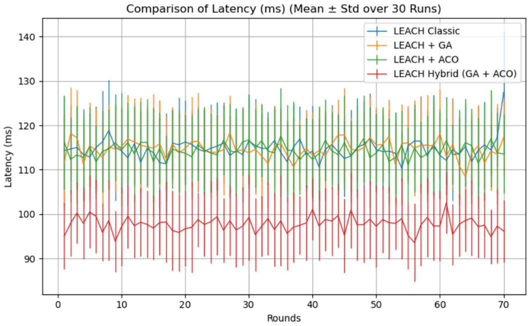

Figure 10: Comparison of latency (50 nodes).

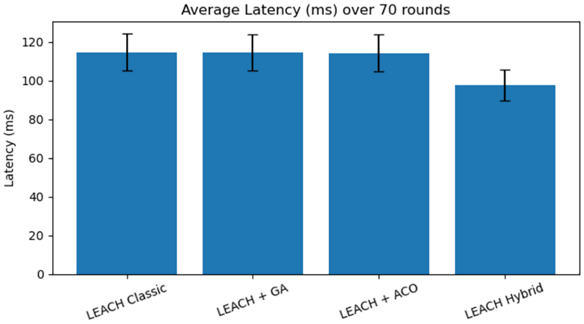

Figure 11: Average latency over all rounds (50 nodes), error bars indicate standard deviation over 30 runs.

Figure 12: Comparison of packet delivery ratio (PDR) for 50 nodes.

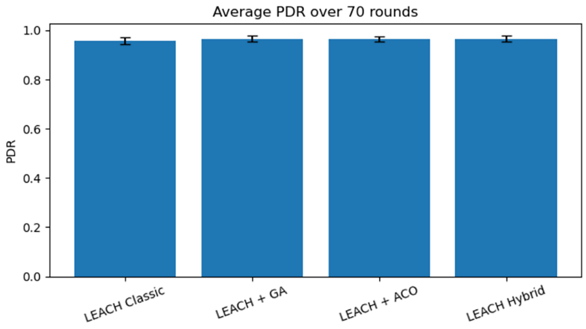

Figure 13: Average PDR over all rounds for 50 nodes; error bars indicate standard deviation over 30 runs.

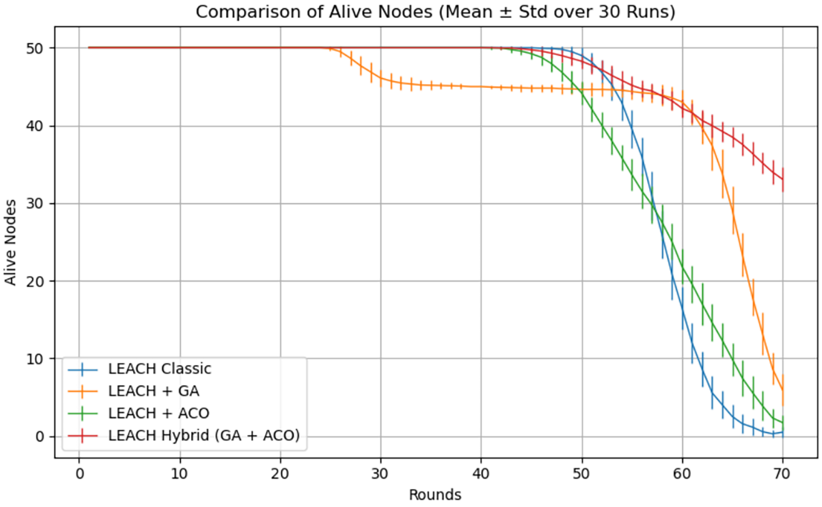

Figure 14: Comparison of lifetime of 50 nodes.

6.2 Simulation Results for 200 Nodes

Figs. 15–21 present the comparative performance results for the 200-node network in terms of energy consumption, latency, packet delivery ratio (PDR), and network lifetime.

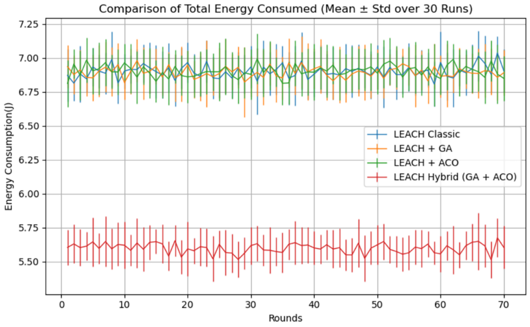

Figure 15: Comparison of energy consumption for 200 nodes.

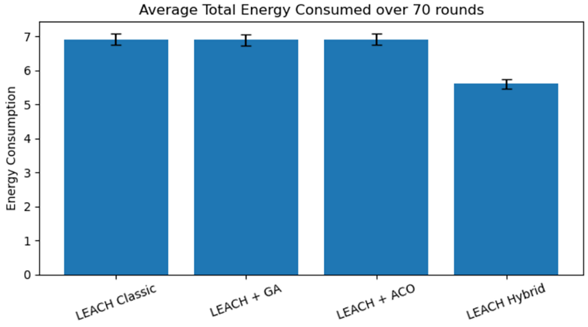

Figure 16: Average energy consumption over all rounds for 200 nodes; error bars indicate standard deviation over 30 runs.

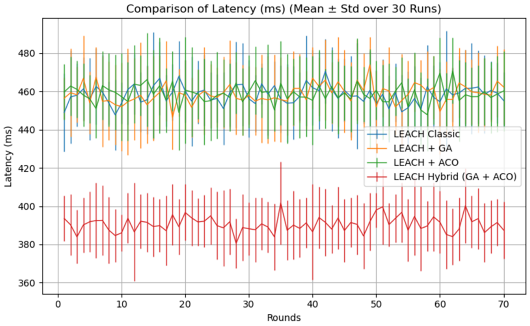

Figure 17: Comparison of latency for 200 nodes.

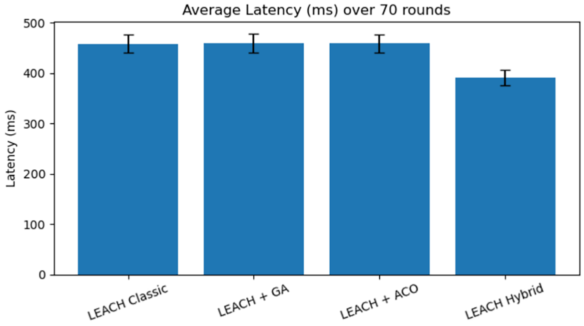

Figure 18: Average latency over all rounds for 200 nodes; error bars indicate standard deviation over 30 runs.

Figure 19: Packet delivery ratio (PDR) for 200 nodes.

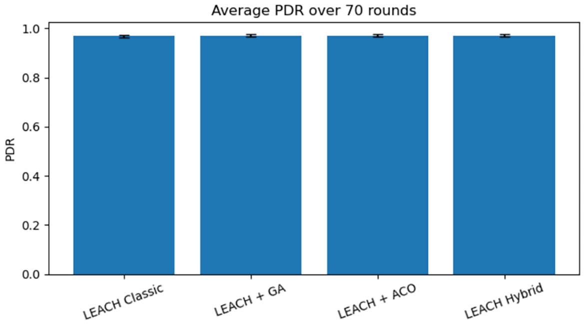

Figure 20: Average PDR over all rounds for 200 nodes; error bars indicate standard deviation over 30 runs.

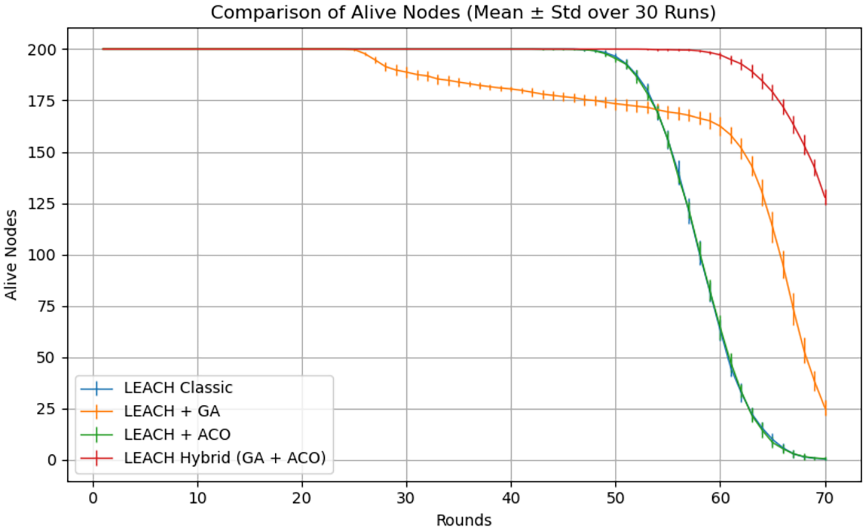

Figure 21: Comparison of lifetime of 200 nodes.

In a 200-node network evaluated over 70 rounds, LEACH Hybrid provides the best overall performance across energy consumption, latency, and packet delivery ratio. LEACH Classic uses the most energy and depletes nodes first, while GA and ACO improve moderately. Efficiency in cluster head selection and improved routing give the hybrid system the lowest energy consumption and longest network lifetime. In contrast to LEACH, GA, and ACO, the Hybrid approach consistently achieves lower and more stable latency. All protocols maintain a high PDR (0.97), but LEACH Classic shows larger fluctuations as nodes begin to fail. Increasing the network size from 50 to 200 nodes improves overall stability and prolongs network longevity, with LEACH Hybrid remaining the most robust and efficient configuration. Table 4 summarizes the comparative performance, highlighting the clear advantages of GA-based, ACO-based, and especially hybrid optimization over classical LEACH.

Table 4: Performance comparison of LEACH variants.

Metric	LEACH Classic	LEACH + GA	LEACH + ACO	LEACH Hybrid (GA + ACO)
Latency	High	Moderate	High	Very low
Energy Consumption	High	Medium	Medium–High	Low
PDR	1.0 (less stable)	1.0	1.0	1.0 (most stable)

These results represent the average of 30 independent simulation runs, with standard deviation bars used to illustrate performance variability across rounds

Although the simulation environment does not explicitly model low-level MAC collisions or interference patterns, packet loss is implicitly considered through a probabilistic delivery model dependent on the communication distance. This abstraction ensures a fair comparison of routing and clustering strategies while keeping the simulation scalable.

6.3 Computational Time Comparison

To assess execution time, each algorithm was executed five times under identical conditions, and the average execution time was recorded for networks with 50 and 200 nodes. Table 5 provides a summary of the findings.

Table 5: Performance comparison of LEACH variants.

Protocol	Average Execution Time (s)—50 nodes	Average Execution Time (s)—200 nodes
LEACH	0.180	1.677
LEACH + GA	0.397	2.751
LEACH + ACO	86.443	948.022
LEACH Hybrid (GA + ACO)	177.463	1950.915

The dominant operations of the proposed methods primarily drive their computational complexity. LEACH has a linear complexity that depends on the number of nodes. On the other hand, LEACH-ACO has extra costs that depend on the number of ants and iterations. The hybrid LEACH-ACO-GA further increases complexity due to population-based GA operations such as fitness evaluation, crossover, and mutation. Although computationally more demanding, these operations are executed at the base station and justify themselves with substantial improvements in energy efficiency, latency, and network lifetime. This behavior can also be explained from a theoretical complexity perspective.

As anticipated, the time required for the computation increases with the size of the network and the complexity of the algorithm. The classic LEACH protocol is the fastest due to its simple cluster leader selection procedure. The LEACH + GA and LEACH + ACO methodologies incorporate supplementary optimization procedures that prolong the execution time. The LEACH-ACO-GA hybrid model that has been proposed necessitates the most computation time due to its implementation of two-level optimization, which is performed both locally (ACO) and globally (GA). However, the significant improvements in energy efficiency, latency, and network lifetime shown in the previous sections make this processing burden acceptable.

Although the hybrid LEACH-ACO-GA approach incurs a higher computational cost, this overhead is handled at the base station rather than at the sensor nodes. As a result, the energy-constrained sensors are not burdened by the optimization process, making the performance gains in network lifetime and energy efficiency acceptable for dense and long-term WSN deployments.

Note that the reported execution times correspond to centralization optimization performed at the base station and are not intended for real-time execution. In practical deployments, the proposed ACO- and GA-based optimizations are assumed to operate in an offline or semi-offline manner, where clustering and routing decisions are updated periodically rather than continuously. This assumption makes the proposed framework suitable for long-term and energy-constrained WSN applications while avoiding real-time computational requirements at sensor nodes.

From a theoretical perspective, the computational complexity of the evaluated protocols can be approximated as follows. Classical LEACH exhibits a per-round complexity $\mathcal{O}(N)$ due to its probabilistic cluster head selection. LEACH-GA introduces genetic operations, resulting in a complexity of approximately $\mathcal{O}(I_{GA} \cdot N)$, while LEACH-ACO incurs an iterative pheromone-based process with a complexity of $\mathcal{O}(I_{ACO} \cdot N)$. In the proposed LEACH-ACO-GA framework, local ACO-based cluster head selection and global GA-based routing lead to an overall complexity of approximately $\mathcal{O}(I_{ACO} \cdot N + I_{GA} \cdot K)$, where K denotes the number of clusters. These expressions provide an order-of-magnitude comparison rather than exact bounds and are intended to support the interpretation of the measured execution times.

7 Discussion of Results

The simulations evaluated the efficacy of several variations of the LEACH protocol (LEACH Classic, LEACH-GA, LEACH-ACO and hybrid LEACH-ACO-GA) in terms of energy consumption, packet delivery rate (PDR), latency, and network stability. The comparison of LEACH Classic, LEACH-GA, LEACH-ACO and hybrid LEACH-ACO-GA underscores the benefits of metaheuristic optimization in enhancing network performance and scalability.

7.1 Energy Consumption

The hybrid approach achieves the lowest and most stable energy consumption across all rounds and network sizes. Compared to LEACH, LEACH-ACO, and LEACH-GA, the two stage optimization reduces variance by producing balanced clusters and effective routing. These results confirm the robustness of the hybrid approach, especially when scaling from 50 to 200 nodes.

7.2 Packet Delivery Ratio (PDR)

The LEACH-ACO-GA hybrid protocol has the highest and most stable PDR on both network scales (50 and 200 nodes). LEACH Classic shows a lot of variation and sometimes gets worse over cycles, while

LEACH-GA and LEACH-ACO improve things a bit. The hybrid technique always maintains the PDR above 0.97 with less variation, demonstrating that it is more reliable and performs better for sending data.

7.3 Latency Performance

The LEACH-ACO-GA hybrid protocol consistently exhibits the lowest latency on both network sizes (50 and 200 nodes), setting it apart from other methods. LEACH, LEACH-GA, and LEACH-ACO are always grouped together with higher latency values, but the hybrid approach benefits from the best of both worlds: efficient cluster head selection and improved inter-cluster routing. Two-level optimization reduces routing overhead and pheromone convergence delays, making end-to-end transmission faster and more stable. The advantage becomes much more noticeable as the network grows larger.

7.4 Overall Comparison and Performance Evaluation

The overall performance stabilizes when the network size is increased from 50 to 200 nodes, especially for the hybrid LEACH-ACO-GA protocol. In the 200-node network, the hybrid method maintains lower energy consumption, reduced latency, and a longer operational lifetime across all simulation rounds. Combining ACO to improve cluster heads and GA to manage traffic between clusters makes sure that energy use is balanced and that nodes don't lose power too fast. These findings confirm that the proposed hybrid meta-heuristic is scalable and well-suited for dense IoT deployments. Across both network sizes, LEACH-ACO-GA consistently outperforms LEACH, LEACH-GA, and LEACH-ACO. Dual-level optimization improves cluster formation and routing stability, improving energy management and network durability.

7.5 Ablation Analysis of Components

An ablation study was performed to evaluate LEACH, LEACH-GA, and LEACH-ACO-GA, aiming to quantify the contribution of each optimization component. The average results of 70 rounds for 200 nodes are displayed in Table 6.

Table 6: Ablation analysis of the proposed hybrid model compared to LEACH-based variants.

Model	Energy (J)↓	Latency (ms)↓	Lifetime (rounds)↑	Improvement vs. LEACH (%)
LEACH Classic	6.95	460	56	–
LEACH + GA	6.85	455	73	+30%
LEACH + ACO	6.90	470	58	+4%
LEACH Hybrid (GA+ACO)	**5.60**	**390**	**84**	**+50%**

Note: Bold values indicate the best performance among the compared methods.

All ablation study results are averaged over 30 independent simulation runs, and the corresponding standard deviations are computed to assess the robustness of each component across stochastic executions.

The little improvements confirm that ACO makes local CH selection more efficient, GA makes global routing more efficient, and their combination yields the best possible overall trade-off between latency and energy.

Limitation Note: It is important to note that all simulations in this work are conducted under a static WSN assumption, where sensor nodes remain fixed after deployment. As a result, random node failures independent of energy depletion and highly dynamic mobility conditions are not explicitly modeled. In such scenarios, the additional optimization overhead of the hybrid LEACH-ACO-GA framework may outweigh its performance gains, particularly in very small or highly dynamic networks. Extending the proposed approach to handle dynamic node behavior and failure scenarios constitutes a potential direction for future work.

It should be noted that the scalability analysis in this study is limited to networks of up to 200 sensor nodes. While this scale is representative of many practical WSN and IoT scenarios, the computational overhead of the proposed LEACH-ACO-GA framework may increase significantly in very dense deployments. Consequently, the proposed approach is best suited for moderate-scale networks, and its extension to larger-scale scenarios is left for future work.

8 Conclusion

This study presents a hybrid clustering and routing approach for WSNs, integrating Ant Colony Optimization and Genetic Algorithms with the LEACH protocol. The proposed hybrid LEACH-ACO-GA method improves packet delivery ratio (PDR), latency, energy efficiency, and network durability compared to classic LEACH and its independent metaheuristic upgrades (LEACH-GA and LEACH-ACO).

The results corroborate that the proposed regional hybrid LEACH-ACO-GA scheme significantly improves energy utilization, minimizes latency, and extends network lifetime in comparison to current LEACH-based protocols.

The novelty is in the integration of region-based ACO-driven cluster-head selection with GA-based inter-cluster routing within a unified multi-objective formulation. This dual-level optimization framework is well-suited for dense and large-scale IoT WSN deployments, as it guarantees both global stability and local adaptability.

In order to enhance the scalability and robustness of heterogeneous IoT environments, future research will investigate the use of real time reinforcement-learning-based control and dynamic weight adaptation in the objective function. Although the simulations were conducted in a static WSN environment, which aligns with traditional LEACH-based deployments, real networks may experience mobility and intermittent link failures. Extending the hybrid protocol to incorporate mobility-aware clustering and fault-tolerant mechanisms represents a promising direction for future work.

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Availability of Data and Materials: The corresponding author is able to provide simulation data and codes upon a reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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