LETTERS IN BIOMATHEMATICS
An International Journal

RESEARCH ARTICLE

OPEN ACCESS

Mathematical Optimization of Energy-Efficient Wireless Sensor Networks: A Genetic Algorithm-Based Framework for Cluster-Head Selection and Reliable Data Transmission

Amer O. Abu Salem[1*], Hebatullah Khattab[1], Louai A. Maghrabi[2]

[1]Department of Computer Science, Faculty of Information Technology, Zarqa University, Zarqa, Jordan; [2]Department of Software Engineering, College of Engineering, University of Business and Technology, Jeddah 21448, Saudi Arabia

ABSTRACT

Clustering protocols derived from Low-Energy Adaptive Clustering Hierarchy (LEACH) prolong the lifetime of wire- less sensor networks, but the cluster head remains a single point of failure: when it runs out of energy in the middle of a round, the readings it has buffered are lost and its members are orphaned. In earlier work we proposed LEACH-GV, which elects cluster heads with genetically tuned weights and assigns each one a vice cluster head that takes over after the head dies. That scheme improved the half-dead-node lifetime but brought the first node death forward. This paper traces that weakness to the reactive trigger of the vice and proposes LEACH-AGV, an adaptive genetic vice-cluster-head protocol. LEACH-AGV combines a distributed election weighted by residual energy, distance to the sink and node density; a vice chosen for its ability to finish the round; and a proactive handover that transfers the cluster-head role at a frame boundary once the head's energy falls below a safety multiple of its frame budget. A genetic algorithm tunes the weights and the safety factor offline on training deployments. LEACH-AGV was evaluated on 30 unseen deployments in each of three scenarios with a packet-level energy model, and compared with LEACH, LEACH-G, LEACH-V and LEACH-GV. It reduced readings lost to cluster-head failure by at least 97.9% and delayed the first node death by 2.5–5.2% relative to LEACH and by 1.9–5.9% relative to LEACH-GV. All of these improvements were significant under Holm-corrected Wilcoxon tests. Energy per delivered reading stayed practically the same, and half-network lifetime showed no significant loss. An ablation study shows that the proactive handover is the essential component, and that genetic tuning provides one half to two thirds of the stability gain.

ARTICLE HISTORY
Received April 7, 2026
Accepted May 25, 2026

KEYWORDS
Wireless Sensor Networks,
LEACH,
Genetic Algorithm,
Cluster Head Selection,
Vice Cluster Head,
Fault Tolerance,
Energy Efficiency,
Network Lifetime

1. Introduction

Wireless Sensor Networks (WSNs) are the sensing layer of many Internet-of-Things (IoT) systems, from precision agriculture and smart forestry to structural and environmental monitoring (Buratti et al., 2009; Prasad & Periyasamy, 2023). A WSN consists of many small, battery-powered nodes that sense their surroundings and forward readings to a sink, or Base Station (BS). Replacing batteries after deployment is usually impractical, so the energy spent on communication decides how long the network remains useful (Al-Karaki & Kamal, 2004).

Hierarchical clustering is one of the most effective ways to save that energy. Low-Energy Adaptive Clustering Hierarchy (LEACH) (Heinzelman et al., 2002; Heinzelman et al., 2000) divides time into rounds. In each round, a random subset of nodes be- comes Cluster Heads (CHs). Every other node joins its nearest CH, and each CH fuses its members' data and sends one aggregate packet to the BS. Rotating the CH role spreads the energy load, and LEACH has inspired a large family of descendants (Daanoune et al., 2021; Siamantas et al., 2025). Two weaknesses are shared by most of them. First, the probabilistic election ignores the state of the node, so a node with little energy left, or one far from the BS, may be elected. Second, the CH is a single point of failure: when it runs out of energy during the steady-state phase, the readings it has buffered are lost and its members are orphaned for the rest of the round.

Research has attacked the first weakness with fitness driven elections tuned by metaheuristics, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO) and hybrid swarm methods (Del-Valle-Soto et al., 2023; El Khediri et al., 2024; Kuila & Jana, 2014; Liu & Ravishankar, 2011; Pour & Javidan, 2021; Roberts et al., 2024), and more recently with

CONTACT Amer O. Abu Salem: abusalem@zu.edu.jo

neural and reinforcement- learning models (El-Sayed et al., 2024; Zhang & Liu, 2025). It has attacked the second with backup cluster heads and fault-tolerant clustering (Salami et al., 2022; Siamantas et al., 2025). The two lines have rarely been combined, and when a backup is used it is typically activated only after the primary CH has already failed.

In a preliminary study Abu Salem (2019), proposed LEACH-GV. LEACH-GV elects CHs with a GA-weighted score of residual energy and distance to the sink, and assigns every CH a Vice Cluster Head (VCH) that takes over when the CH dies. Compared with a GA-weighted LEACH without a vice (LEACH- G), LEACH-GV extended the Half-Dead-Node (HDN) lifetime by 23.9% but shortened the First-Dead-Node (FDN) lifetime by 2%. This paper explains that FDN penalty and removes it. Our analysis shows that a *reactive* VCH cannot save the node that fails. The CH still drains its battery to zero, and the readings already in its buffer are still lost. The remedy is to hand the CH role over *before* failure, to a vice chosen for its ability to finish the round.

The contributions of this paper are as follows:

1. LEACH-AGV, an Adaptive Genetic Vice-cluster- head LEACH protocol. It combines (i) a GA- weighted, fully distributed CH election over residual energy, distance to the sink and node density; (ii) a predictive VCH that maximizes the energy left after serving the rest of the round; and (iii) a *proactive*, energy-budget-triggered handover whose safety factor is tuned by the GA.

2. A packet-level simulation model in which a CH can fail inside a TDMA frame. This makes the cost of CH failure (buffered data loss and orphaned members) measurable instead of hidden by round-granular accounting.

3. A reproducible evaluation. GA tuning uses training deployments that are disjoint from 30 test deployments in each of three scenarios, and all comparisons are paired Wilcoxon signed-rank tests with Holm correction (Derrac et al., 2011). The evaluation also includes an ablation study of each component.

The rest of the paper is organized as follows. Section 2 reviews related work, and Section 3 gives the system model. Section 4 presents LEACH-AGV, and Section 5 describes the experimental setup. Section 6 discusses the results, and Section 7 concludes the paper.

2. Related Work

2.1 LEACH and Its Descendants

LEACH (Heinzelman et al., 2000) and its centralized variant LEACH-C (Heinzelman et al., 2002) established the round-based rotation of the CH role. LEACH-DCHS (Handy et al., 2002) scales the election threshold by the ratio of residual to initial energy, which prolongs the FDN lifetime. HEED (Younis & Fahmy, 2004) elects CHs iteratively with residual energy as the primary parameter and intra- cluster communication cost as the secondary one. Later energy-aware refinements of the threshold include those of Zhao et al. (2018) and Pour and Javidan (2021). Daanoune et al. (2021) and Siamantas et al. (2025) survey dozens of LEACH variants. They conclude that election criteria and multi-hop forwarding are the most explored axes, and that robustness to CH failure has received far less attention.

2.2 Metaheuristic and Learning-Based Election

LEACH-GA (Liu & Ravishankar, 2011) runs a GA at the BS to find the optimal CH probability. Kuila and Jana (2014) solve clustering and routing with PSO. Recent surveys (Del-Valle-Soto et al., 2023; Prasad & Periyasamy, 2023) report a shift toward multi-criteria fitness functions optimized by GA, PSO and hybrid swarm algorithms. Regilan and Hema (2024) select CHs with a GA on a grid topology. Batool et al. (2025) extend LEACH with a GA for 3D forest deployments, and Feng et al. (2022) use a bamboo- forest growth optimizer in heterogeneous WSNs. Hybrid metaheuristic frameworks (El Khediri et al., 2024; Roberts et al., 2024) separate CH se- lection from route construction. Learning-based methods train a neural network to predict suitable CHs (El-Sayed et al., 2024), or couple reinforcement learning with a metaheuristic (Zhang & Liu, 2025). Most of these methods optimize the election again in every round at the BS, which adds control overhead and latency. They also do not address what happens when an elected CH fails.

Table 1: Feature Comparison with Representative Protocols

Protocol	State-Aware	Opt. Tuned	Backup CH	Proactive
LEACH (Heinzelman et al., 2002)	–	–	–	–
LEACH-DCHS (Handy et al., 2002)	✓	–	–	–
HEED (Younis & Fahmy, 2004)	✓	–	–	–
LEACH-GA (Liu & Ravishankar, 2011)	–	✓	–	–
EEL-GA (Batool et al., 2025)	✓	✓	–	–
FTBC (Salami et al., 2022)	✓	–	✓	–
LEACH-GV (Abu Salem, 2019)	✓	✓	✓	–

LEACH-AGV (Ours)	✓	✓	✓	✓

2.3 Backup Cluster Heads and Fault Tolerance

Fault-tolerant clustering keeps a secondary node ready to replace a failing CH. Salami et al. (2022) maintain backup CHs to avoid interrupted transmission in underwater networks. Yadawad and Joshi (2024) combine hunter–prey optimization with deep Q-learning for fault-tolerant clustering and routing. Our earlier LEACH-V and LEACH-GV Abu Salem (2019) introduced a VCH with the highest residual energy in the cluster. These schemes share a *reactive* trigger: the backup is activated once the primary has failed. Table 1 positions LEACH-AGV against representative protocols. To the best of our knowledge, it is the first LEACH variant in which a GA jointly tunes the election weights and the trigger of a *proactive* vice handover.

3. System Model

3.1 Network Assumptions

N static, homogeneous nodes with initial energy E_0 are deployed uniformly at random in a square field of side A. A single BS with unconstrained energy is placed either inside or outside the field. Each node knows its distance to the BS, which is obtained once at deployment from received signal strength. Radios can adjust their transmission power to the distance of the receiver, and links are symmetric. Every node sense one reading per TDMA frame.

3.2 Radio Energy Model

We use the first-order radio model (Heinzelman et al., 2002). Sending an $l - bit$ packet over distance d and receiving it cost

$$E_{\mathrm{Tx}}(l,d) = \begin{cases} lE_{\mathrm{elec}} + l\varepsilon_{\mathrm{fs}}d^2, & d < d_0, \\ lE_{\mathrm{elec}} + l\varepsilon_{\mathrm{mp}}d^4, & d \geq d_0, \end{cases} \tag{1}$$

$$E_{\mathrm{Rx}}(l) = lE_{\mathrm{elec}}, \tag{2}$$

where $d_0 = \sqrt{\frac{\varepsilon_{\mathrm{fs}}}{\varepsilon_{\mathrm{mp}}}}$. A CH additionally spends E_{DA} per bit for every signal it fuses.

3.3 Round Structure and the CH-Failure Event

Each round has a set-up phase and a steady-state phase of F TDMA frames. In LEACH, node n becomes a CH when a uniform random number falls below

$$T(n) = \begin{cases} \frac{p}{1 - p\left(r \bmod \frac{1}{p}\right)}, & n \in G, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

Table 2: Results of the Preliminary Study (Abu Salem, 2019) (Lifetimes in Rounds; RE: Residual Energy in J). Improvement is LEACH-GV Relative to the Baseline

Metric	LEACH-G	LEACH-V	LEACH-GV	vs. G	vs. V
FDN	226.4	212.5	221.4	−2%	+4%
$\mathrm{RE}_{\mathrm{FDN}}$	0.5718	0.7863	0.9663	+69%	+22%
HDN	289.2	305.95	358.35	+23.9%	+17%
$\mathrm{RE}_{\mathrm{HDN}}$	0.1060	0.1187	0.1218	+14.9%	+2.5%

Where p is the desired CH fraction, r is the current round, and G is the set of nodes that have not served as CH in the current epoch of $1/p$ rounds.

Most LEACH simulators debit energy once per round, so a CH that cannot afford the whole round simply dies at the end of it without side effects. Our model debits energy packet by packet in slot order. Therefore, if a CH exhausts its battery while receiving slot k, the readings buffered from slots 1. k are lost, and members in slots $> k$ have no CH. Without a VCH, those members send directly to the BS for the rest of the round, at a much higher cost. This is the failure mode the proposed protocol targets.

4. The Proposed LEACH-AGV Protocol

4.1 Background: The Preliminary LEACH-GV Study

This preliminary study Abu Salem (2019) compared three protocols. LEACH-G elects CHs with GA-optimized weights for residual energy, node density and distance to the sink.

LEACH-V is plain LEACH plus a VCH, the highest- energy member, which replaces a dead CH. LEACH- GV combines a GA-weighted election over residual energy and distance with the VCH. Table 2 restates the results reported there. The VCH brought large gains in HDN lifetime and in residual energy. Dropping density from the election also helped, as LEACH-GV outperformed LEACH-V on every metric. However, LEACH- GV reached FDN 2% earlier than LEACH-G. The VCH protects the cluster but not the CH itself: the primary still runs to exhaustion, and the first node to die is likely to be such a CH. LEACH-AGV keeps the GA-weighted election and the VCH of LEACH-GV, and changes *when* and *to whom* the CH role is passed.

4.2 GA-Weighted Distributed Election

Every node computes a suitability score

$$\Phi(n) = w_{\mathrm{E}} \frac{E_n}{E_0} + w_{\mathrm{D}} \left(1 - \frac{d_{n,\mathrm{BS}}}{d_{\max}}\right) + w_{\rho} \frac{\rho_n}{\rho_{\max}}, \tag{4}$$

where E_n is the residual energy of node n, $d_{n,BS}$ is its distance to the BS, and ρ_n is the number of alive neighbors within the expected cluster radius $\frac{A}{\sqrt{\pi p N}}$. The weights are non-negative and satisfy $w_E + w_D + w_\rho = 1$. The LEACH threshold is then modulated as

$$T'(n) = \min\left\{1, T(n)\frac{\Phi(n)}{\bar{\Phi}}\right\}, \tag{5}$$

where ϕ is the mean score of alive nodes, piggy-backed by the BS on its round-start beacon. The division by ϕ keeps the expected number of CHs at pN,so the weights change which nodes lead but not how many. The election remains distributed and costs no extra messages.

Algorithm 1 One round of LEACH-AGV

Input: weights (w_E, w_D, w_ρ) and safety factor θ from the GA.

1: BS broadcasts $\bar{\phi}$; each $n \in G$ becomes CH with probability $T'(n)$, Eq. (5).

2: CHs advertise; every other node joins the nearest CH.

3: for each CH h: select VCH v^* by Eq. (7) and notify it.

4: for frame f = 1 to F do

5: for each cluster (h, M_h, v^*) do

6: if $E_h < \theta B_h$ and $E_{v^*} > E_h$ then

7: swap the roles of h and v^*; re-select v^*.

8: members transmit in TDMA slots; the CH fuses and forwards.

9: if the CH fails inside the frame, then v^* serves the remaining slots.

4.3 Predictive Vice Cluster Head

Let M_h be the members of CH h. The energy needed to serve one frame as CH for k members at distance d from the BS is

$$B(k,d) = k(E_{\mathrm{elec}} + E_{\mathrm{DA}})B(k,d) = k(E_{\mathrm{elec}} + E_{\mathrm{DA}}) + E_{\mathrm{DA}}l + E_{\mathrm{Tx}}(l,d), \tag{6}$$

which counts receiving and fusing k readings, fusing the CH's own reading, and forwarding the aggregate. LEACH-GV picks the member with maximum $\mathrm{E_m}$. LEACH-AGV instead picks the member with the most energy left after serving the remaining f_{rem} frames of the round:

$$v^* = \arg\max_{m \in M_h} \left(E_m - f_{\mathrm{rem}} B\left(|M_h| - 1, d_{m,\mathrm{BS}}\right)\right) \tag{7}$$

A high-energy member far from the BS can therefore lose to a slightly weaker member that is closer to it.

4.4 Proactive Energy-Budget Handover

Before every frame, CH h compares its residual energy with its own frame budget $B_h = B\left(|M_h|, d_{h,\mathrm{BS}}\right)$ from (6). It

hands the role to v^* if

$$E_h < \theta B_h \text{ and } E_{v^*} > E_h, \tag{8}$$

where $\theta \in [1, 3]$ is a safety factor tuned by the GA. The VCH announces itself with one control packet, and the former CH continues as an ordinary member. A new VCH is then chosen with (7). Because the handover

happens at a frame boundary, no buffered reading is lost and the former CH survives. A reactive VCH is kept as a fallback if a CH fails despite the check, for example when all members are weak. Algorithm 1 summarizes one round.

4.5 Offline Genetic Tuning

The chromosome $x \in [0,1]^4$encodes $(w_E, w_D, w_\rho, \theta)$. The weights are normalized to sum to one, and $\theta = 1 + 2x_4$. The GA runs once, offline at the BS or before deployment, so the sensor nodes pay nothing for it. It uses a population of 20, 30 generations, binary tournament selection, $\mathrm{BLX}-\alpha$ crossover $(\alpha = 0.3, p_c = 0.9)$, Gaussian mutation $(p_m = 0.2, \sigma = 0.15)$ and two elite individuals. The fitness of x is its mean over a set Ω of four training deployments, normalized by plain LEACH on the same deployment:

Table 3: Simulation Parameters

Parameter	Value
Scenario S1	N = 30, 30 × 30 m, BS at (15, 15)
Scenario S2	N = 100, 100 × 100 m, BS at (50, 50)
Scenario S3	N = 100, 100 × 100 m, BS at (50, 150)
Initial Energy E_0	0.5 J
CH Fraction p; Frames Per Round F	0.1; 4
E_{elec} (Tx/Rx electronics)	50 nJ/bit
ε_{fs} / ε_{mp}	10 pJ/bit/m^2 / 0.0013 pJ/bit/m^4
E_{DA} (Data Aggregation)	5 nJ/bit/signal
Data / Control Packet	4000 / 200 bits
GA: Population, Generations	20, 30
Training / Test Deployments	4 / 30 (disjoint seeds)

$$f(x) = \frac{1}{3|\Omega|}\sum_{s\in\Omega}\left(\frac{\mathrm{FDN}_s}{\mathrm{FDN}_s^L} + \frac{\mathrm{HDN}_s}{\mathrm{HDN}_s^L} + \frac{D_s}{D_s^L}\right) \tag{9}$$

where D_s is the number of readings delivered to the BS up to HDN. The first two terms reward lifetime, and the third rewards the reliability that the handover is designed to add. Residual energy is deliberately excluded. A protocol that keeps nodes alive longer usually has less energy left at its (later) FDN, so rewarding residual energy at FDN conflicts with lifetime. For a faithful comparison, LEACH-G and LEACH-GV are retuned with the same GA but with their original objectives (Abu Salem, 2019): FDN and HDN for LEACH-G, and additionally residual energy at FDN and HDN for LEACH-GV.

Overhead. Compared with LEACH, LEACH-AGV adds one control packet per cluster per round (the VCH notification) and two control exchanges per handover. Evaluating (4) – (8) takes O (1) time per node and O $(|M_h|)$time per CH.

5. Experimental Setup

Scenarios. We use three scenarios (Table 3). S1 and S2 keep the two network sizes of the preliminary study (Abu Salem, 2019): 30 nodes in a 30 × 30 m field and 100 nodes in a 100 × 100 m field, here with the BS at the center. S3 moves the BS 50 m outside the 100 × 100 m field, so that CH-to-BS links operate in the multipath (d^4) regime and distance to the sink matters. The preliminary study used 0.1 J per node. Here we use $F = 4$ frames per round, which models the multi-frame steady state of the original LEACH design and exposes mid-round CH failures. We raise the initial energy to 0.5 J, the common setting in the LEACH literature (Daanoune et al., 2021; Heinzelman et al., 2002), which keeps lifetimes in a range of rounds comparable to the earlier study. The absolute numbers below are therefore not directly comparable with Table 2.

Protocols. We compare LEACH (Heinzelman et al., 2002), LEACH- G, LEACH-V and LEACH-GV (Abu Salem, 2019), and the proposed LEACH-AGV. All protocols share the same simulator, radio model, p and random deployment. The GA-based protocols are tuned per scenario, only on the training deployments.

Metrics. We report FDN (stability period), HDN, and Last Node Dead (LND) in rounds; residual network energy at FDN and HDN (REFDN, REHDN, in J); readings delivered to the BS over the whole lifetime (Delivered); readings lost because a CH failed while holding them (Lost); and the energy spent per delivered reading (EPR, in mJ).

Statistical protocol. Every protocol runs on the same 30 test deployments (seeds 0–29), which the GA never saw. We compare LEACH-AGV with each baseline using the paired two-sided Wilcoxon signed-rank test and apply the Holm correction across the four comparisons for each metric (Derrac et al., 2011), at α = 0.05. The simulator, GA and analysis scripts are released with the paper.

6. Results and Discussion

6.1 Tuned Parameters

Table 5 lists the parameters found by the GA, and Figure 2 shows its convergence. The best fitness stabilizes within 5–25 generations in every run, so the bud- get of 30 generations is sufficient. Fitness values are comparable only within one protocol, because the three protocols use different objectives. Three observations stand out. First, the handover safety factor θ converges to the upper end of its range (2.93–3.00) in all scenarios. The GA therefore prefers to hand over *early*, while the CH still has two to three frames of energy left. Second, when density is available, the GA gives it a large weight in the dense 100-node field (0.76 in S2). The preliminary study concluded that density hurts CH selection (Abu Salem, 2019); this result shows that the conclusion does not hold in general. Third, the energy-plus-distance objective of LEACH-GV drives its weights almost entirely to distance ($w_D \approx 1$) in S1 and S2, a consequence that Section 6.5 examines.

6.2 Network Lifetime

Table 4 and Figure 1 report lifetime on the unseen test deployments, and Table 6 gives the paired tests. LEACH-AGV delays the first node death in every scenario. Its FDN is 2.5%, 3.1% and 5.2% later than LEACH in S1–S3, and 2.6%, 5.9% and 1.9% later than LEACH-GV. All twelve FDN comparisons are significant after Holm correction. Relative to LEACH, the gain is largest in S3, where CH-to-BS links are long and the frame budget B_h of a CH is highest, so an exhausted CH is most likely to fail in the middle of a frame.

HDN changes little. LEACH-AGV is significantly better than LEACH-G and LEACH-GV in S1 and S2, statistically tied with LEACH and LEACH-V in all scenarios, and tied with every baseline in S3 (differences within ± 3.3%). The price of the gain in stability is a shorter tail. LND is 11–14% earlier than LEACH, because rotating the CH role away from weak nodes spends the remaining energy more evenly, and the last nodes die close together (the steep final segment in Figure 1). Many applications consider the network unusable once coverage is lost, and for them this trade-off is favorable. Where a few long-lived survivors are useful, the long tail of LEACH-GV in S1 is preferable. That tail is produced by peripheral nodes that the distance-only election never selects as CH.

Table 4: Performance on 30 Unseen Test Deployments per Scenario: Mean (Standard Deviation). Lifetimes in Rounds, Residual Energy (RE) in J, Delivered in Readings, EPR in mJ per Delivered Reading. Best Value per Scenario in Bold (RE is not Ranked, See Section 6.4)

Scn	Protocol	FDN	HDN	LND	RE_{FDN}	RE_{HDN}	Delivered	Lost	EPR
S1	LEACH	241.8 (10.7)	310.4 (5.1)	414.6 (19.0)	3.29 (0.53)	0.75 (0.19)	37,759 (288)	98.0 (26.3)	0.397 (0.003)
	LEACH-G	243.5 (9.2)	308.8 (6.7)	414.3 (18.0)	3.22 (0.45)	0.79 (0.18)	37,810 (296)	94.8 (24.4)	0.397 (0.003)
	LEACH-V	241.7 (10.6)	310.3 (5.1)	395.3 (17.0)	3.29 (0.53)	0.73 (0.19)	37,555 (270)	93.6 (23.4)	0.399 (0.003)
	LEACH-GV	241.5 (11.8)	302.4 (5.9)	543.7 (13.4)	3.38 (0.56)	1.15 (0.21)	38,426 (341)	98.4 (29.6)	0.390 (0.003)
	LEACH-AGV	247.8 (10.1)	312.4 (5.2)	358.2 (12.3)	2.99 (0.48)	0.55 (0.15)	37,467 (282)	1.3 (2.1)	0.400 (0.003)
S2	LEACH	218.8 (9.2)	280.3 (2.4)	343.3 (10.2)	10.93 (1.64)	1.95 (0.26)	111,577 (354)	405.1 (72.6)	0.448 (0.001)
	LEACH-G	218.5 (11.0)	278.0 (2.0)	352.0 (12.2)	10.94 (1.97)	2.24 (0.24)	111,361 (383)	411.5 (71.6)	0.449 (0.002)
	LEACH-V	218.6 (9.2)	280.5 (2.4)	325.5 (5.4)	10.94 (1.64)	1.86 (0.26)	110,973 (368)	401.8 (58.2)	0.451 (0.001)
	LEACH-GV	213.0 (8.1)	274.2 (2.3)	360.1 (13.9)	11.81 (1.44)	2.90 (0.33)	110,068 (526)	439.9 (58.0)	0.454 (0.002)
	LEACH-AGV	225.5 (10.7)	279.5 (2.1)	305.0 (4.6)	9.65 (1.93)	1.52 (0.29)	110,999 (384)	8.0 (11.1)	0.450 (0.002)
S3	LEACH	177.5 (7.1)	235.4 (5.4)	335.7 (13.2)	12.45 (1.32)	3.16 (0.39)	95,245 (1,264)	363.1 (45.7)	0.525 (0.007)
	LEACH-G	178.8 (7.7)	235.5 (5.1)	333.0 (10.9)	12.41 (1.37)	3.11 (0.32)	95,525 (1,340)	362.3 (42.5)	0.524 (0.007)
	LEACH-V	177.5 (7.1)	237.2 (5.1)	321.2 (7.5)	12.45 (1.32)	3.01 (0.38)	95,556 (1,235)	395.2 (44.4)	0.523 (0.007)
	LEACH-GV	183.3 (6.4)	235.4 (4.2)	323.7 (8.1)	11.64 (1.26)	3.06 (0.25)	96,268 (1,191)	425.3 (60.6)	0.519 (0.006)
	LEACH-AGV	186.8 (7.8)	236.7 (5.6)	292.8 (7.2)	10.78	2.68	96,403	7.4 (8.1)	0.519

	(1.47)	(0.39)	(1,253)		(0.007)

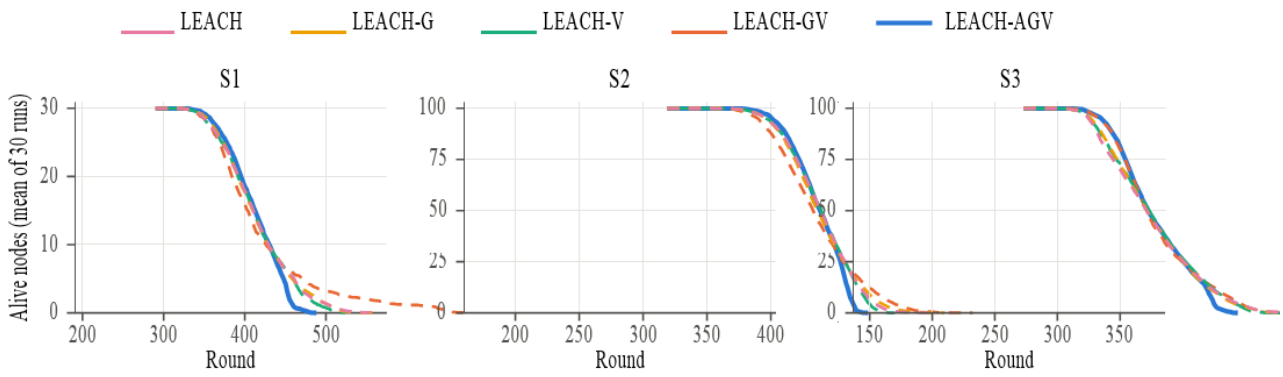


Figure 1: Alive Nodes Versus Rounds, Averaged Over the 30 Test Deployments of each Scenario

Table 5: Parameters Found by the GA on the Training Deployments (Weights Normalized to Sum to 1; θ for LEACH-AGV only)

Scn.	Protocol	w_E	w_D	w_p	θ	Fitness
S1	LEACH-G	0.36	0.33	0.31	–	1.026
	LEACH-GV	0.00	1.00	–	–	1.059
	LEACH-AGV	0.44	0.40	0.16	2.98	1.039
S2	LEACH-G	0.16	0.09	0.75	–	1.042
	LEACH-GV	0.00	1.00	–	–	1.060
	LEACH-AGV	0.17	0.07	0.76	2.93	1.039
S3	LEACH-G	0.21	0.22	0.57	–	1.013
	LEACH-GV	0.37	0.63	–	–	1.015
	LEACH-AGV	0.26	0.43	0.31	3.00	1.030

Table 6: LEACH-AGV Versus each Baseline: Holm-Adjusted Wilcoxon p-values and Wins/Ties/Losses Over 30 Paired Deployments (for Lost, a Win Means Fewer Lost Readings). $p < 0.05$ in Bold

Scn.	Metric	LEACH	LEACH-G	LEACH-V	LEACH-GV
S1	FDN	0.007 23/3/4	0.005 22/1/7	0.007 23/3/4	0.046 19/2/9
	HDN	0.111 16/1/13	0.002 24/1/5	0.111 16/1/13	1.1e–5 28/0/2
	Delivered	1.1e–5 2/0/28	1.5e–8 1/0/29	0.025 12/0/18	5.2e–6 0/0/30
	Lost	6.9e–6 30/0/0	6.9e–6 30/0/0	6.9e–6 30/0/0	6.9e–6 30/0/0
S2	FDN	0.007 21/1/8	1.2e–5 28/0/2	0.007 21/1/8	4.2e–4 27/0/3
	HDN	0.478 10/4/16	5.0e–4 22/5/3	0.478 11/5/14	7.0e–6 29/1/0
	Delivered	5.2e–6 0/0/30	5.2e–6 0/0/30	0.299 18/0/12	7.5e–9 30/0/0
	Lost	6.9e–6 30/0/0	6.9e–6 30/0/0	6.9e–6 30/0/0	6.9e–6 30/0/0
S3	FDN	1.9e–4 26/1/3	1.9e–4 26/1/3	1.9e–4 26/1/3	0.042 20/0/10
	HDN	0.247 18/4/8	0.250 17/3/10	0.657 11/6/13	0.250 15/5/10
	Delivered	5.2e–6 30/0/0	7.5e–9 30/0/0	5.2e–6 30/0/0	8.0e–4 23/0/7
	Lost	6.9e–6 30/0/0	6.9e–6 30/0/0	6.9e–6 30/0/0	6.9e–6 30/0/0

6.3 Reliability: Lost and Delivered Readings

The clearest effect of LEACH-AGV is on data loss. Readings lost to CH failure fall from 98.0 to 1.3 per net- work lifetime in S1, from 405.1 to 8.0 in S2, and from 363.1 to 7.4 in S3. This is a reduction of at least 97.9% against every baseline, and LEACH-AGV has fewer lost readings in all 30 paired deployments of every comparison. A *reactive* VCH alone does not help: LEACH-V and LEACH-GV lose a similar number of readings as LEACH (between 5% fewer and 17% more), because the buffered readings are gone by the time the vice takes over.

Total delivered readings depend on how long the net- work lives as well as on loss, so this metric reflects both the longer stability period and the shorter tail. In S3, LEACH-AGV delivers the most readings of all proto- cols (+1.2% against LEACH, significant against every baseline). In S1 and S2 it delivers –0.8% and –0.5% against LEACH, because survivors in the tails of the baselines keep sending directly to the sink. These differences are below 1% against LEACH (2.5% against LEACH-GV in S1) but statistically consistent, and we report them as a limitation rather than hide them.

6.4 Energy

Energy per delivered reading (EPR) is practically the same for all protocols: within ± 2.6 in S1 and within ± 1.2 in S2

and S3. The handover overhead is therefore negligible: 92–98 handovers occur over a whole lifetime in S2 and S3, fewer than one every three rounds. Residual energy at FDN and HDN, the objective of the preliminary study, must be read with care. LEACH- AGV reaches FDN *later*, so less energy remains at that moment. Its lower REFDN (e.g., 9.65 J against 11.81 J for LEACH-GV in S2) indicates that energy was used longer before the first failure, not that it was wasted. This is why residual energy was removed from the fit- ness function of LEACH-AGV.

6.5 Revisiting the Preliminary Findings

The new model reproduces the FDN penalty of the reactive vice observed in Abu Salem (2019). In S2, LEACH-GV reaches FDN −2.5% relative to LEACH-G, close to the −2% reported earlier, and in S1 the difference is −0.8%. The large HDN gain of LEACH-GV (+23.9%) is not reproduced: here the difference is −2.1% and −1.4% in S1 and S2. The present study uses a different simulation model and parameters (Section 5), notably packet-level accounting in which a vice cannot recover readings that a dead CH had already buffered, so the two sets of absolute results should not be compared directly. We also note that optimizing residual energy pushes LEACH- GV toward a distance-only election, which loads the central nodes. LEACH-AGV removes the FDN penalty in all three scenarios, which confirms the diagnosis of Section 4.

6.6 Ablation Study

Table 7 isolates each component using the GA-tuned parameters. Removing the proactive handover destroys both gains: FDN returns to the level of LEACH, and lost readings return to 90–432. The handover is there- fore the essential mechanism. Replacing the *predictive* VCH rule (7) with the energy-only rule of LEACH-GV gives results that are indistinguishable (identical FDN, HDN within 0.1 rounds). A likely reason is that, once handover is proactive, the vice with the most energy is almost always the one best able to finish the round, so the simpler rule can be used in practice. Replacing *GA* tuning with equal weights and $\theta = 1$ also keeps losses near zero. However, it recovers only part of the FDN gain (e.g., 180.7 against 186.8 rounds in S3), so tuning contributes between one half and two thirds of the FDN improvement over LEACH.

Table 7: Ablation of LEACH-AGV (means over 30 Test Deployments)

Scn.	Variant	FDN	HDN	Delivered	Lost
S1	Full LEACH-AGV	247.8	312.4	37,467	1.3
	Without proactive handover	242.4	310.0	37,592	90.2
	Energy-only VCH rule	247.8	312.4	37,467	1.3
	Without GA tuning	244.8	309.2	37,648	0.0
	LEACH-GV (reference)	241.5	302.4	38,426	98.4
S2	Full LEACH-AGV	225.5	279.5	110,999	8.0
	Without proactive handover	218.7	278.2	110,686	432.2
	Energy-only VCH rule	225.5	279.5	110,997	8.2
	Without GA tuning	220.8	278.0	111,132	0.3
	LEACH-GV (reference)	213.0	274.2	110,068	439.9
S3	Full LEACH-AGV	186.8	236.7	96,403	7.4
	Without proactive handover	177.6	237.3	96,017	413.9
	Energy-only VCH rule	186.8	236.7	96,401	6.9
	Without GA tuning	180.7	236.9	96,316	2.4
	LEACH-GV (reference)	183.3	235.4	96,268	425.3

6.7 Limitations

The evaluation uses static, homogeneous nodes, an ideal MAC and a single-hop CH-to-BS link, as in the LEACH literature. It compares LEACH-family protocols under identical conditions rather than recent swarm or learning-based protocols, whose published results rely on different energy models. The GA saturated θ at its upper bound, so a wider range may give further gains. Extending LEACH-AGV to multi-hop inter-cluster routing, heterogeneous energy and mobile sinks, and vali- dating it on a testbed, are left for future work.

7. Conclusion

This paper revisited LEACH-GV, a genetically tuned LEACH protocol with a vice cluster head, and identified the reactive trigger of the vice as the cause of its earlier first node death. The proposed LEACH-AGV keeps the distributed, GA-weighted election, and replaces the reactive takeover with a proactive handover at frame boundaries whose safety factor is tuned by the GA. On 30 unseen deployments in each of three scenarios, LEACH-AGV reduced readings lost to cluster-head failure by at least 97.9%. It also delayed the first node death by 2.5–5.2% relative to LEACH and by 1.9–5.9% relative to LEACH-

GV, with significant differences in every comparison. Energy per delivered reading was practically unchanged, and half-network lifetime showed no significant loss. The ablation study showed that the proactive handover is the component that matters, that the simpler energy-only vice rule performs as well as the predictive rule, and that genetic tuning contributes a large part of the gain in stability. The cost is a shorter tail after half of the nodes have died. The analysis also qualified two conclusions of the preliminary study: node density can be a useful election criterion in dense fields, and residual energy at first node death is a misleading optimization objective.

Future work will widen the range of the handover factor, extend LEACH-AGV to multi-hop routing be- tween clusters, heterogeneous nodes and mobile sinks, and validate the protocol on a hardware testbed.

7.1 Data Availability

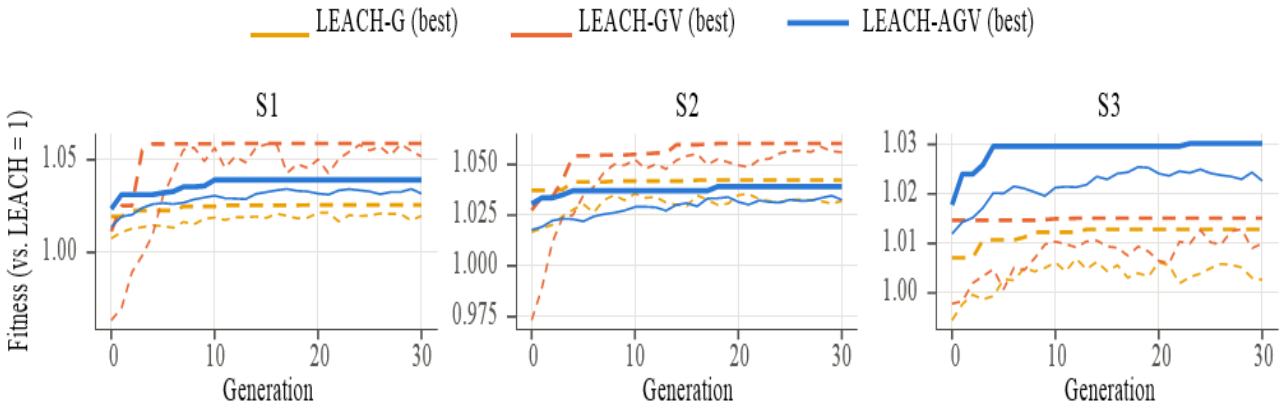


Figure 2: GA Convergence on the Training Deployments: Best (Thick) and Population Mean (Thin) Fitness per Generation. Fitness is Normalized by LEACH and is Comparable only within a Protocol.

The simulator, the genetic tuning code, the raw per-deployment results and the scripts that generate every table and figure are available from the author on request.

8. References

Abu Salem, A. O. (2019). A Novel Leach Routing Protocol using Genetic Algorithm for Wireless Sensor Networks. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(5).

Al-Karaki, J. N., & Kamal, A. E. (2004). Routing techniques in wireless sensor networks: a survey. *IEEE wireless communications*, *11*(6), 6-28.

Batool, F., Ali, K., Lasebae, A., Windridge, D., & Kiyani, A. (2025). EEL-GA: An evolutionary clustering framework for energy-efficient 3D wireless sensor networks in smart forestry. *Sensors*, *25*(17), 5250.

Buratti, C., Conti, A., Dardari, D., & Verdone, R. (2009). An overview on wireless sensor networks technology and evolution. *Sensors*, *9*(9), 6869-6896.

Daanoune, I., Abdennaceur, B., & Ballouk, A. (2021). A comprehensive survey on LEACH-based clustering routing protocols in Wireless Sensor Networks. *Ad Hoc Networks*, *114*, 102409.

Del-Valle-Soto, C., Rodríguez, A., & Ascencio-Piña, C. R. (2023). A survey of energy-efficient clustering routing protocols for wireless sensor networks based on metaheuristic approaches: C. Del-Valle-Soto et al. *Artificial Intelligence Review*, *56*(9), 9699-9770.

Derrac, J., García, S., Molina, D., & Herrera, F. (2011). A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm and evolutionary computation*, *1*(1), 3-18.

El-Sayed, H. H., Abd-Elgaber, E. M., Zanaty, E., Alsubaei, F. S., Almazroi, A. A., & Bakheet, S. S. (2024). An efficient neural network LEACH protocol to extended lifetime of wireless sensor networks. *Scientific Reports*, *14*(1), 26943.

El Khediri, S., Selmi, A., Khan, R. U., Moulahi, T., & Lorenz, P. (2024). Energy efficient cluster routing protocol for wireless sensor networks using hybrid metaheuristic approache's. *Ad Hoc Networks*, *158*, 103473.

Feng, Q., Chu, S.-C., Pan, J.-S., Wu, J., & Pan, T.-S. (2022). Energy-efficient clustering mechanism of routing protocol for

heterogeneous wireless sensor network based on bamboo forest growth optimizer. *Entropy*, *24*(7), 980.

Handy, M., Haase, M., & Timmermann, D. (2002). Low energy adaptive clustering hierarchy with deterministic cluster-head selection. 4th international workshop on mobile and wireless communications network,

Heinzelman, W. B., Chandrakasan, A. P., & Balakrishnan, H. (2002). An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications*, *1*(4), 660-670.

Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. Proceedings of the 33rd annual Hawaii international conference on system sciences,

Kuila, P., & Jana, P. K. (2014). Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach. *Engineering Applications of Artificial Intelligence*, *33*, 127-140.

Liu, J.-L., & Ravishankar, C. V. (2011). LEACH-GA: Genetic algorithm-based energy-efficient adaptive clustering protocol for wireless sensor networks. *International Journal of Machine Learning and Computing*, *1*(1), 79-85.

Pour, S. E., & Javidan, R. (2021). A new energy aware cluster head selection for LEACH in wireless sensor networks. *IET Wireless Sensor Systems*, *11*(1), 45-53.

Prasad, V. K., & Periyasamy, S. (2023). Energy Optimization-Based Clustering Protocols in Wireless Sensor Networks and Internet of Things-Survey. *International Journal of Distributed Sensor Networks*, *2023*(1), 1362417.

Regilan, S., & Hema, L. (2024). Optimizing energy efficiency and routing in wireless sensor networks through genetic algorithm-based cluster head selection in a grid-based topology. *Journal of High Speed Networks*, *30*(4), 569-582.

Roberts, M. K., Thangavel, J., & Aldawsari, H. (2024). An improved dual-phased meta-heuristic optimization-based framework for energy efficient cluster-based routing in wireless sensor networks. *Alexandria Engineering Journal*, *101*, 306-317.

Salami, A. F., Adedokun, E. A., Bello-Salau, H., & Sadiq, B. O. (2022). Fault-tolerant backup clustering algorithm for smart connected underwater sensor networks. *arXiv preprint arXiv:2203.02187*.

Siamantas, G., Rountos, D., & Kandris, D. (2025). Energy saving in wireless sensor networks via LEACH-based, energy-efficient routing protocols. *Journal of Low Power Electronics and Applications*, *15*(2), 19.

Yadawad, S., & Joshi, S. (2024). Efficient energy consumption and fault tolerant method for clustering and reliable routing in wireless sensor network. *Peer-to-Peer Networking and Applications*, *17*(3), 1552-1568.

Younis, O., & Fahmy, S. (2004). HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. *IEEE Transactions on mobile computing*, *3*(4), 366-379.

Zhang, S., & Liu, X. (2025). Improving the functionality of wireless sensor networks through the use of reinforcement learning and metaheuristic based energy efficient system. *Scientific Reports*, *15*(1), 30758.

Zhao, L., Qu, S., & Yi, Y. (2018). A modified cluster-head selection algorithm in wireless sensor networks based on LEACH. *EURASIP Journal on Wireless Communications and Networking*, *2018*(1), 287.