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Automated Configuration-Level Fitness Evaluation for Load-Balanced Artificial Bee Colony Clustering in Energy-Constrained Sensor Networks

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ABSTRACT

Energy-efficient clustering is essential for extending the operational period of energy-constrained wireless sensor networks. This study proposes Enhanced artificial bee colony (ABC)-low-energy adaptive clustering hierarchy (LEACH), a configuration-level fitness refinement for ABC clustering based on LEACH. The proposed method performs automated, round-by-round cluster-head (CH) configuration evaluation using current residual energy, member-to-CH distance, CH-to-base-station distance, and cluster-load distribution. Each food source represents a complete CH set, while the ABC search procedure remains identical to that of ABC-LEACH, thereby isolating the effect of the refined fitness function. Over 30 paired simulation runs with 100 nodes, Enhanced-ABC-LEACH reduced member-to-CH distance by 29.8% and the cluster-load coefficient of variation by 55.4% relative to ABC-LEACH. It delayed the half-node-death round by 16.2 rounds, although the first-node-death round occurred 7.1 rounds earlier. Across seven one-factor-at-a-time scenarios, improvements in member-to-CH distance, load balance, and the half-node-death round were consistent, whereas first-node death and cumulative delivery were scenario-dependent. The selected weights were non-dominated but not uniformly optimal, while a harmonized contemporary comparator exhibited a different stability–survival profile. These findings show that the proposed refinement improves clustering structure and mid-lifetime stability, although its benefits involve lifetime trade-offs rather than uniform superiority across all metrics.

1. INTRODUCTION

Wireless sensor networks (WSNs) consist of spatially distributed sensor nodes that observe environmental conditions and transmit the collected information to a base station (BS). These networks have been applied in environmental monitoring, agriculture, industrial automation, healthcare, and infrastructure supervision [1, 2]. In many deployments, however, sensor nodes rely on batteries that are difficult or impractical to replace. Energy consumption therefore becomes a fundamental constraint because node failure may reduce sensing coverage and eventually interrupt network operation [3]. Various energy-efficient routing and computational intelligence methods have been investigated to address this limitation [4, 5].

Clustering is commonly used to reduce communication overhead in WSNs. Sensor nodes are divided into groups, and one node in each group is selected as the cluster head (CH). Member nodes transmit their data to the corresponding CH, which aggregates the received packets before forwarding them to the BS [6]. Its effectiveness, however, depends heavily on cluster formation and CH selection. A CH with low residual energy, a long distance from its members, or too many assigned nodes can deplete its battery earlier than the other nodes [7, 8].

From an automation perspective, CH selection is a recurring decision taken without human intervention. At the start of every round, the BS or another central controller uses the residual energy and positions reported by the nodes to decide which nodes serve as CHs. The same structure appears in monitoring systems for agriculture, the environment, civil structures, and industrial Internet of Things (IoT) installations [2, 9], and edge-oriented IoT architectures move such decisions closer to the sensing layer [10]. The quality of the rule used to evaluate candidate decisions is therefore as important as the search procedure that proposes them.

Low-energy adaptive clustering hierarchy (LEACH) periodically rotates the CH role among sensor nodes to distribute energy consumption [11], but it selects CHs through a probabilistic threshold without directly considering the complete cluster configuration, and CH selection and cluster-load distribution remain important factors in network lifetime [12, 13]. Metaheuristic algorithms can examine many possible CH combinations without exhaustively evaluating every configuration. The artificial bee colony (ABC) algorithm models the food-searching behaviour of a bee colony through

employed-bee, onlooker-bee, and scout-bee phases [14, 15], uses few control parameters [16], and has been used for energy-efficient CH selection and routing in WSNs [17-20] and IoT networks [21].

Several recent ABC variants modify the fitness function, the update rule, the routing structure, or the communication model at the same time [22-26]. This makes it difficult to determine whether an observed improvement is produced by the fitness formulation or by additional modifications to the search procedure. Moreover, the suitability of one CH cannot be evaluated independently of the other selected CHs, because cluster membership, communication distance, and load distribution only become clear after a complete CH set has been formed.

This study therefore examines the fitness function as a configuration-evaluation strategy for the automated CH-selection decision rather than as a new search algorithm: ABC-LEACH and the proposed Enhanced-ABC-LEACH share every ABC search component and differ only in the fitness evaluation. The contributions are: (i) a configuration-level fitness that jointly evaluates residual energy, member-to-CH distance, CH-to-BS distance, and cluster-load balance for a complete CH set; (ii) a controlled comparison in which the search procedure is held fixed, so that performance differences can be attributed to the evaluation strategy; (iii) a reproducible evaluation with paired runs, paired statistics, a predefined weight-sensitivity and ablation analysis, a seven-condition one-factor-at-a-time (OFAT) robustness analysis, and a harmonized contemporary comparator; and (iv) an explicit analysis of the trade-off among the first-node-death (FND), half-node-death (HND), and last-node-death (LND) rounds.

2. RELATED WORK

LEACH rotates the CH role without requiring a complex centralized optimization process [7], the hybrid energy-efficient distributed clustering approach HEED incorporates residual energy and communication cost into distributed CH selection [8], and chain-based schemes such as power-efficient gathering in sensor information systems (PEGASIS) replace clusters with a transmission chain [27]. Several reviews have identified CH selection, cluster formation, and load distribution as central issues in energy-efficient WSN routing [4, 6, 28].

The application of ABC to WSN clustering was reported by Karaboga et al. [17], who showed that bee-colony search could generate energy-efficient cluster configurations. Mann and Singh applied ABC to combined clustering and routing [18] and later proposed an improved ABC metaheuristic [19]; Wang et al. [20], Yousefi et al. [21], and Nebti and Redjimi [22] proposed improved, IoT-oriented, and multi-objective ABC variants, and other studies combined ABC with particle swarm optimization and mobile BS routing [23], hierarchical clustering [24], improved CH selection and routing [25], or multi-hop clustering [26]; Table 1 summarizes these and the more recent approaches discussed below.

Table 1. Comparison of related cluster-head selection approaches with the present study

Method	Search or Decision Mechanism	Solution Representation	Fitness or Selection Terms	Component Changed
ABC clustering and routing [17-20]	ABC variants	differs among studies	energy- and communication-related criteria	search, routing and fitness
SWARAM [9]	osprey optimization	each osprey treated as a sensor node	residual-energy ratio and distance	optimizer
AVOACS [29]	African vulture optimization	not stated	four weighted terms (0.5, 0.25, 0.15, 0.1)	optimizer, dual-hop links
IZOACP [30]	zebra optimization with Gaussian mutation and opposition-based learning	not stated	energy, neighbourhood density, intra-cluster distance, latency	optimizer, inter-cluster routing
HGORSA [31]	hybrid gazelle optimization and reptile search	continuous decision vector	weighted node function for cluster formation	optimizer, cluster formation
ESBOA [32]	secretary bird optimization, chaotic initialization, local search	not specified	multi-term fitness (weights not reported)	optimizer
BSBOC [33]	binary secretary bird optimization	binary vector, one bit per node	CH energy, member distance, CH-sink distance, CH degree, Voronoi-area variance	optimizer and fitness
QPSODRL [34]	quantum particle swarm clustering, deep-reinforcement-learning routing	not stated	energy-distribution entropy guides the search	optimizer, learning-based routing
ABC-LEACH (baseline)	ABC	complete set of distinct CHs	residual energy divided by CH-to-BS distance	–
Enhanced-ABC-LEACH (this study)	same ABC as ABC-LEACH	complete set of distinct CHs	residual energy, member-to-CH distance, CH-to-BS distance, load balance	fitness only

Note: ABC: artificial bee colony; BS: base station; BSBOC: binary secretary bird optimization clustering; CH: cluster head; IoT: Internet of Things; LEACH: low-energy adaptive clustering hierarchy.

Recent work has also moved beyond ABC. Osprey-based CH selection for WSN-based IoT [9], African-vulture-based clustering [29], modified zebra optimization with opposition-based learning [30], a hybrid gazelle and reptile-search clustering scheme [31], and enhanced [32] or binary [33] secretary-bird optimization illustrate the continuing use of population-based search with weighted multi-term fitness functions, and learning-assisted schemes combine metaheuristic clustering with deep reinforcement learning for routing decisions [34]. Table 1 compares these approaches with the present study. Most of them change the optimizer, add routing or learning components, or alter the solution representation together with the fitness; the present study keeps the ABC search and the complete-CH-set representation fixed and changes only the fitness, which isolates the contribution of the evaluation strategy.

3. PROPOSED METHOD

The proposed method changes only the fitness evaluation of ABC-LEACH: each food source is a complete cluster-head configuration, and the discrete ABC procedure is shared by both protocols (Figure 1).

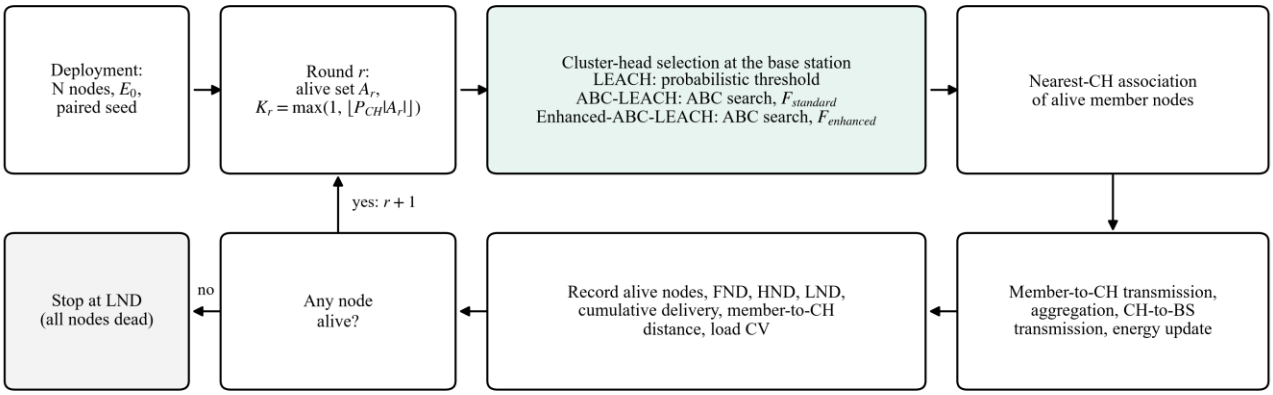


Figure 1. Overall simulation flow of the evaluated clustering protocols
Note: ABC: artificial bee colony; BS: base station; CH: cluster head; CV: coefficient of variation; FND, HND and LND: first-, half- and last-node-death rounds; LEACH: low-energy adaptive clustering hierarchy; the ABC search is identical for both ABC-based protocols and only the fitness differs.

3.1 Network model and assumptions

The network consists of N homogeneous sensor nodes randomly distributed over a two-dimensional sensing area. All nodes are stationary after deployment and have the same initial energy E_0. In the reference condition, the BS is fixed outside the sensing area; Section 4 also examines BS positions inside and on the boundary of the field. Each node is assumed to know its position and residual energy, and the BS is assumed to collect this information before each CH decision; these assumptions are discussed in Section 6.

Network operation is divided into rounds. At the beginning of each round, nodes with positive residual energy form the alive-node set A_r, and CHs are selected according to the evaluated protocol: LEACH uses probabilistic CH election, whereas ABC-LEACH and Enhanced-ABC-LEACH search for a complete CH configuration using ABC. Every alive non-CH node joins the nearest selected CH, which aggregates the received packets with its own sensing packet and transmits one aggregated packet to the BS. The node energy is updated after each transmission, reception, and aggregation operation, and a node is declared dead when its residual energy reaches zero. For both ABC-based protocols, the number of CHs in round r is

$$K_r = \max(1, \lfloor P_{\mathrm{CH}}|A_r| \rfloor) \tag{1}$$

where, P_{CH} is the desired CH proportion, so the number of CHs decreases as nodes die. LEACH retains its probabilistic CH election; if no eligible node is selected in a LEACH round, the eligible node with the highest residual energy is selected.

3.2 Radio energy model

The simulation uses the first-order radio model commonly adopted in LEACH-based studies [11]. The energy required to transmit an l-bit packet over distance d is

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

where, E_{elec} is the electronic energy per bit, $\varepsilon_{\mathrm{fs}}$ and $\varepsilon_{\mathrm{mp}}$ are the free-space and multipath amplifier coefficients, and d_0 is the distance threshold. The threshold, the receiving energy, and the aggregation energy of a CH that aggregates n_p packets of l bits are

$$d_0 = \sqrt{\varepsilon_{\mathrm{fs}}/\varepsilon_{\mathrm{mp}}} \tag{3}$$

$$E_{\mathrm{RX}}(l) = l\, E_{\mathrm{elec}} \tag{4}$$

$$E_{\mathrm{DA}}^{\mathrm{CH}}(n_p, l) = n_p\, l\, E_{\mathrm{DA}} \tag{5}$$

where, E_{DA} is the aggregation energy per bit and n_p is the number of member packets received by the CH plus its own packet. A member transmission succeeds when the member can transmit and the CH can receive the packet, and the aggregated packets reach the BS only when the CH has sufficient energy for aggregation and CH-to-BS transmission.

3.3 Configuration-level solution representation

The CH-selection problem is formulated as a discrete configuration-optimization problem whose decision variable is the complete CH set S_i of food source i. A feasible solution contains exactly K_r distinct alive nodes:

$$S_i = \{\mathrm{CH}_{i,1}, \mathrm{CH}_{i,2}, \ldots, \mathrm{CH}_{i,K_r}\}, \quad \mathrm{CH}_{i,j} \in A_r \tag{6}$$

After S_i is formed, every alive non-CH node is assigned to its nearest CH in that set, which determines cluster membership, member-to-CH distance, and cluster loads. A neighbouring solution V_i replaces one randomly chosen CH of S_i by an alive node that is not already in the configuration.

3.4 Standard fitness of the baseline protocol

ABC-LEACH uses the original node-level score based on residual energy and distance to the BS. For CH candidate j

with residual energy E_j and Euclidean distance $d_{j,\mathrm{BS}}$ to the BS, the score and its configuration-level aggregate are

$$f_j = \frac{E_j}{d_{j,\mathrm{BS}} + \varepsilon_s} \tag{7}$$

$$F_{\mathrm{standard}}(S_i) = \frac{1}{K_r} \sum_{j \in S_i} f_j \tag{8}$$

where, $\varepsilon_s = 10^{-6}$ prevents division by zero. This fitness favours CH candidates with higher energy and shorter distance to the BS, but it does not evaluate the distance between member nodes and their CHs, nor whether members are distributed evenly among the CHs.

3.5 Proposed refined fitness function

Enhanced-ABC-LEACH evaluates each CH configuration with four scores in the interval from zero to one, where a higher value indicates a better configuration. The mean residual energy of the selected CHs is compared with the mean energy of all alive nodes and transformed by a bounded hyperbolic tangent:

$$R_E(S_i) = \frac{\frac{1}{K_r} \sum_{j \in S_i} E_j}{\frac{1}{|A_r|} \sum_{n \in A_r} E_n + \varepsilon} \tag{9}$$

$$F_E(S_i) = 0.5 + 0.5 \tanh[\alpha(R_E(S_i) - 1)] \tag{10}$$

where, $\alpha = 1.2$ controls the sensitivity of the score and $\varepsilon = 10^{-12}$ is a stabilizing constant. The bounded transformation prevents the energy score from dominating when a few nodes retain unusually high energy. For each alive non-CH node $n \in M_r = A_r \backslash S_i$, with $d(n, j)$ the Euclidean distance between node n and CH j, the mean member-to-CH distance and its score are

$$\bar{d}_{\mathrm{member}}(S_i) = \frac{1}{|M_r|} \sum_{n \in M_r} \min_{j \in S_i} d(n, j) \tag{11}$$

$$F_{Dm}(S_i) = 1 - \min\left(1, \frac{\bar{d}_{\mathrm{member}}(S_i)}{D_f}\right) \tag{12}$$

where, D_f is the diagonal length of the sensing field ($\bar{d}_{\mathrm{member}} = 0$ when $M_r = \varnothing$). The mean CH-to-BS distance $\bar{d}_{\mathrm{BS}}$ is normalized by the maximum BS distance among the alive nodes, $d_{\mathrm{BS,max}}$, which is recomputed in every round:

$$\bar{d}_{\mathrm{BS}}(S_i) = \frac{1}{K_r} \sum_{j \in S_i} d_{j,\mathrm{BS}} \tag{13}$$

$$F_{\mathrm{DBS}}(S_i) = 1 - \min\left(1, \frac{\bar{d}_{\mathrm{BS}}(S_i)}{\max(d_{\mathrm{BS,max}}, \varepsilon)}\right) \tag{14}$$

$$d_{\mathrm{BS,max}} = \max_{n \in A_r} d_{n,\mathrm{BS}} \tag{15}$$

Let L_j denote the number of non-CH members assigned to CH j. Cluster-load variation is measured by the coefficient of variation (CV) of the loads, and the load-balance score is

$$CV_L(S_i) = \frac{\sigma(L_1, \ldots, L_{K_r})}{\mu(L_1, \ldots, L_{K_r}) + \varepsilon} \tag{16}$$

$$F_L(S_i) = \frac{1}{1 + CV_L(S_i)} \tag{17}$$

where, σ and μ are the population standard deviation and mean of the cluster loads ($CV_L = 0$ when $K_r = 1$). The complete refined fitness is

$$\begin{aligned} F_{\mathrm{enhanced}}(S_i) = {} & w_E F_E(S_i) + w_{Dm} F_{Dm}(S_i) \\ & + w_{\mathrm{DBS}} F_{\mathrm{DBS}}(S_i) + w_L F_L(S_i) \end{aligned} \tag{18}$$

with the tested weight vector $W_0 = (w_E, w_{Dm}, w_{\mathrm{DBS}}, w_L) = (0.40, 0.25, 0.20, 0.15)$. Residual energy receives the largest weight because node survival remains the main concern, and member-to-CH distance the second-largest because every member transmits in each round. CH-to-BS distance receives a smaller weight because only the CHs perform this transmission, and load balance prevents a few CHs from serving disproportionately large clusters. The sensitivity of these weights is analysed in Section 5.3.

3.6 Discrete artificial bee colony search procedure

A population of $SN' = \min(SN, |A_r|)$ food sources is generated by randomly sampling K_r distinct alive nodes and evaluated with the protocol fitness F_m (F_{standard} for ABC-LEACH, F_{enhanced} for Enhanced-ABC-LEACH). In the employed-bee phase, one neighbouring configuration is generated for every food source with the one-CH replacement operator, and the candidate replaces the current source only when its fitness is higher; otherwise, the trial counter of the source is increased. In the onlooker-bee phase, food sources are selected with probability

$$p_i = \frac{F_m(S_i)}{\sum_{q=1}^{SN'} F_m(S_q)} \tag{19}$$

(uniform when the sum is zero), followed by the same operator and greedy rule. A source whose trial counter exceeds the limit is replaced by a new random configuration (scout-bee phase). After MCN cycles, the configuration with the highest fitness in the final population is returned as the CH set of the round (Algorithm 1).

Algorithm 1. Configuration-level ABC cluster-head selection in round r

Input: A_r, residual energies, node and BS positions, P_{CH}, SN, MCN, limit, fitness mode m
1: if $A_r = \varnothing$ return $\varnothing$; $K_r \leftarrow \max(1, \lfloor P_{\mathrm{CH}} |A_r| \rfloor)$
2: for $i = 1..SN'$ ($SN' = \min(SN, |A_r|)$): $S_i \leftarrow$ K_r random distinct alive nodes; $F_i \leftarrow F_m(S_i)$; $t_i \leftarrow 0$
3: for cycle $= 1..MCN$ do
4: employed bees: for each i, $V_i \leftarrow$ replace one CH of S_i by an unselected alive node
5: if $F_m(V_i) > F_i$ then $S_i \leftarrow V_i$, $t_i \leftarrow 0$ else $t_i \leftarrow t_i + 1$
6: $p_i \leftarrow F_i / \sum_q F_q$ (uniform if $\sum_q F_q = 0$)
7: onlooker bees: SN' times select i with probability p_i and apply steps 4-5

8: scout bees: every S_i with $t_i >$ limit is regenerated at random; $t_i \leftarrow 0$
9: end for
10: return the food source with the highest fitness in the final population
($F_m = F_{\text{standard}}$ for ABC-LEACH, $F_m = F_{\text{enhanced}}$ for Enhanced-ABC-LEACH)

3.7 Round-based operation

After the CH set is returned, each alive non-CH node is connected to its nearest CH. Member transmissions are processed first, and a transmitting member consumes energy even if the destination CH later lacks the energy to receive its packet. Each active CH then aggregates its received packets with its own sensing packet and attempts to transmit them to the BS. The overall procedure is illustrated in Figure 1.

4. EXPERIMENTAL SETUP

4.1 Simulation environment and implementation

The reference network consisted of 100 homogeneous nodes randomly deployed in a 100 m × 100 m field with the BS at (50, 150) m, that is, outside the field (Table 2). Each protocol was run on the same 30 deployments with paired seeds (42-71); within a run, all protocols experienced the same node positions, initial energy, radio model, packet size, and stopping rule. Every run was continued until the last node died (limit 3,000 rounds; no run was censored). The simulator was implemented as a modular Python package and was verified to reproduce the original simulation script exactly, including the selected CH sets and the energy state of every node in every round.

Table 2. Simulation parameters of the reference condition

Parameter	Value	Parameter	Value
Nodes, N	100	Packet size, l	4,000 bit
Field	100 m × 100 m	P_{CH}	0.1
BS position	(50, 150) m	Food sources, SN	20
Initial energy, E_0	0.2 J	ABC cycles, MCN	20
E_{elec}	50 nJ/bit	Trial limit	10
ε_{fs}	10 pJ/bit/m ^{2}	α	1.2
ε_{mp}	0.0013 pJ/bit/m ^{4}	W_0	(0.40, 0.25, 0.20, 0.15)
E_{DA}	5 nJ/bit	Runs (paired seeds)	30 (42-71)
d_0	87.7 m	Round limit	3,000 (no censoring)

Note: ABC: artificial bee colony; BS: base station; CH: cluster head; MCN: maximum number of cycles; SN: number of food sources; W_0: tested weight vector.

4.2 Performance metrics

FND, HND, and LND are the first rounds at which at least one node, at least half of the nodes, and all nodes have died, respectively; the post-FND lifetime is LND minus FND. The cumulative end-to-end delivery ratio is the number of source packets delivered to the BS divided by the number generated, both summed from the first round to the protocol's own HND. The member-to-CH distance and the load CV are pre-round values of the selected configuration, averaged over the rounds up to the protocol's own HND. Residual energy at a protocol's own FND or HND is a descriptive milestone-conditioned metric: because protocols reach these milestones in different rounds, it is not direction-classified between protocols and is reported only in the Supplementary Material.

4.3 Statistical analysis

Results are reported as mean ± standard deviation (SD) over the paired runs. For each comparison, the paired mean difference is reported with a t-based 95% confidence interval (CI); the Wilcoxon signed-rank test is applied to the paired differences, the p-values are Holm-adjusted within each family of comparisons, and the matched-pairs rank-biserial correlation r_{rb} is reported as the paired effect size. Direction, effect magnitude, uncertainty, and adjusted significance are interpreted jointly; a non-significant result is not interpreted as evidence of equivalence.

4.4 Weight-sensitivity, robustness and comparator designs

Nine alternative weight vectors were predefined: four local perturbations of ±0.05 (W1-W4), equal weights (W5), and four component-dominant vectors (W6-W9), together with four ablations that remove one component and renormalize the remaining weights (A_E, A_Dm, A_DBS, A_L). Seeds 42-51 were used only for implementation checks, and all weight comparisons use the 20 evaluation seeds 52-71. Robustness was examined with seven OFAT conditions: the reference condition; N = 50 and N = 150 in the same field, so that network size and node density change together; the BS at the field centre (50, 50) m and on the upper field boundary (50, 100) m; and E_0 = 0.1 J and 0.3 J. Each condition used 30 paired seeds with a scenario-specific seed policy, the weights were not re-tuned, interactions among the factors were not tested, and no run was censored.

For the contemporary comparator, recent metaheuristic CH-selection methods (2023-2026) were screened for an official full text, a complete fitness definition, a defined CH-count rule, and a radio model compatible with Section 3.2. The enhanced secretary bird method [32] was excluded because several components were unspecified, and the 2025 binary secretary bird optimization clustering (BSBOC) method [33] was the closest candidate. It was therefore evaluated as H-BSBOC, a harmonized implementation of the 2025 BSBOC method used as an additional contemporary comparator. The published BSBOC description did not specify a cardinality-repair rule or dead-node handling. For comparison under a common round-based environment, the implementation used latent-score ranking to enforce the required number of alive CHs and excluded dead nodes from the candidate space. A secondary repair sensitivity analysis was conducted to assess dependence on this assumption. H-BSBOC used the published fitness weights and setting of 50 candidate solutions and 30 iterations; a secondary variant with 27 solutions and 15 iterations matched the search effort of the ABC-based protocols.

5. RESULTS AND DISCUSSION

5.1 Reference-condition performance

Figure 2 shows the mean number of alive nodes per round, and Table 3 summarizes the reference-condition results.

LEACH began losing nodes earliest. Relative to ABC-LEACH, the FND of Enhanced-ABC-LEACH differed by −7.1 [−10.3, −3.9] rounds (Holm-adjusted $p < 0.001$), whereas its HND was later by +16.2 [14.6, 17.7] rounds (+4.0%) and its LND by +28.4 [27.0, 29.7] rounds relative to ABC-LEACH. Relative to LEACH, it improved FND by 83.4 rounds and HND by 24.6 rounds but reached LND 93.6 rounds earlier, because LEACH leaves a long tail in which only a few nodes survive.

The structural metrics changed most. Relative to ABC-LEACH, Enhanced-ABC-LEACH reduced the member-to-CH distance by 7.41 m (29.8%) and the load CV by 0.602 (55.4%), with $r_{rb} = -1.00$ for both, meaning that the difference had the same sign in every run. The cumulative end-to-end delivery ratio to the own HND was higher by 0.0045 (+0.46%), a consistent but practically small difference. Variation among runs was limited for all protocols (Table 3); the largest SD of a lifetime milestone for Enhanced-ABC-LEACH was 9.6 rounds for FND.

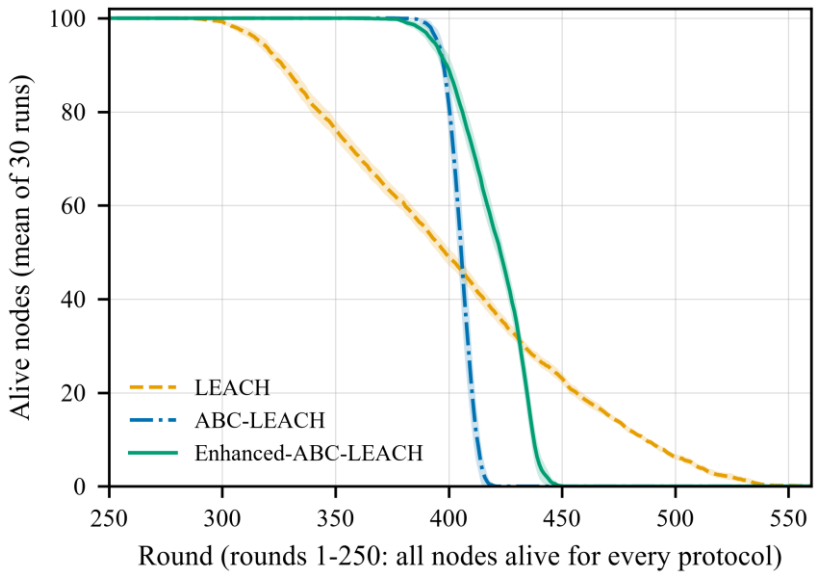


Figure 2. Mean number of alive nodes per round in the reference condition (30 paired runs; shaded bands: 95% confidence interval of the mean; a run contributes zero after its last node dies); all nodes are alive before round 250 for every protocol. ABC, artificial bee colony; LEACH, low-energy adaptive clustering hierarchy

Table 3. Reference-condition results (mean ± SD over 30 paired runs) and paired differences of Enhanced-ABC-LEACH

Metric	LEACH	ABC-LEACH	Enhanced-ABC-LEACH	Diff. vs ABC-LEACH [95% CI]	Holm p	r_{rb}	Diff. vs LEACH [95% CI]	Holm p
FND (round)	300.5 ± 9.4	391.0 ± 5.7	383.9 ± 9.6	−7.1 [−10.3, −3.9]	<0.001	−0.77	+83.4 [80.5, 86.3]	<0.001
HND (round)	397.9 ± 8.4	406.3 ± 3.9	422.5 ± 5.6	+16.2 [14.6, 17.7]	<0.001	1.00	+24.6 [22.9, 26.2]	<0.001
LND (round)	534.6 ± 15.5	412.6 ± 4.0	441.0 ± 4.0	+28.4 [27.0, 29.7]	<0.001	1.00	−93.6 [−99.0, −88.3]	<0.001
Post-FND lifetime (rounds)	234.1 ± 17.5	21.6 ± 3.7	57.0 ± 9.7	+35.5 [31.5, 39.4]	<0.001	1.00	−177.1 [−183.4, −170.7]	<0.001
Delivery ratio to own HND (%)	99.08 ± 0.13	98.98 ± 0.13	99.43 ± 0.20	+0.45 [0.37, 0.54]	<0.001	0.99	+0.35 [0.26, 0.44]	<0.001
Member-to-CH distance (m)	18.42 ± 0.46	24.86 ± 1.06	17.46 ± 0.52	−7.41 [−7.73, −7.08]	<0.001	−1.00	−0.96 [−1.08, −0.84]	<0.001
Load CV	0.602 ± 0.016	1.085 ± 0.049	0.484 ± 0.041	−0.602 [−0.616, −0.587]	<0.001	−1.00	−0.118 [−0.136, −0.101]	<0.001

Note: ABC: artificial bee colony; CH: cluster head; CI: confidence interval; CV: coefficient of variation; FND, HND and LND: first-, half- and last-node-death rounds; LEACH: low-energy adaptive clustering hierarchy; r_{rb}: matched-pairs rank-biserial correlation (vs ABC-LEACH); SD: standard deviation. Differences are Enhanced-ABC-LEACH minus the comparator; Wilcoxon signed-rank p-values are Holm-adjusted across the seven one-factor-at-a-time (OFAT) conditions.

5.2 Trade-off among the first-, half- and last-node-death rounds

The negative FND difference relative to ABC-LEACH reflects how the two fitness functions distribute the CH role. The standard fitness ranks nodes by residual energy divided by BS distance, so ABC-LEACH repeatedly selects the same high-energy nodes near the BS. In the reference condition, the node nearest the BS served as CH for an average longest uninterrupted streak of 40.7 rounds under ABC-LEACH, compared with 12.4 rounds under Enhanced-ABC-LEACH. Consistent with this concentration, ABC-LEACH loses most of its nodes within a short interval once the first node has died: it has the latest FND but a post-FND lifetime of only 21.6 rounds, compared with 57.0 rounds for Enhanced-ABC-LEACH. The refined fitness rotates the CH role more widely and balances cluster loads, so one node may exhaust its energy slightly earlier while most of the network remains operational longer. The method is therefore designed for sustained operation of a large active portion of the network (HND) and for balanced clustering, not for the latest possible first node death.

5.3 Weight sensitivity and ablation

Figure 3 places every predefined configuration in the FND-HND plane. No alternative weight vector dominated W_0 across all primary outcomes, so W_0 is a non-dominated configuration among those tested; it is not universally optimal, because alternative weights improved some metrics while worsening others. HND was comparatively stable: its mean changed by at most 1.0% across W1-W9. FND ranged from −12.9% (W8) to +5.3% (W9) and LND from −0.9% (W1) to +4.2% (W8), with configurations that raised FND tending to shorten the post-FND period. The local perturbations W1-W4 changed HND, LND, delivery, and member distance by at most 3.3%, whereas the load CV changed by −21.4% (W4) to +8.5% (W3); several of these small differences are statistically significant, so their limited size, not their absence, is the relevant conclusion (Supplementary Tables S1-S3).

The ablations show that each component influences different outcomes rather than improving every metric. Removing the energy score (A_E) shortened FND by 36.4% and HND by 3.1% relative to W_0. Removing the load-balance score (A_L) improved FND by 35.4 rounds [31.7, 39.1] and HND by 12.3 rounds, but it increased the load CV by 94.7% and shortened the post-FND lifetime by 58.7%. The load-balance term therefore mainly controls workload uniformity and late-stage operation, and the adopted weights represent an intermediate design choice.

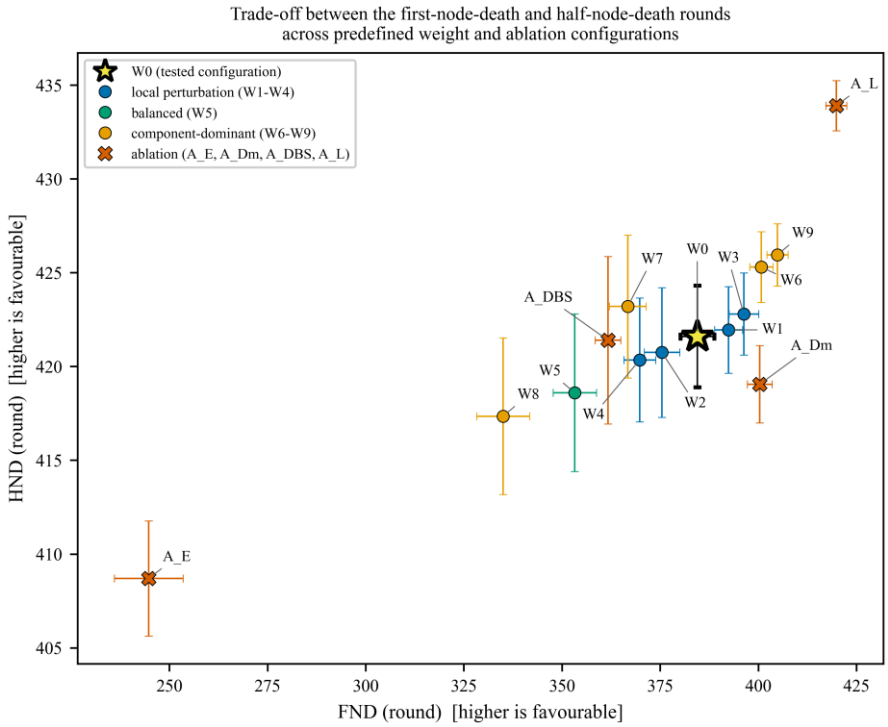


Figure 3. First-node-death (FND) versus half-node-death (HND) round for the predefined weight configurations (W0-W9) and ablations (A_E, A_Dm, A_DBS, A_L) of Enhanced-ABC-LEACH (ABC, artificial bee colony; LEACH, low-energy adaptive clustering hierarchy); markers: means over the 20 evaluation runs, error bars: 95% confidence intervals

5.4 Robustness under different network conditions

Table 4 classifies the paired differences across the seven OFAT conditions. Relative to ABC-LEACH, Enhanced-ABC-LEACH reduced the member-to-CH distance and the load CV in every condition and produced a small but consistent HND improvement. LND was later in six conditions and inconclusive for the centre BS, whereas FND, the post-FND lifetime, and the cumulative delivery to the own HND were scenario-dependent, particularly under changes in BS position. Relative to LEACH, Enhanced-ABC-LEACH improved FND and HND in all conditions but reached LND earlier, indicating improved early-to-mid network stability at the expense of the final sparse-node survival tail. The largest FND difference occurred with the BS at the field centre (426.7 vs 262.2 rounds), where ABC-LEACH kept the node nearest the BS as CH for a mean longest streak of 118.0 consecutive rounds (Enhanced-ABC-LEACH: 3.3); this condition-specific effect is not a general advantage (Tables S1-S4 and Figures S1-S6 in the Appendix).

5.5 Contemporary comparator

Table 5 compares the protocols with H-BSBOC. Enhanced-ABC-LEACH provided a substantially longer stability period: its FND occurred at 383.9 rounds on average, compared with 167.7 rounds for H-BSBOC (paired difference 216.2 rounds [200.5, 231.9]). H-BSBOC, in turn, had a slightly later HND (428.1 vs 422.5 rounds), a later LND (482.6 vs 441.0 rounds), a shorter member-to-CH distance, and a lower load CV. The cumulative delivery ratio over the whole lifetime was marginally higher for Enhanced-ABC-LEACH, a practically small difference. H-BSBOC used 3.68 times as many fitness evaluations per round, and the budget-matched variant showed the same general trade-off (Supplementary Tables S8-S9). Neither method was uniformly superior: Enhanced-ABC-LEACH favours early and mid-life stability with a smaller search effort, whereas H-BSBOC favours structural balance and a longer late-stage survival tail.

Table 4. Robustness across the seven OFAT conditions (30 paired runs each)

Metric	vs ABC-LEACH	vs LEACH
Member-to-CH distance	7/7 improved (−41.9 to −22.4%)	7/7 improved (−16.4 to −2.2%)
Load CV	7/7 improved (−70.8 to −55.2%)	7/7 improved (−56.3 to −13.8%)
HND	7/7 improved (+1.0 to +4.9%)	7/7 improved (+2.9 to +8.5%)
LND	6/7 improved, 1/7 inconclusive (−0.1 to +7.1%)	7/7 worsened (−18.5 to −10.6%)
FND	mixed: 3/7 improved, 4/7 worsened (−8.6 to +62.8%)	7/7 improved (+13.4 to +35.2%)
Post-FND lifetime	mixed: 5/7 improved, 2/7 worsened (−71.5 to +256.7%)	7/7 worsened (−89.1 to −61.5%)
Delivery ratio to own HND	mixed: 6/7 improved, 1/7 worsened (−0.4 to +0.5%)	7/7 improved (+0.2 to +0.8%)

Note: Enhanced-ABC-LEACH versus each comparator; ranges are percentage differences. ABC: artificial bee colony; CH: cluster head; CV: coefficient of variation; FND, HND and LND: first-, half- and last-node-death rounds; LEACH: low-energy adaptive clustering hierarchy; OFAT: one-factor-at-a-time. Improved/worsened: Holm-adjusted $p < 0.05$ and 95% confidence interval excluding zero, otherwise inconclusive; mixed: scenario-dependent.

Table 5. Comparison with H-BSBOC, a harmonized implementation of the 2025 BSBOC method (30 paired runs)

Protocol	FND (round)	HND (round)	LND (round)	Delivery Ratio (Whole Lifetime)	Member-to-CH Distance (m)	Load CV	Fitness Evaluations per Round
LEACH	300.5 ± 9.4	397.9 ± 8.4	534.6 ± 15.5	0.9840	18.42	0.602	0
ABC-LEACH	391.0 ± 5.7	406.3 ± 3.9	412.6 ± 4.0	0.9865	24.86	1.085	822.4
Enhanced-ABC-LEACH	383.9 ± 9.6	422.5 ± 5.6	441.0 ± 4.0	0.9909	17.46	0.484	827.9
H-BSBOC	167.7 ± 39.6	428.1 ± 8.8	482.6 ± 8.0	0.9887	16.44	0.234	3,047.5

Note: Values are means (± SD for lifetime milestones). ABC: artificial bee colony; BSBOC: binary secretary bird optimization clustering; CH: cluster head; CV: coefficient of variation; FND, HND and LND: first-, half- and last-node-death rounds; LEACH: low-energy adaptive clustering hierarchy; SD: standard deviation. H-BSBOC is a harmonized implementation used as an additional contemporary comparator; its primary results use latent-rank cardinality repair because the published BSBOC description did not specify cardinality repair or dead-node handling. Repair sensitivity, runtime, and the lifetime figure are in the Supplementary Material (Tables S7-S9, Figures S10-S14 and S16).

The mean FND change caused by replacing the latent-rank repair rule exceeded the prespecified operational 10% sensitivity threshold; however, the paired 95% confidence interval included zero (FND change +12.5%, paired 95% CI −9.3 to 47.7 rounds over 10 seeds), so the sensitivity was classified as high under the magnitude rule without any claim of statistical significance. The other metrics changed by less than 5% and no comparison direction reversed, so the conclusion that Enhanced-ABC-LEACH reaches FND later is unchanged, whereas the size of the FND gap depends on the unspecified repair rule (Supplementary Section S4).

6. LIMITATIONS AND PRACTICAL IMPLICATIONS

6.1 Practical implications

The refinement is relevant to applications in which a central node periodically reorganizes battery-powered sensors, such as environmental and agricultural monitoring, structural-health monitoring, industrial sensing, and the monitoring of remote infrastructure [1, 2, 9]. Because the CH decision is evaluated at the BS, the additional computation is not borne by the sensor nodes, and Enhanced-ABC-LEACH required about 27% of the fitness evaluations per round of the author-budget comparator (Section 5.5). The evidence, however, comes from simulation only. A deployment would have to account for localization and information-collection overhead, synchronization, distribution of the CH assignment, hardware variability, interference, collisions, fading, node failures, and imperfect links. Energy estimation errors or node mobility would degrade the information on which the fitness relies, and their effect on the selected configurations was not quantified.

6.2 Limitations

The study has the following limitations: (i) the evaluation is simulation-only, with no hardware or testbed validation; (ii) nodes are homogeneous and stationary, and ideal knowledge of position and residual energy is assumed; (iii) optimization is centralized at the BS; (iv) the first-order radio model and single-hop CH-to-BS communication are used; (v) one sensing-field size was examined; (vi) robustness was studied with an OFAT design rather than a factorial design, and varying the number of nodes also changes the node density; (vii) the weight search covered a finite set of predefined vectors and is not a global optimization; (viii) H-BSBOC is a harmonized implementation because two rules were unspecified in the publication, and its FND depends on the repair assumption; and (ix) the computational overhead of CH optimization at the BS grows with the search budget and was measured only in the present implementation.

7. CONCLUSION

This study presented a configuration-level fitness refinement for ABC-based CH selection in which the ABC search is shared with ABC-LEACH, so that the evaluation strategy is the only difference. The refinement consistently improved the structural clustering metrics: across all seven tested conditions it shortened member-to-CH distances and reduced cluster-load variation relative to ABC-LEACH. Its HND improvement was consistent but modest, whereas the effects on FND, LND, and the late-stage survival tail involved trade-offs that depended on the network condition. The adopted weight vector is a tested non-dominated configuration rather than a universally optimal one, and the comparison with a harmonized implementation of a recent secretary-bird method showed a different stability-versus-tail-survival profile rather than uniform superiority of either method. Future work will validate the approach on hardware testbeds and in dynamic networks with mobility, heterogeneous energy, and

imperfect links, extend the evaluation to multi-hop and multi-objective settings, and examine adaptive or learning-based weight selection.

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NOMENCLATURE

A_r	set of alive sensor nodes in round r
CV_L	coefficient of variation of cluster loads, dimensionless
$d(n,j)$	Euclidean distance between member node n and CH j, m
$d_{j,\mathrm{BS}}$	distance between node j and the base station, m
$\bar{d}_{\mathrm{BS}}$	mean CH-to-BS distance of a configuration, m
$d_{\mathrm{BS,max}}$	maximum distance from an alive node to the base station, m
$\bar{d}_{\mathrm{member}}$	mean member-to-CH distance of a configuration, m
d_0	threshold distance of the radio model, m
D_f	diagonal length of the sensing field, m
E_0	initial energy of a node, J
E_j	residual energy of node j, J
E_{DA}	data-aggregation energy per bit, J/bit
$E_{\mathrm{DA}}^{\mathrm{CH}}$	aggregation energy of a CH in one round, J
E_{elec}	electronic energy per bit, J/bit
E_{RX}, E_{TX}	energy to receive and to transmit a packet, J
f_j	node-level score of CH candidate j, J/m
F_E, F_{Dm}	energy and member-distance scores, dimensionless
F_{DBS}, F_L	CH-to-BS-distance and load-balance scores, dimensionless
F_{standard}	standard configuration fitness, J/m
F_{enhanced}	refined configuration fitness, dimensionless
F_m	fitness of the protocol under evaluation
K_r	number of cluster heads in round r
l	packet length, bit
L_j	number of members assigned to CH j
M_r	set of alive non-CH nodes in round r
MCN	maximum number of ABC cycles
N	number of deployed sensor nodes
n_p	number of packets aggregated by a CH
p_i	selection probability of food source i
P_{CH}	desired proportion of cluster heads
r	simulation round
r_{rb}	matched-pairs rank-biserial correlation
R_E	ratio of mean CH energy to mean alive-node energy
S_i	CH configuration of food source i
SN, SN'	number of food sources; $SN' = \min(SN, \lvert A_r \rvert)$
V_i	neighbouring configuration generated from S_i
W_0	tested weight vector $(w_E, w_{Dm}, w_{\mathrm{DBS}}, w_L)$

Greek symbols

α	sensitivity of the energy-score transformation, dimensionless
ε, ε_s	small constants preventing division by zero
$\varepsilon_{\mathrm{fs}}$	free-space amplifier coefficient, J/bit/m ^{2}
$\varepsilon_{\mathrm{mp}}$	multipath amplifier coefficient, J/bit/m ^{4}
μ, σ	mean and population standard deviation of cluster loads

APPENDIX

Table S1. Mean ± SD per OFAT condition (30 paired runs each)

Condition.	Protocol	FND	HND	LND	Post-FND	Delivery to own HND	Member Distance (m)	Load CV
Reference	LEACH	300.5 ± 9.4	397.9 ± 8.4	534.6 ± 15.5	234.1 ± 17.5	0.9908 ± 0.0013	18.42 ± 0.46	0.602 ± 0.016
Reference	ABC-LEACH	391.0 ± 5.7	406.3 ± 3.9	412.6 ± 4.0	21.6 ± 3.7	0.9898 ± 0.0013	24.86 ± 1.06	1.085 ± 0.049
Reference	Enhanced-ABC-LEACH	383.9 ± 9.6	422.5 ± 5.6	441.0 ± 4.0	57.0 ± 9.7	0.9943 ± 0.0020	17.46 ± 0.52	0.484 ± 0.041
N = 50	LEACH	290.7 ± 13.4	374.6 ± 12.9	482.5 ± 15.0	191.8 ± 13.9	0.9900 ± 0.0026	27.31 ± 1.38	0.510 ± 0.019
N = 50	ABC-LEACH	377.4 ± 10.2	387.4 ± 7.4	392.5 ± 7.4	15.1 ± 4.6	0.9904 ± 0.0018	31.23 ± 1.70	0.774 ± 0.058
N = 50	Enhanced-ABC-LEACH	393.2 ± 8.2	406.4 ± 6.2	414.1 ± 5.9	20.9 ± 5.5	0.9925 ± 0.0019	24.22 ± 1.15	0.287 ± 0.073
N = 150	LEACH	295.3 ± 12.1	408.7 ± 5.4	558.0 ± 13.8	262.7 ± 18.5	0.9911 ± 0.0012	14.61 ± 0.28	0.629 ± 0.013
N = 150	ABC-LEACH	401.8 ± 5.9	424.0 ± 2.5	431.2 ± 2.6	29.4 ± 5.3	0.9896 ± 0.0014	20.41 ± 0.83	1.209 ± 0.048
N = 150	Enhanced-ABC-LEACH	367.2 ± 8.4	428.9 ± 4.9	454.6 ± 3.6	87.4 ± 8.4	0.9929 ± 0.0015	14.29 ± 0.36	0.542 ± 0.027
BS (50, 50) m	LEACH	376.4 ± 14.4	469.7 ± 3.9	553.8 ± 12.1	177.4 ± 15.7	0.9885 ± 0.0016	18.72 ± 0.46	0.601 ± 0.015
BS (50, 50) m	ABC-LEACH	262.2 ± 30.1	478.9 ± 4.5	495.4 ± 18.3	233.2 ± 35.8	0.9945 ± 0.0016	22.44 ± 1.04	0.832 ± 0.045
BS (50, 50) m	Enhanced-ABC-LEACH	426.7 ± 11.5	483.5 ± 1.5	495.1 ± 4.5	68.4 ± 13.8	0.9962 ± 0.0009	15.66 ± 0.45	0.263 ± 0.017
BS (50, 100) m	LEACH	368.3 ± 12.6	457.3 ± 3.9	562.6 ± 16.6	194.3 ± 21.6	0.9890 ± 0.0017	18.68 ± 0.43	0.602 ± 0.015
BS (50, 100) m	ABC-LEACH	343.3 ± 12.6	458.2 ± 4.1	468.3 ± 3.9	125.0 ± 12.8	0.9966 ± 0.0013	26.94 ± 0.94	1.167 ± 0.031
BS (50, 100) m	Enhanced-ABC-LEACH	451.9 ± 5.6	470.4 ± 1.7	487.5 ± 11.9	35.6 ± 15.0	0.9925 ± 0.0016	15.64 ± 0.42	0.340 ± 0.041
E0 = 0.1 J	LEACH	144.9 ± 6.6	199.4 ± 4.2	273.5 ± 7.8	128.5 ± 9.8	0.9804 ± 0.0034	18.53 ± 0.45	0.604 ± 0.018
E0 = 0.1 J	ABC-LEACH	190.0 ± 3.5	204.9 ± 2.3	210.8 ± 2.2	20.8 ± 3.5	0.9805 ± 0.0026	24.69 ± 1.13	1.074 ± 0.048
E0 = 0.1 J	Enhanced-ABC-LEACH	185.4 ± 5.3	212.5 ± 2.5	224.5 ± 2.2	39.1 ± 4.9	0.9851 ± 0.0042	17.31 ± 0.52	0.470 ± 0.039
E0 = 0.3 J	LEACH	458.2 ± 11.6	597.7 ± 12.1	798.6 ± 22.0	340.4 ± 25.2	0.9938 ± 0.0011	18.39 ± 0.46	0.603 ± 0.013
E0 = 0.3 J	ABC-LEACH	593.2 ± 6.7	608.1 ± 6.1	614.2 ± 5.6	21.0 ± 3.6	0.9928 ± 0.0008	24.88 ± 1.05	1.089 ± 0.052
E0 = 0.3 J	Enhanced-ABC-LEACH	583.0 ± 12.8	632.3 ± 8.1	658.0 ± 6.4	75.0 ± 13.1	0.9963 ± 0.0012	17.49 ± 0.51	0.488 ± 0.041

Note: SD, standard deviation; OFAT, one-factor-at-a-time; N, number of nodes; E0, initial energy. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy.

Table S2. Enhanced-ABC-LEACH vs ABC-LEACH: paired difference as % of the comparator mean [95% CI]

Condition	FND	HND	LND	Post-FND	Delivery to Own HND	Member Distance (m)	Load CV
Reference	−1.8 [−2.6, −1.0]	4.0 [3.6, 4.4]	6.9 [6.6, 7.2]	164.5 [146.3, 182.6]	0.5 [0.4, 0.5]	−29.8 [−31.1, −28.5]	−55.4 [−56.8, −54.1]
N = 50	4.2 [3.6, 4.8]	4.9 [4.6, 5.2]	5.5 [5.1, 6.0]	38.9 [21.4, 56.5]	0.2 [0.1, 0.3]	−22.4 [−23.7, −21.2]	−62.9 [−65.4, −60.4]
N = 150	−8.6 [−9.6, −7.6]	1.2 [0.8, 1.6]	5.4 [5.1, 5.8]	196.9 [182.7, 211.2]	0.3 [0.3, 0.4]	−30.0 [−31.0, −28.9]	−55.2 [−56.5, −53.9]
BS (50, 50) m	62.8 [58.4, 67.1]	1.0 [0.7, 1.3]	−0.1 [−1.5, 1.4]	−70.7 [−76.6, −64.8]	0.2 [0.1, 0.2]	−30.2 [−31.9, −28.5]	−68.4 [−70.4, −66.3]
BS (50, 100) m	31.6 [30.1, 33.2]	2.7 [2.3, 3.0]	4.1 [3.2, 5.0]	−71.5 [−77.7, −65.4]	−0.4 [−0.5, −0.3]	−41.9 [−43.3, −40.5]	−70.8 [−72.2, −69.5]
E0 = 0.1 J	−2.4 [−3.6, −1.3]	3.7 [3.3, 4.1]	6.5 [6.1, 6.9]	87.8 [76.7, 98.9]	0.5 [0.3, 0.7]	−29.9 [−31.3, −28.4]	−56.2 [−57.7, −54.8]
E0 = 0.3 J	−1.7 [−2.3, −1.1]	4.0 [3.6, 4.4]	7.1 [6.8, 7.5]	256.7 [234.4, 279.1]	0.3 [0.3, 0.4]	−29.7 [−31.0, −28.4]	−55.2 [−56.7, −53.7]

Note: Holm-adjusted p >= 0.05 (not evidence of equivalence). Holm adjustment across the seven conditions per comparison and metric. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy.

Table S3. Enhanced-ABC-LEACH vs LEACH: paired difference as % of the comparator mean [95% CI]

Condition	FND	HND	LND	Post-FND	Delivery to Own HND	Member Distance (m)	Load CV
Reference	27.8 [26.8, 28.7]	6.2 [5.8, 6.6]	−17.5 [−18.5, −16.5]	−75.6 [−78.3, −72.9]	0.4 [0.3, 0.4]	−5.2 [−5.8, −4.6]	−19.6 [−22.5, −16.8]
N = 50	35.2 [33.5, 37.0]	8.5 [7.7, 9.3]	−14.2 [−15.3, −13.0]	−89.1 [−91.9, −86.3]	0.3 [0.1, 0.4]	−11.3 [−12.4, −10.3]	−43.7 [−48.8, −38.5]
N = 150	24.3 [22.8, 25.9]	4.9 [4.6, 5.3]	−18.5 [−19.4, −17.6]	−66.7 [−69.5, −64.0]	0.2 [0.1, 0.3]	−2.2 [−2.8, −1.6]	−13.8 [−15.5, −12.1]
BS (50, 50) m	13.4 [11.4, 15.3]	2.9 [2.6, 3.2]	−10.6 [−11.4, −9.8]	−61.5 [−65.9, −57.1]	0.8 [0.7, 0.8]	−16.4 [−17.2, −15.5]	−56.3 [−57.3, −55.2]
BS (50, 100) m	22.7 [21.3, 24.1]	2.9 [2.6, 3.1]	−13.4 [−14.6, −12.1]	−81.7 [−86.3, −77.1]	0.4 [0.3, 0.4]	−16.2 [−17.0, −15.5]	−43.4 [−46.1, −40.8]
E0 = 0.1 J	27.9 [25.9, 29.9]	6.5 [5.9, 7.2]	−17.9 [−19.0, −16.9]	−69.6 [−72.9, −66.3]	0.5 [0.3, 0.7]	−6.6 [−7.2, −6.0]	−22.2 [−24.8, −19.6]
E0 = 0.3 J	27.2 [26.6, 27.9]	5.8 [5.3, 6.3]	−17.6 [−18.6, −16.6]	−78.0 [−80.6, −75.3]	0.2 [0.2, 0.3]	−4.9 [−5.5, −4.3]	−19.1 [−21.9, −16.3]

Note: Holm-adjusted p >= 0.05 (not evidence of equivalence). Holm adjustment across the seven conditions per comparison and metric. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy.

Table S4. Centre-BS diagnostic: CH-duty concentration and the first node death

Condition	Quantity	Protocol	Mean	Median
BS centre	FND	ABC-LEACH	262.2	260.5
BS centre	FND	Enhanced-ABC-LEACH	426.7	425.0
BS centre	max_duty_single_node	ABC-LEACH	201.4	205.0
BS centre	max_duty_single_node	Enhanced-ABC-LEACH	81.6	77.5
BS centre	top1_duty_share	ABC-LEACH	0.044	0.045
BS centre	top1_duty_share	Enhanced-ABC-LEACH	0.017	0.016
BS centre	top5_duty_share	ABC-LEACH	0.162	0.160
BS centre	top5_duty_share	Enhanced-ABC-LEACH	0.072	0.071
BS centre	duty_share_of_5_nodes_nearest_bs	ABC-LEACH	0.148	0.150
BS centre	duty_share_of_5_nodes_nearest_bs	Enhanced-ABC-LEACH	0.064	0.063
BS centre	gini_ch_duty	ABC-LEACH	0.274	0.277
BS centre	gini_ch_duty	Enhanced-ABC-LEACH	0.071	0.069
BS centre	nodes_ever_ch	ABC-LEACH	100.0	100.0
BS centre	nodes_ever_ch	Enhanced-ABC-LEACH	100.0	100.0
BS centre	spearman_distance_vs_duty	ABC-LEACH	0.097	0.103
BS centre	spearman_distance_vs_duty	Enhanced-ABC-LEACH	−0.360	−0.333
BS centre	nearest_node_duty	ABC-LEACH	187.5	195.0
BS centre	nearest_node_duty	Enhanced-ABC-LEACH	65.4	65.0
BS centre	nearest_node_max_consecutive_ch_rounds	ABC-LEACH	118.0	108.5
BS centre	nearest_node_max_consecutive_ch_rounds	Enhanced-ABC-LEACH	3.3	3.0
BS centre	max_consecutive_ch_rounds_any_node	ABC-LEACH	139.9	140.0
BS centre	max_consecutive_ch_rounds_any_node	Enhanced-ABC-LEACH	10.5	7.0
BS centre	first_dead_best_duty_rank	ABC-LEACH	2.3	1.500
BS centre	first_dead_best_duty_rank	Enhanced-ABC-LEACH	3.1	3.0
BS centre	first_dead_best_distance_rank	ABC-LEACH	1.233	1.000
BS centre	first_dead_best_distance_rank	Enhanced-ABC-LEACH	1.733	1.000
BS centre	max_standard_fitness_selected_ch	ABC-LEACH	0.053	0.045
BS centre	max_standard_fitness_selected_ch	Enhanced-ABC-LEACH	0.053	0.045
BS centre	mean_over_rounds_min_ch_bs_distance_m	ABC-LEACH	23.0	23.0
BS centre	mean_over_rounds_min_ch_bs_distance_m	Enhanced-ABC-LEACH	16.1	16.2
Reference	FND	ABC-LEACH	391.0	391.5
Reference	FND	Enhanced-ABC-LEACH	383.9	384.5
Reference	max_duty_single_node	ABC-LEACH	228.1	231.5
Reference	max_duty_single_node	Enhanced-ABC-LEACH	157.9	162.0
Reference	top5_duty_share	ABC-LEACH	0.221	0.222
Reference	top5_duty_share	Enhanced-ABC-LEACH	0.138	0.139
Reference	duty_share_of_5_nodes_nearest_bs	ABC-LEACH	0.205	0.207
Reference	duty_share_of_5_nodes_nearest_bs	Enhanced-ABC-LEACH	0.117	0.115
Reference	gini_ch_duty	ABC-LEACH	0.365	0.368
Reference	gini_ch_duty	Enhanced-ABC-LEACH	0.267	0.266
Reference	spearman_distance_vs_duty	ABC-LEACH	−0.440	−0.442
Reference	spearman_distance_vs_duty	Enhanced-ABC-LEACH	−0.984	−0.984

Note: Diagnostic results were obtained from the stored CH lists without additional simulation. No node was located at the BS, and all standard-fitness values were finite. The +62.8% FND difference in the centre-BS condition is condition-specific and does not represent a general advantage. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND, and LND, first-, half-, and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy.

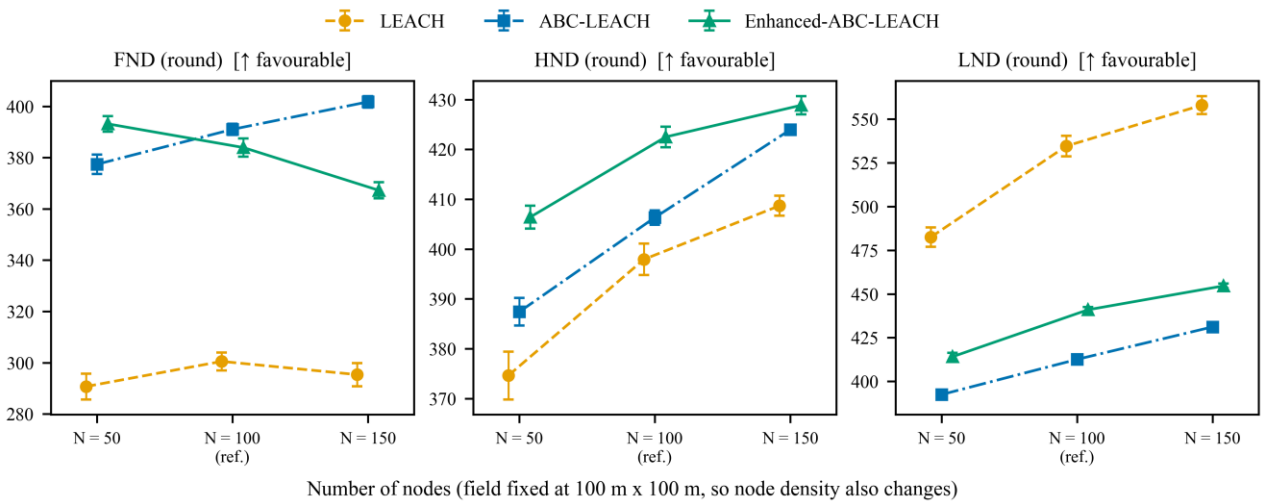


Figure S1. FND, HND and LND for N = 50, 100 and 150 nodes in the same field (means with 95% confidence intervals over 30 paired runs). ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy

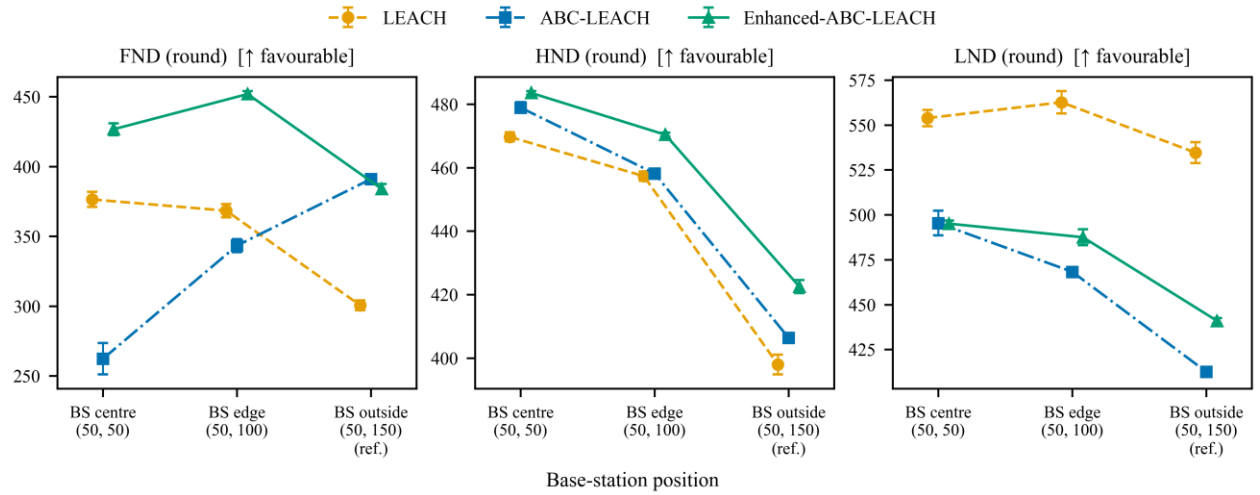


Figure S2. FND, HND and LND for three BS positions. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy

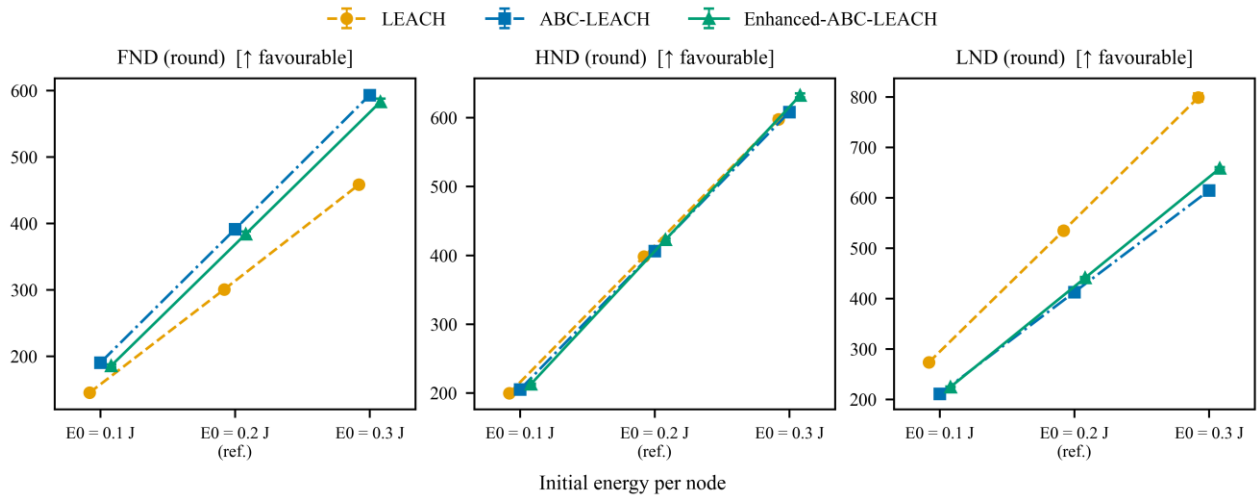


Figure S3. FND, HND and LND for initial energies of 0.1, 0.2 and 0.3 J. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy

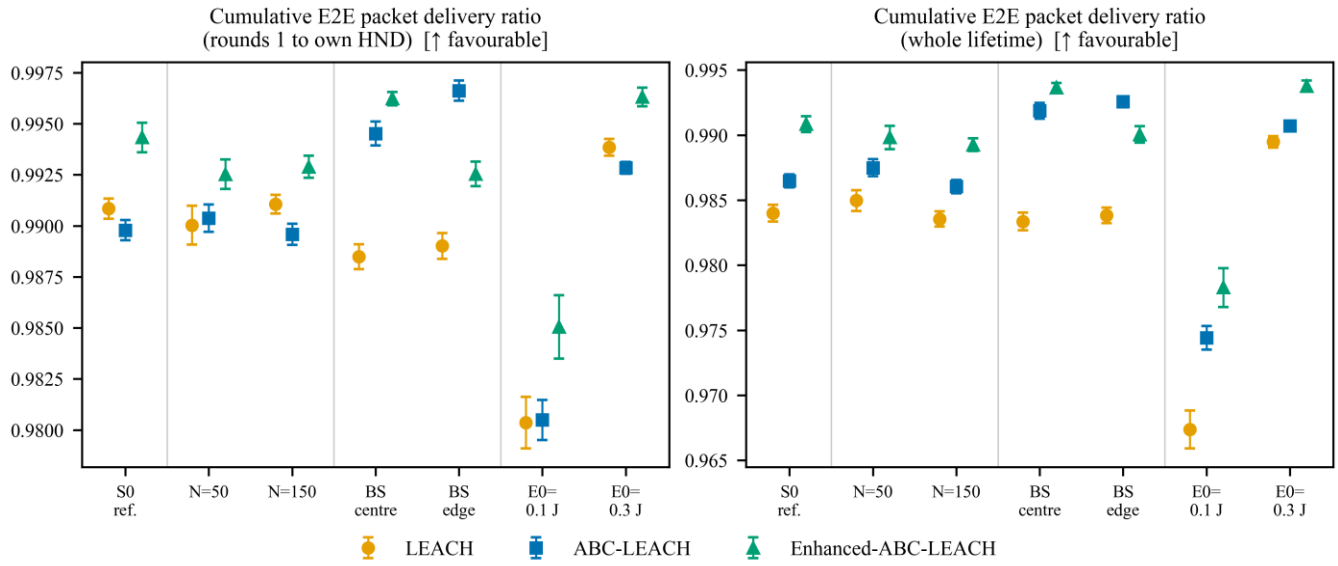


Figure S4. Cumulative end-to-end delivery ratio in the seven OFAT conditions. OFAT, one-factor-at-a-time. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy

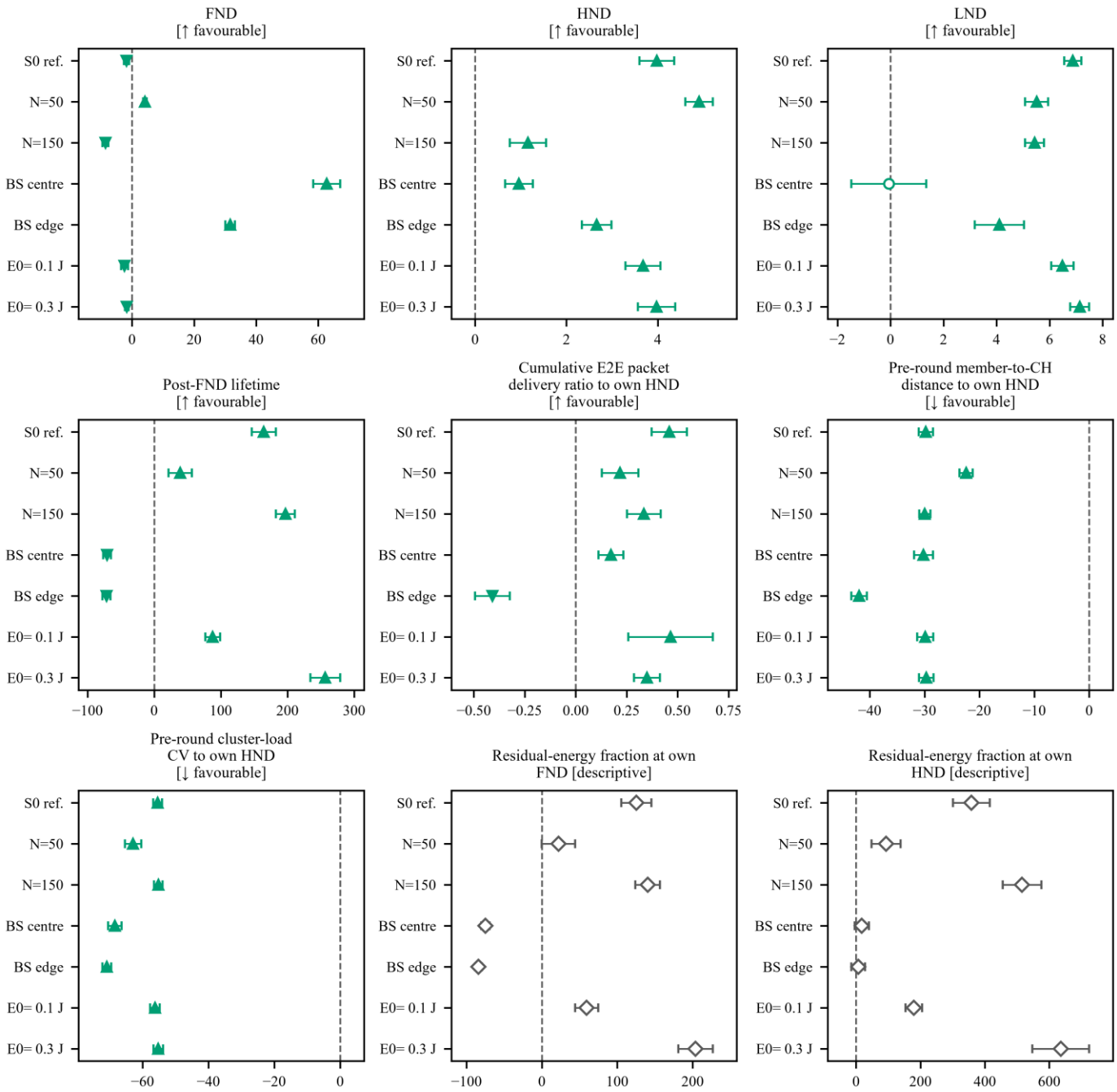


Figure S5. Paired percentage differences of Enhanced-ABC-LEACH relative to ABC-LEACH in the seven OFAT conditions (95% confidence intervals; markers show the Holm-based classification). The two residual-energy panels show residual energy at protocol-specific milestone, a descriptive milestone-conditioned metric: FND and HND occur in different rounds for each protocol, so these panels use a neutral marker and no direction class. OFAT, one-factor-at-a-time. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy

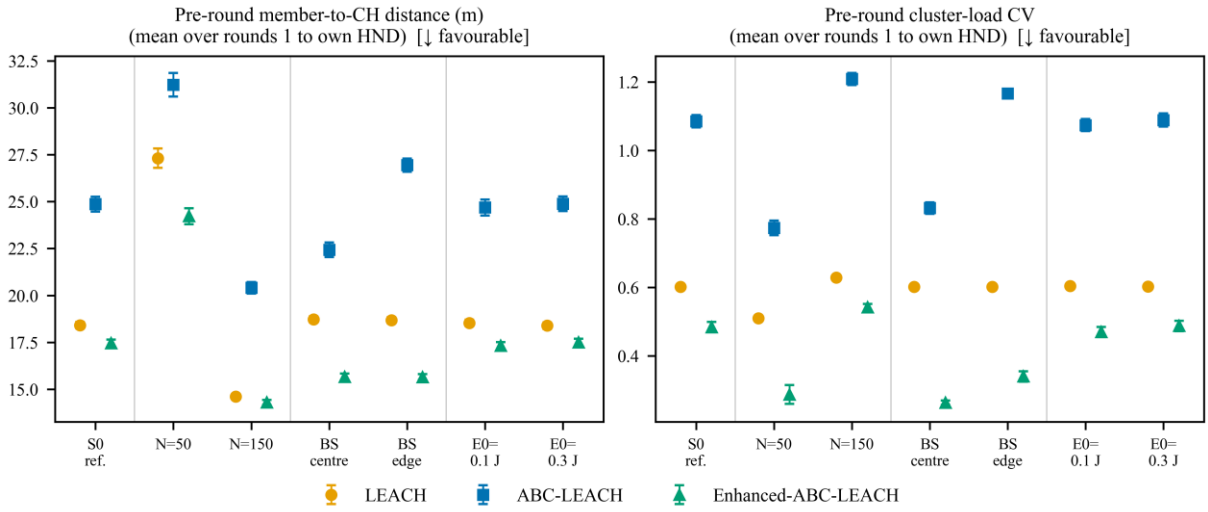


Figure S6. Pre-round member-to-CH distance and cluster-load CV, averaged up to each protocol's own HND, in the seven OFAT conditions (means with 95% confidence intervals over 30 paired runs). E0, initial energy; N, number of nodes; OFAT, one-factor-at-a-time. ABC, artificial bee colony; BS, base station; CH, cluster head; CV, coefficient of variation; FND, HND and LND, first-, half- and last-node-death rounds; LEACH, low-energy adaptive clustering hierarchy