FUDMA Journal of Engineering and Technology
ISSN: 3092-9385
https://fjet.fudutsinma.edu.ng/index.php/fjet/
Volume 2, Issue 2, 2026, 158-168

Improvement of Power Efficiency of Sensor Network Using Ant Colony Optimization and K-Means Clustering Technique

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Abstract

Energy-constrained routing remains a central limitation in wireless sensor networks (WSNs), because repeated transmission, poor cluster-head selection, and unreliable paths accelerate battery depletion and fragment sensing coverage. This paper presents a K-means-guided adaptive multi-objective ant colony optimization (KMA-MOACO) framework that combines logical node clustering, residual-energy-based cluster-head rotation, multi-pheromone route construction, and Pareto-dominance-based selection. The routing problem is formulated to minimize communication energy and end-to-end delay while maximizing packet-delivery reliability, subject to node-energy, transmission-range, link-quality, and delay constraints. A first-order radio model is used in a 100 m × 100 m simulation field with 50–150 stationary nodes; the reported comparative case contains 100 nodes initialized with 2 J, periodic 64-byte packets, and 10–30 ants per routing round. KMA-MOACO is evaluated against a conventional ACO routing scheme and a generic multi-objective ACO implementation. In the reported representative case, KMA-MOACO reduced average energy consumption to 0.5676 J and average end-to-end delay to 0.3585 s, corresponding to approximately 75% reductions relative to both comparators. It achieved a packet-delivery ratio and normalized throughput of 0.92, full node reachability, an energy-delay product of 0.2035, and an energy-reliability product of 0.6170. The generic multi-objective ACO retained the longest raw network lifetime and the largest hypervolume, whereas the proposed method provided the strongest overall compromise between energy, latency, connectivity, and reliability. The findings support adaptive clustering and Pareto-guided pheromone control as a practical direction for resource-constrained WSNs, while also identifying the need for repeated-seed statistical validation and hardware-in-the-loop assessment.

Keywords: Ant colony optimization, clustering, energy efficiency, K-means, multi-objective optimization, routing, wireless sensor networks.

1.0 Introduction

Wireless sensor networks consist of spatially distributed sensing devices that cooperate through low-power wireless links to monitor physical processes and deliver measurements to one or more sinks. Their deployment in environmental monitoring, industrial automation, precision agriculture, infrastructure surveillance, health systems, and disaster response is enabled by low-cost electronics and flexible multi-hop communication[1], [2]. The same characteristics that make WSNs attractive—small batteries, lightweight radios, limited computation, and unattended operation—also make energy expenditure the dominant design constraint. In most deployments, radio communication consumes considerably more energy than sensing or local computation; therefore, an inefficient route can shorten network lifetime even when individual nodes operate correctly.

Hierarchical routing partly addresses this problem by partitioning the network into clusters. Cluster members transmit locally to a cluster head, which aggregates or forwards their data toward the sink. LEACH established the classical principle of probabilistic cluster-head rotation[3]–[6], but random election does not always account for spatial balance, residual energy, link quality, or traffic conditions. K-means can provide a more structured partition by minimizing within-cluster distance, although fixed centroids and repeated re-clustering may introduce overhead. Conversely, ant colony optimization (ACO) is well suited to distributed path discovery because artificial ants reinforce promising links through pheromone updates [7]. Classical ACO, however, may converge prematurely, overemphasize path length, or fail to reconcile energy, delay, and reliability when the network state changes.

These limitations motivate a coupled clustering-and-routing architecture. The present work organizes the physical flat network into logical K-means clusters, rotates cluster heads according to residual energy, and applies an adaptive multi-objective ACO process after clustering. Rather than using one aggregated cost with fixed weights, the algorithm maintains objective-specific pheromone and heuristic information and uses Pareto dominance to retain non-dominated feasible routes. The method therefore treats routing as a constrained multi-objective problem: communication energy and end-to-end delay are minimized, while packet-delivery reliability is maximized.

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

The principal contributions are fourfold. First, the paper formulates an energy-, delay-, and reliability-aware route-selection problem for clustered WSNs under practical energy, distance, packet-reception, and latency constraints. Second, it develops a K-means-guided adaptive multi-pheromone ACO framework with residual-energy-based cluster-head rotation and anti-stagnation control. Third, it evaluates the framework against two ACO baselines using both conventional network metrics and Pareto-quality indicators. Fourth, it distinguishes between raw lifetime maximization and balanced operational performance, showing that the longest survival time does not necessarily imply the most useful combination of energy economy, responsiveness, connectivity, and data delivery.

The remainder of the paper is organized as follows. Section II reviews related energy-efficient clustering and ACO routing research. Section III defines the system and optimization models. Section IV presents the proposed KMA-MOACO framework. Section V describes the simulation design. Section VI reports and interprets the results. VII concludes the paper.

2.0 Related Work

2.1 Energy-Aware Clustering in WSNs

Clustering is among the most widely used mechanisms for controlling WSN communication overhead. LEACH introduced randomized cluster-head election and periodic role rotation, reducing the distance over which most nodes transmit[2]–[4]. Subsequent surveys have shown that clustering performance depends on cluster-head selection, cluster size, re-clustering frequency, data aggregation, and inter-cluster route design[8], [9]. K-means is particularly attractive because it forms compact groups through distance-based assignment and centroid recomputation [10], [11]. Nevertheless, a purely geometric K-means partition can repeatedly select energy-poor nodes near the centroid or require costly reconfiguration when the topology or traffic changes. Energy-aware implementations must therefore augment distance with residual-energy information and carefully manage cluster-head rotation.

Recent hybrid protocols continue to combine clustering with metaheuristic routing. [12]developed a hybrid cluster-routing method for reducing energy imbalance, while [13]combined fuzzy cluster-head selection with quantum annealing and on-demand re-clustering . [3] proposed a geometry-based K-means routing protocol , and [14]coupled whale optimization for cluster-head selection with ACO for route search . These studies confirm the value of separating network organization from path optimization. However, many methods either optimize a dominant objective, depend on centralized processing, or report network lifetime without simultaneously quantifying delay, reliability, reachability, and Pareto-set quality.

2.2 Ant Colony Optimization and Multi-Objective Routing

ACO models the collective foraging behavior of ants through probabilistic path construction and pheromone reinforcement [7]. In WSN routing, pheromone can encode energy cost, hop count, distance, residual energy, or link quality. [15]recently combined K-means clustering and an improved ACO strategy for WSN data transmission, while [16]proposed adaptive pheromone decay and a multi-objective heuristic for energy-efficient and reliable routing. [17]combined an artificial algae algorithm for cluster-head selection with ACO-based route search. These developments show that current research is moving away from shortest-path-only formulations toward adaptive, hybrid, and multi-criteria designs.

Multi-objective optimization is essential because WSN objectives are inherently conflicting. A route with few long hops may reduce hop count but demand high transmission power; a highly reliable path may use additional hops and increase delay; and a route that maximizes the lifetime of a subset of nodes may reduce coverage fairness. [18]classified multi-objective WSN methods and emphasized Pareto-based techniques as a means of preserving trade-offs without imposing a single arbitrary weighting. Despite this progress, three gaps remain pertinent: (i) the clustering stage is often weakly coupled to the route-search state, (ii) algorithms frequently report only energy and lifetime, and (iii) standard ACO variants may lose reachability because of pheromone stagnation or inadequate exploration.

2.3 Research Gap and Design Rationale

The literature suggests that a publishable routing contribution should do more than produce a lower energy value. It should maintain full or near-full connectivity, provide timely delivery, preserve route reliability, control computational convergence, and reveal the trade-offs introduced by its design. The proposed KMA-MOACO framework addresses these requirements by (1) using K-means to reduce local communication distance, (2) rotating cluster heads based on residual energy, (3) applying objective-specific pheromone and heuristic information, (4) preserving non-dominated routes in a Pareto archive, and (5) using adaptive exploration and anti-stagnation mechanisms to prevent route-search collapse.

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

3.0 System Model and Problem Formulation

3.1 Network Assumptions

Consider a WSN represented by an undirected geometric graph G=(V,E), where V contains N stationary, homogeneous sensor nodes and one energy-unconstrained sink. Nodes are randomly distributed in a two-dimensional field [0,Lx]×[0,Ly]. Each node knows or estimates its coordinates, residual energy, the link quality to its neighbors, and the expected local delay. Two nodes i and j can communicate directly when their Euclidean separation satisfies d_ij≤R_max.

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{1}$$

The physical deployment is flat, but K-means creates logical clusters for local communication and data aggregation. Cluster members transmit to their assigned cluster head; cluster heads forward aggregated traffic through one or more cluster heads or intermediate nodes toward the sink. Equation (1) shown the resultant path. All comparative algorithms operate on identical topologies and traffic conditions.

3.2 Radio-Energy Model

The first-order radio model is adopted. For an l-bit packet transmitted over distance d, the transmitter consumes electronic energy and distance-dependent amplifier energy. Free-space and multipath propagation are separated by a threshold distance d0.

$$E_{tx}(I,d) = IE_{elec} + I \in_{fs} d^2 \tag{2}$$

$$E_{tx}(I,d) = IE_{elec} + I \in_{mp} d^4 \tag{3}$$

$$E_{tx}(I) = IE_{elec} \tag{4}$$

The residual energy of a forwarding node is updated after each transmission and reception. A candidate route is infeasible if any participating node would fall below its critical energy threshold. This constraint prevents an apparently short route from repeatedly exhausting the same relay nodes.

3.3 Delay and Reliability Models

End-to-end delay includes transmission, propagation, processing, and queueing terms accumulated over the path P. The path delay is represented by equation (5)

$$D(P) = \sum_{(i,j)\in P}\left[D_{tx}(i,j) + D_{prop}(i,j)\right] \tag{5}$$

Reliability as depicted in equation (6) is quantified through the packet reception ratio (PRR) of each link. Assuming conditional link independence, path delivery reliability is the product of the PRRs along the route.

$$R(P) = \prod_{(i,j)\in P} PRR_{ij} \tag{6}$$

Only links satisfying PRR_ij≥gamma are considered, where gamma is selected in the range 0.8–0.9 according to application criticality. A maximum end-to-end delay D_max is also imposed for delay-sensitive operation.

3.4 Multi-Objective Formulation

For a source-to-sink route P, the optimization objective is to minimize total communication energy E(P) and end-to-end delay D(P), while maximizing reliability R(P). The equivalent minimization vector is equation (7).

Min **F**(P) = [E(P), D(P), 1-R(P)] (7)

subject to node-energy, transmission-range, link-quality, loop-avoidance, and delay constraints. A route P_a dominates P_b when it is no worse in every objective and strictly better in at least one objective. The archive A therefore contains routes for which no other feasible route simultaneously consumes less energy, incurs lower delay, and provides higher reliability.

4.0 Proposed KMA-MOACO Routing Framework

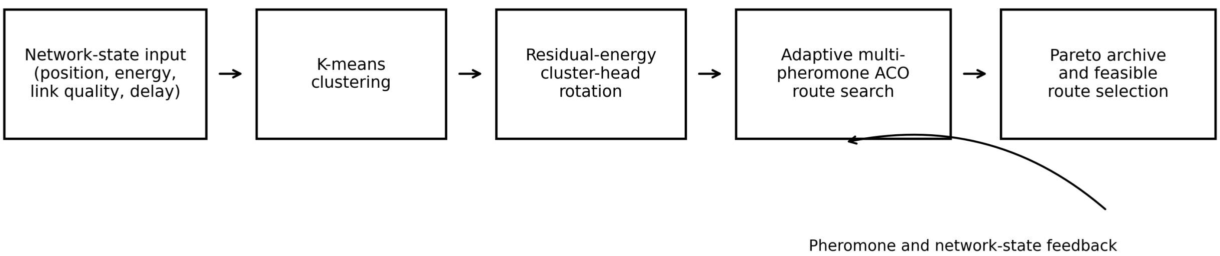

Figure 1: Processing sequence of the proposed K-means-guided adaptive multi-objective ACO framework

4.1 K-Means Clustering and Energy-Aware Cluster-Head Rotation

At initialization, K-means partitions the node-coordinate matrix into K logical clusters by alternating node assignment and centroid recomputation until the assignments stabilize. The compact clusters reduce the average local communication distance and create a smaller cluster-head-level routing graph. Because the geometric centroid is not necessarily an energy-suitable relay, the operational cluster head is selected from the cluster members using residual energy and proximity to the centroid. At subsequent rounds, the cluster head is re-evaluated using equation 8; a member with greater residual energy can replace the current head, preventing persistent forwarding burden on one device. Figure. 1. Depict the processing sequence of the proposed K-means-guided adaptive multi-objective ACO framework.

$$CH_k = \arg max \left[WE\,\frac{E_i}{E_{max}} - 1wd\right]mu_k \tag{8}$$

where C_k is cluster k, mu_k is its centroid, and w_E and w_d control energy and geometric preference. In the implementation represented by the source study, residual energy is the primary rotation criterion, while the K-means assignment establishes spatial compactness.

4.2 Multi-Pheromone Route Construction

Each artificial ant constructs a loop-free route by moving from its current node i to an unvisited feasible neighbor j. Separate pheromone trails and heuristics are maintained for energy, delay, and reliability. The transition probability is proportional to a weighted product of these components as shown in equation (9).

$$P_{ij} = \frac{\prod_{m\in\{E,D,R\}} \tau_{m,ij}^{\alpha m}}{\sum_{h\in N_i m} \prod_{\{E,D,R\}} \tau_{m,ij}^{\alpha m}} \tag{9}$$

The energy heuristic favors neighbors with high residual energy and low communication cost; the delay heuristic favors low-latency links; and the reliability heuristic favors high-PRR, temporally stable links. Maintaining objective-specific components prevents one metric from being hidden inside a single cost and allows the algorithm to change its search emphasis as network conditions evolve.

4.3 Pareto Archive and Adaptive Pheromone Updating

After all ants complete their routes, feasible solutions are ranked using Pareto dominance. Non-dominated routes are added to an external archive, and dominated or duplicate routes are removed. Pheromone reinforcement is stronger on archive routes with favorable objective values and adequate diversity, while evaporation reduces the influence of obsolete paths.

$$\tau_{m,ij}(t+1) = [1 - \rho_m(t)]\tau_{m,ij}(t) + \Delta \tag{10}$$

The evaporation rate is adapted within a bounded interval. When the solution archive shows little improvement, increased evaporation and exploratory selection reduce stagnation; when the search is improving, stronger exploitation consolidates high-quality routes as shown in equation (10). Lower and upper pheromone bounds prevent complete route abandonment or excessive domination by an early solution.

4.4 Computational Procedure

Table 1: Algorithm 1. KMA-MOACO Routing Procedure

Step	Operation
1	Deploy nodes; initialize energy, neighbor lists, link quality, delay, and pheromone matrices.
2	Apply K-means to node coordinates and determine the logical clusters.
3	Select/rotate each cluster head using residual energy and centroid proximity.
4	Dispatch ants from sources or cluster heads; construct feasible loop-free routes using the multi-pheromone transition rule.
5	Evaluate route energy, delay, reliability, and constraints.
6	Update the non-dominated archive; compute diversity and hypervolume indicators.
7	Evaporate and reinforce objective-specific pheromones; trigger anti-stagnation exploration where required.

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

Step	Operation
8	Select an operational route from the Pareto archive according to current service priorities.
9	Transmit data, update residual energy and network state, and repeat until the stopping condition is met.

Table 1 depicted the algorithm for the KMA-MOACO routing procedure. For N nodes, K clusters, A ants, and I optimization iterations, K-means has an approximate cost $O(NKI\_k)$, where I_k denotes the clustering iterations. ACO route construction is topology dependent and is approximately $O(IA|E|)$ in a sparse neighbor graph. The additional archive operations increase overhead, but the reported results show that the longer optimization process can be justified when energy and communication quality dominate start-up latency.

5.0 Simulation Design

The framework was implemented in Python using NumPy for numerical operations, Network X for graph representation, SciPy for supporting optimization, Pandas for result logging, and Matplotlib for visualization. Simulations used a 100 m × 100 m field with randomly and uniformly deployed nodes. Density scenarios ranged from 50 to 150 nodes, and the comparative tables discussed below correspond to the documented 100-node representative case. All nodes started with 2 J and generated one 64-byte packet every 5 s. The sink was placed either centrally or at an edge/corner depending on the scenario. Each routing round used 10–30 ants, and pheromone evaporation was tuned within 0.2–0.5. Simulation continued for 500–1000 s or until critical energy depletion. The specification of the simulation configuration is shown in Table 2.

Table 2. Representative Simulation Configuration

Parameter	Setting
Deployment field	100 m × 100 m
Node population	50–150 nodes; reported comparison: 100 nodes
Node mobility	Stationary / moderately dynamic link conditions
Initial node energy	2 J
Traffic	One packet per node every 5 s
Packet payload	64 bytes
Sink location	Center or edge/corner, scenario dependent
Radio model	First-order radio; distance-dependent path loss
Artificial ants	10–30 per routing round
Pheromone evaporation	0.2–0.5
Simulation horizon	500–1000 s or until critical depletion
Compared schemes	Advanced ACO (proposed), ACO Routing, ACO-MO

The compared algorithms were executed under identical network configurations. The evaluation covered average energy consumption, minimum/maximum/average end-to-end delay, packet-delivery ratio (PDR), normalized throughput, first-node death (FND), half-node death (HND), last-node death (LND), convergence iterations, hypervolume, solution spacing, Pareto spread, link stability, energy-delay product (EDP), energy-reliability product (ERP), and node reachability. The source dataset provides deterministic summary values rather than distributions from independent random seeds; accordingly, the present analysis is descriptive and does not claim statistical significance.

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

6.0 Results and Discussion

6.1 Energy Consumption and End-to-End Delay

Table 3: Energy and delay performance

Metric	Advanced ACO	ACO Routing	ACO-MO
Average energy (J)	0.5676	2.2735	2.3021
Minimum delay (s)	0.1047	0.2219	0.2510
Maximum delay (s)	0.7978	3.3357	3.9473
Average delay (s)	0.3585	1.4458	1.4355

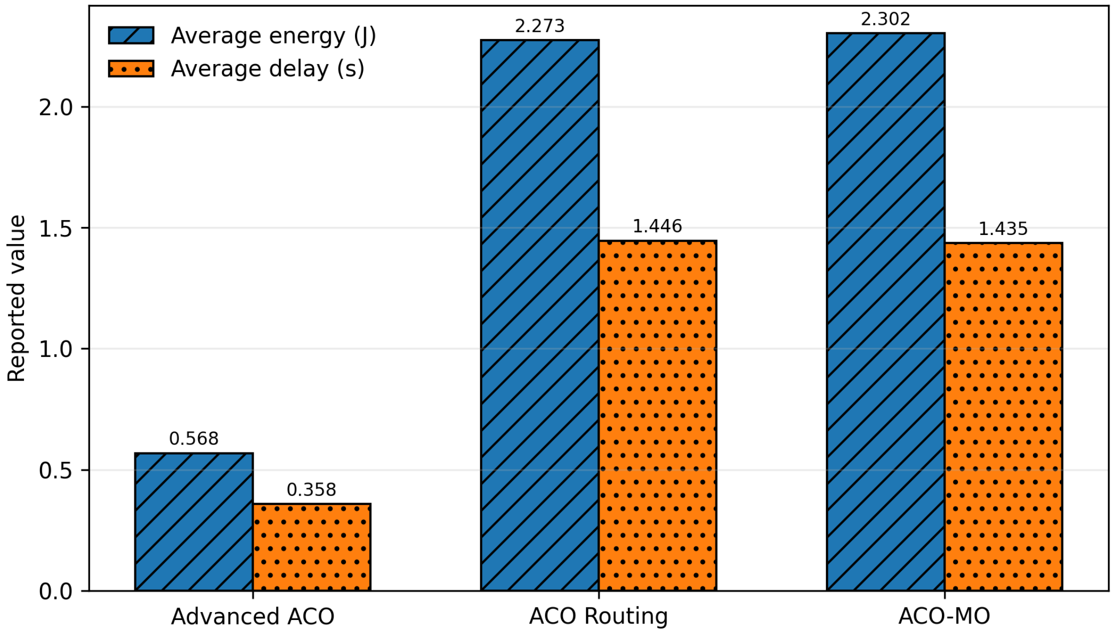

Figure 2: Average energy consumption and end-to-end delay for the three routing schemes

The proposed Advanced ACO consumed 0.5676 J on average, compared with 2.2735 J for conventional ACO Routing and 2.3021 J for ACO-MO as shown in Table 3 and Figure 2 respectively. These values represent energy reductions of 75.03% and 75.34%, respectively. The improvement is consistent with three design choices: spatially compact clustering, avoidance of energy-depleted relays, and adaptive reinforcement of paths that remain favorable as node energy changes.

Average end-to-end delay was 0.3585 s for Advanced ACO, versus 1.4458 s and 1.4355 s for the two comparators. Thus, delay was reduced by approximately 75.20% relative to ACO Routing and 75.03% relative to ACO-MO. The lower maximum delay is particularly important because a low mean accompanied by a very large tail would still be unsuitable for real-time sensing. Advanced ACO limited the reported maximum delay to 0.7978 s, while both comparison schemes exceeded 3.3 s.

6.2 Packet Delivery, Throughput, and Reachability

Table 4: Reliability and Connectivity Performance

Metric	Advanced ACO	ACO Routing	ACO-MO
Packet-delivery ratio	0.92	0.36	0.92
Normalized throughput	0.92	0.36	0.92
Reachable nodes	100/100	23/100	100/100
Unreachable nodes	0	77	0

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

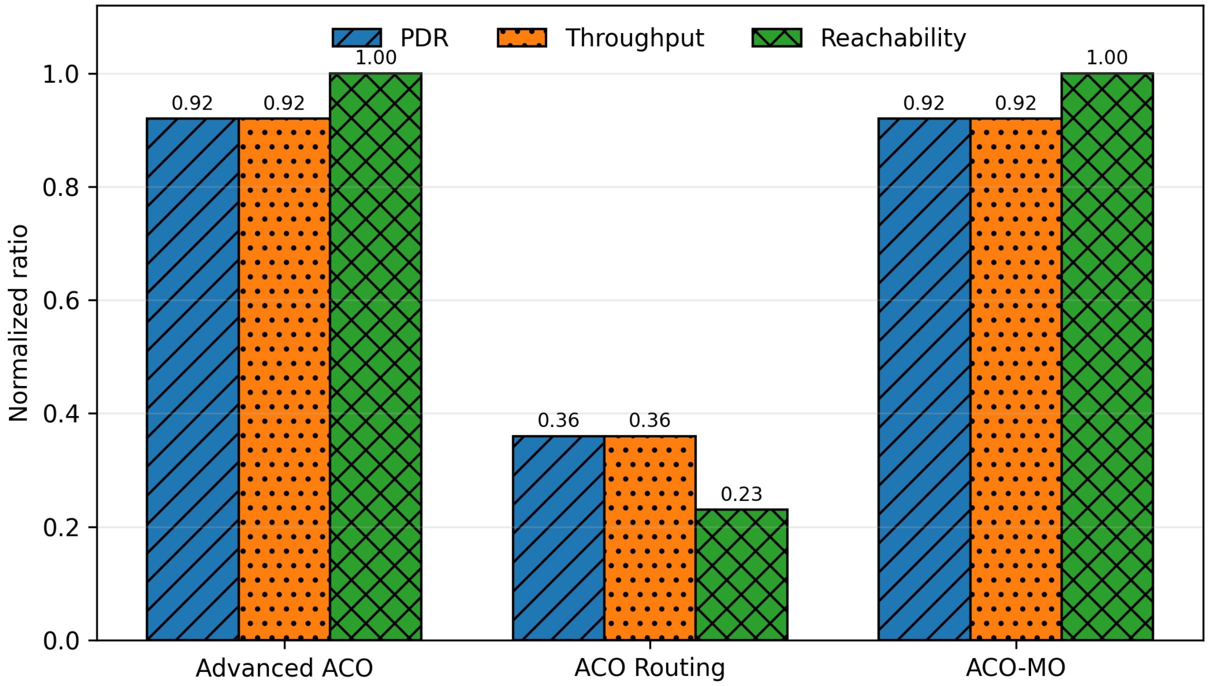

Figure 3: Packet delivery, normalized throughput, and node reachability

Advanced ACO and ACO-MO each achieved a PDR and normalized throughput of 0.92. The conventional ACO baseline achieved only 0.36 and found valid routes for 23 of 100 nodes. This is illustrated with Table 4 and Figure 3. The 77 unreachable nodes indicate a severe route-search failure rather than a modest quality degradation: disconnected nodes expend energy during unsuccessful discovery, reachable relays carry disproportionate traffic, and the sensed field loses spatial coverage.

The proposed method obtained full reachability without the energy and latency premium observed for ACO-MO. This result is central to the paper because network energy cannot be interpreted independently of coverage and delivery. A method may appear to conserve energy simply because it fails to transmit from a large part of the field. Here, the proposed algorithm simultaneously preserved all node-to-sink routes and reduced the energy required for successful communication.

6.3 Network Lifetime and Convergence

Table 5: Lifetime and Convergence

Metric	Advanced ACO	ACO Routing	ACO-MO
FND (rounds)	350	352	383
HND (rounds)	470	467	488
LND (rounds)	550	553	590
Convergence (iterations)	101	50	68

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

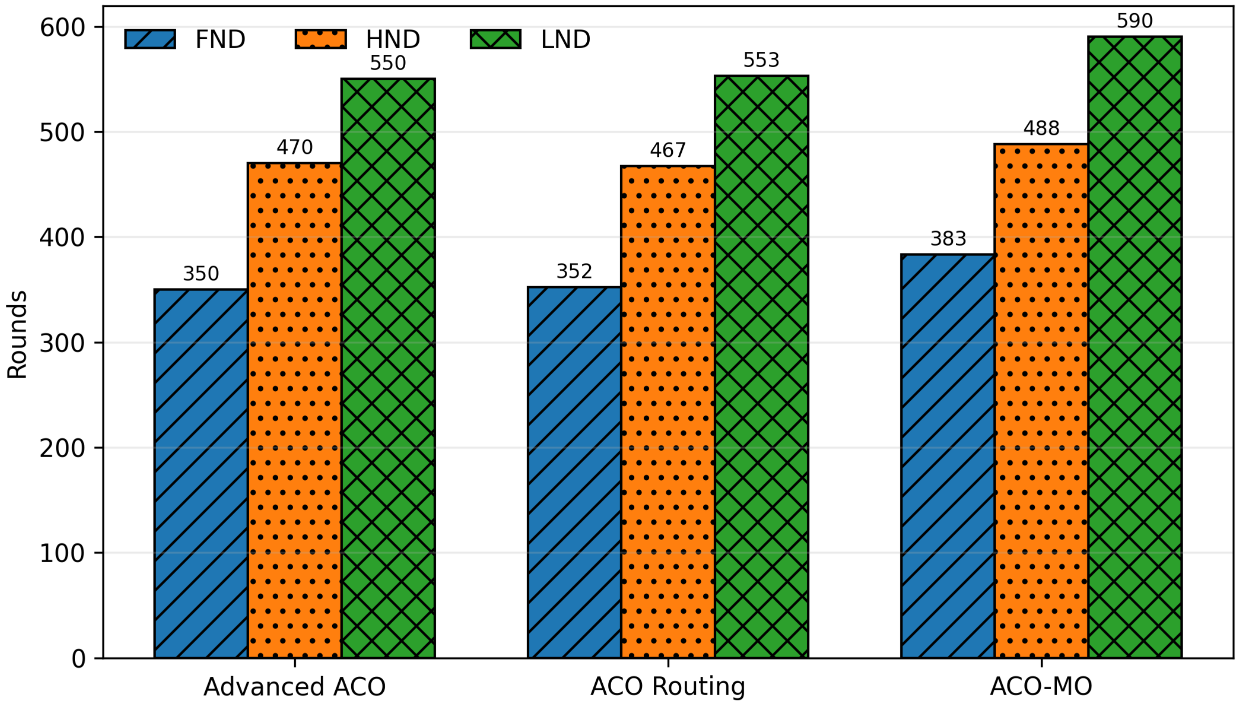

Figure 4: First-, half-, and last-node-death values

ACO-MO achieved the largest raw lifetime values: 383 rounds to FND, 488 rounds to HND, and 590 rounds to LND. Advanced ACO recorded 350, 470, and 550 rounds as shown in Table 5 and Figure 4 respectively. The result demonstrates an important multi-objective distinction. ACO-MO preserves some nodes for longer, but its average energy and delay are approximately four times those of the proposed scheme. Advanced ACO instead promotes more even and operationally efficient depletion while retaining full reachability and high PDR.

Conventional ACO Routing converged in 50 iterations, ACO-MO in 68, and Advanced ACO in 101. The longer convergence period reflects broader exploration and objective balancing rather than necessarily poor optimization. Conventional ACO's rapid convergence coincided with 77 unreachable nodes and low PDR, which is consistent with premature stagnation. Nevertheless, the computational overhead is a genuine design cost; applications requiring immediate route setup should use warm starts, bounded archives, or event-triggered re-optimization.

6.4 Pareto Quality and Composite Efficiency

Table 6: Multi-Objective and Composite Indicators

Metric	Advanced ACO	ACO Routing	ACO-MO
Hypervolume	0.8277	0.8149	0.8520
Spacing	0.1983	0.1873	0.2365
Pareto spread	0.5552	0.5266	Not reported
Link stability	0.7510	0.7903	0.8615
ERP	0.6170	6.3152	2.5023
EDP	0.2035	3.2869	3.3048

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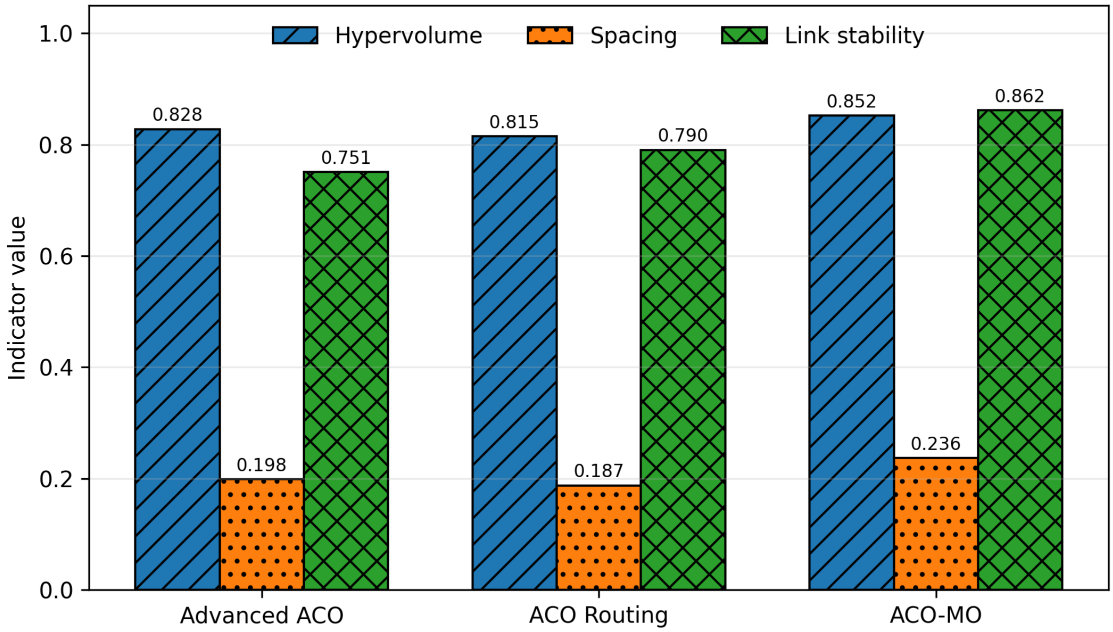

Figure 5: Hypervolume, solution spacing, and link-stability indicators

ACO-MO produced the largest hypervolume (0.8520) and the greatest link stability (0.8615), indicating a broad set of trade-off solutions and conservative route persistence. Advanced ACO's hypervolume was only 2.85% lower, while its operational energy and latency were substantially better. Its reported spacing of 0.1983 indicates a reasonably distributed non-dominated set, and its Pareto spread exceeded that of conventional ACO Routing. This is depicted in Table 6 and Figure 5.

The composite metrics provide the clearest summary. Advanced ACO reduced ERP from 6.3152 to 0.6170 relative to the conventional baseline—a 90.23% reduction—and from 2.5023 to 0.6170 relative to ACO-MO—a 75.34% reduction. EDP fell from 3.2869 and 3.3048 to 0.2035, corresponding to reductions of 93.81% and 93.84%. These results show that the proposed method does not improve one metric by merely transferring cost to another; it achieves a substantially stronger joint energy–QoS compromise.

6.5 Comparison with Recent Design Trends

Table 7: Positioning Relative to Representative Routing Directions

Study / approach	Clustering	Routing/optimization	Reported design emphasis	Distinguishing feature of this work
[3], [5]	Random CH rotation	Single-hop hierarchy	Energy and lifetime	Geometry-aware clusters and multi-hop Pareto routing
[15]	K-means	Improved ACO	Coverage and energy	Explicit energy-delay-reliability archive and broad metrics
[9]	K-means/geometric	Geometric routing	Lifetime and utilization	Adaptive multi-pheromone route construction
[14]	Whale optimizer	ACO	Energy-efficient hybrid routing	Residual-energy CH rotation plus Pareto constraints
[16]	Not central	Modified ACO	Energy, reliability, scalability	K-means front end and solution-set quality analysis

Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026

Study / approach	Clustering	Routing/optimization	Reported design emphasis	Distinguishing feature of this work
Present KMA-MOACO	K-means + energy rotation	Adaptive multi-objective ACO	Energy, delay, reliability, connectivity, Pareto quality	Full reachability with low ERP and EDP

The proposed framework is aligned with recent hybrid routing research (Table 7) but differs in the breadth of its evaluation and in its explicit separation of objective-specific pheromone information. The results further show why a high-impact evaluation should report connectivity and joint metrics rather than lifetime alone. ACO-MO led the raw lifetime and hypervolume indicators, yet Advanced ACO was preferable for applications that require low energy, low delay, complete node participation, and high delivery reliability.

7.0 Conclusion

This paper developed a K-means-guided adaptive multi-objective ACO framework for energy-efficient and reliable WSN routing. The method uses K-means to form compact logical clusters, rotates cluster heads according to residual energy, constructs routes through energy-, delay-, and reliability-specific pheromone information, and retains non-dominated feasible routes in a Pareto archive. In the reported 100-node case, the proposed Advanced ACO reduced average energy and delay by approximately 75% relative to both ACO comparators, achieved 0.92 PDR and throughput, maintained full node reachability, and produced major reductions in ERP and EDP. ACO-MO achieved longer raw lifetime and a slightly greater hypervolume, but incurred substantially higher energy and delay.

Therefore, WSN routing should be judged as a multi-dimensional service problem rather than as a single lifetime-maximization task. The proposed framework offers the strongest reported balance across energy, responsiveness, connectivity, and reliability. Future work should validate the method through repeated random trials, heterogeneous and mobile networks, realistic MAC/PHY modeling, comparisons with recent hybrid protocols, and hardware-in-the-loop or physical sensor-node experiments.

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Received: 18/06/2026; Revised: 29/07/2026; Accepted: 30/07/2026; Published: 14/08/2026