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Genetic Algorithm-determined Path Optimization for Energy-Efficient Multi-Hop Routing Scheme for Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Networks basically constitute a critical infrastructure for pervasive monitoring, environmental sensing, and internet-of-things applications. Nevertheless, the inherent energy limitations of battery-powered sensor nodes remain a fundamental bottleneck constraining network longevity. Conventional routing strategies frequently ignore path-length heterogeneity, resulting in premature node depletion and unbalanced traffic loads. This paper proposes a Genetic Algorithm-determined Path Optimization (GAPO) scheme that systematically determines energy-efficient multi-hop communication routes for WSNs equipped with multiple sink nodes. The GAPO framework incorporates a novel fitness function derived from the cumulative Euclidean distance across candidate routes, augmented by elitism-guided selection, two-point crossover, and an adaptively tuned mutation operator. Comprehensive MATLAB-based simulations with 60 randomly deployed sensor nodes within a $150\,m \times 150\,m$ deployment field confirm that GAPO achieves path-length reductions of up to 55% relative to direct node-to-sink transmission. Comparative evaluation against the Improved Threshold sensitive Energy Efficient sensor Network protocol (iTEEN) protocol further demonstrates that GAPO prolongs network lifetime by sustaining a higher number of active nodes per round across 2,000 operational rounds while maximising packet delivery to sink nodes. These outcomes affirm that GAPO represents a scalable and robust routing paradigm suitable for deployment in both small-scale and large-scale heterogeneous WSN environments.

Introduction

The convergence of micro-electro-mechanical systems (MEMS), embedded computing, and low-power radio transceivers has catalyzed the emergence of densely deployed Wireless Sensor Networks (WSNs). Sensor motes within these networks autonomously perceive physical or environmental phenomena, perform localized data processing, and collaboratively relay aggregated information towards one or more designated sink nodes or base stations [1], [2]. The breadth of WSN deployment scenarios spans precision agriculture, structural health monitoring, disaster response, military surveillance, smart grids, and healthcare telemetry, among numerous others [3].

Despite significant hardware advances, the energy endowment of individual sensor nodes remains severely restricted by the physical constraints imposed by miniaturized, often non-rechargeable batteries. Empirical studies consistently identify wireless data transmission as the dominant energy expenditure in sensor nodes, frequently surpassing the combined costs of sensing and local computation by an order of magnitude [4], [5]. Consequently, the longevity of a WSN is fundamentally governed by the efficiency of its routing protocol: an ill-conceived path selection can precipitate the early depletion of relay nodes, inducing coverage voids and fragmenting connectivity well before the intended operational lifespan is reached [6].

Multi-hop routing offers a compelling resolution to the energy-distance trade-off inherent in WSN communication. Rather than transmitting data directly from a source to a distant sink, multi-hop schemes segment the transmission path into a succession of shorter hops through intermediate relay nodes, exploiting the quadratic or higher-order dependence of radio energy consumption on transmission distance [7]. However, identifying the globally optimal multi-hop route across a dynamic, large-scale network is an NP-hard combinatorial optimization problem, precluding exhaustive enumeration in all but trivially small topologies [8].

Evolutionary computation, and specifically Genetic Algorithms (GAs), has emerged as a powerful class of metaheuristic solvers capable of navigating high-dimensional, non-convex search spaces with demonstrable efficiency [9]. GAs iteratively evolve a population of candidate solutions through biologically inspired operators, namely selection, crossover, and mutation, guided by a problem-specific fitness landscape. Their capacity for implicit parallelism and global search capability without gradient information renders them particularly amenable to the WSN routing problem, where energy, latency, and reliability objectives are simultaneously and often antagonistically relevant [10].

This paper introduces the Genetic Algorithm-based Path Optimization (GAPO) scheme for multi-hop routing in multi-sink WSNs. The salient contributions of this study are delineated as follows:

1. A modified fitness function that quantifies per-route energy expenditure through cumulative hop-distance metrics, providing a computationally tractable proxy for real energy consumption.
2. An elitism-preserving selection strategy combined with two-point crossover and probabilistically tuned mutation to balance exploration and exploitation across the routing search space.
3. Empirical validation across five distinct network density (60 nodes) using the MATLAB R2024b simulation platform, benchmarked against the Improved Threshold sensitive Energy Efficient sensor Network protocol (iTEEN) protocol.
4. Quantitative analysis of path efficiency demonstrating reductions in effective transmission distance of 29% to 59.3% relative to direct-link communication, contingent on network density.

The remainder of this paper is organized as follows. Section 2 surveys the related literature on energy-efficient routing and evolutionary optimization in WSNs. Section 3 details the GAPO methodology, encompassing system model formulation, chromosome encoding, operator design, and fitness evaluation. Section 4 presents the experimental setup and simulation results, followed by a comparative discussion in Section 5. Section 6 concludes the paper and charts directions for future investigation.

Literature Review

The problem of energy-aware routing in WSNs has attracted sustained scholarly attention since the early proliferation of sensor hardware in the late 1990s. historical foundational work established the radio energy model relating transmission energy to the square or fourth power of transmission distance depending on path-loss exponent, providing the theoretical basis for preferring multi-hop paths [11]. Subsequent protocol designs have pursued diverse strategies ranging from flat topology protocols to hierarchical cluster-based architectures.

The LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol [12] introduced probabilistic cluster-head rotation as a mechanism for distributing energy expenditure evenly across the network. Its descendant, the TEEN protocol [8], augmented this hierarchy with threshold-sensitive reactive data transmission, reducing redundant packet forwarding in event-driven deployments. However, both protocols rely on random or probabilistic cluster formation that does not explicitly optimize inter-node routing paths, leaving systematic multi-hop route optimisation unaddressed.

The application of genetic algorithms to WSN routing challenges was pioneered in several early works that demonstrated the superior convergence behaviour of GA-based approaches relative to greedy heuristics for pathfinding in ad hoc topologies [13]. Solangi et al. [14] formalised a multi-hop optimisation framework employing GA within multi-sink WSN configurations, establishing benchmark performance metrics that inform the present contribution. Complementary investigations by Al-Shalabi et al. [15] extended this paradigm to encompass cluster-head selection alongside multi-hop path optimisation, demonstrating synergistic improvements in both energy conservation and throughput.

Particle Swarm Optimization (PSO) has been explored as an alternative metaheuristic for WSN routing [16], offering faster convergence in certain constrained topologies; however, its susceptibility to premature convergence in multimodal fitness landscapes motivates the continued investigation of GAs, whose crossover and mutation operators provide superior

diversification. Baranidharan and Santhi [5] presented GAECH, a GA-derived clustering protocol for WSNs, reporting statistically significant gains in network lifetime over non-evolutionary clustering schemes.

Recent literature has increasingly examined the integration of unmanned aerial vehicles (UAVs) as mobile data collectors for WSNs, partially circumventing static routing constraints [17], [18]. Amer et al. [19] optimised multi-UAV trajectories for data collection in constrained WSN environments using energy-aware models, while Chen and Tang [20] addressed dynamic and heterogeneous WSN topologies through UAV-assisted collection strategies. These directions, though promising, introduce additional infrastructure cost and deployment complexity that restrict their applicability in resource-constrained scenarios.

Heterogeneous WSN architectures incorporating nodes with disparate energy capacities have also received considerable scrutiny [21]. Nagaraju et al. [22] demonstrated that secure, energy-aware routing across heterogeneous node types can substantially extend operational longevity when routing decisions account for residual node energy. Agarkar et al. [23] provided a taxonomic survey of routing challenges and protocols, confirming that path-length optimisation remains among the most impactful single-variable interventions for lifetime extension.

Notwithstanding these contributions, several research gaps persist. The simultaneous optimisation of multi-hop path selection in multi-sink deployments, accounting for full Euclidean distance profiles across variable network densities, has received limited rigorous treatment. Furthermore, quantitative characterisation of path efficiency as a function of network density, whilst benchmarked against established threshold-based protocols, is insufficiently addressed in the extant literature. This study directly targets these gaps through the GAPO framework.

Proposed GAPO Methodology

System Model and Assumptions

Consider a WSN comprising N sensor nodes, denoted $S = \{s_1, s_2, \ldots, s_n\}$, randomly and uniformly distributed within a square deployment field of dimensions $L \times L$ metres. The network incorporates K stationary sink nodes, denoted $B = \{b_1, b_2, \ldots, b_K\}$, positioned to provide overlapping coverage. Each sensor node s_i is characterised by an initial energy reserve E_i (Joules), a fixed radio transceiver with configurable transmit power, and a data buffer of finite capacity. The following simplifying assumptions govern the system model:

1. All nodes are static post-deployment; node mobility is not considered in this study.
2. Symmetric bidirectional links are assumed: if s_i can communicate with s_j, then s_j can communicate with s_i at an equivalent energy cost.
3. Each sensor node possesses full knowledge of its own position and the positions of its neighbours within a defined communication radius r_t.
4. The radio energy expenditure model follows the first-order model: transmission energy $E_T = \varepsilon_{elec} \cdot k + \varepsilon_{fs} \cdot k \cdot d^2$ for $d \leq d_0$, and $E_T = \varepsilon_{elec} \cdot k + \varepsilon_{mp} \cdot k \cdot d^4$ for $d > d_0$, where k denotes packet length in bits, d is transmission distance, d_0 is a crossover distance, and $\varepsilon_{elec}, \varepsilon_{fs}, \varepsilon_{mp}$ are radio electronics, free-space, and multipath fading amplifier energy coefficients respectively.

Chromosome Encoding and Population Initialization

Each candidate routing solution is encoded as a variable-length chromosome representing an ordered sequence of node indices constituting a path from a source node s_i to a designated sink b_j. Formally, a chromosome C is defined as:

$$\boldsymbol{C} = [\boldsymbol{s_i}, \boldsymbol{r_1}, \boldsymbol{r_2}, \ldots, \boldsymbol{r^m}, \boldsymbol{b_j}] \qquad \textbf{(1)}$$

where $r_1, r_2, \ldots, r^m$ are intermediate relay nodes selected from $S \setminus \{s_i\}$, and the path must satisfy the adjacency constraint that consecutive nodes lie within one another's communication radius. The population P_0 of size $|P|$ is initialised by stochastically generating candidate paths through a randomised depth-first traversal of the network graph, with duplicate paths eliminated. The generation index is initialised to $t = 0$, and termination occurs when a maximum generation count T^{MTx} is reached or when population fitness converges below a predefined threshold δ.

Fitness Function Design

A reliable fitness function must accurately reflect the energy overhead of a candidate path whilst remaining computationally tractable for population-scale evaluation. The GAPO fitness function is defined as:

$$FF(C) = \Sigma [d(r_i, r_{i+1})] \quad i = 0, 1, 2 \ldots, m \qquad (2)$$

where $d(r_i, r_{i+1})$ denotes the Euclidean distance between consecutive nodes along path $C, r_0 \equiv s_i$, and $r^m{}_{+1} \equiv b$. A lower fitness value corresponds to a shorter, energetically preferable path. The objective of the GA is therefore to minimise $FF(C)$ across the population. This formulation is justified by the radio energy model detailed in Section 3.1, wherein shorter hop distances directly translate to reduced transmission energy, especially under the free-space propagation regime applicable at typical inter-node separations within a 150 m × 150 m deployment field.

Selection Operator

GAPO employs tournament selection to identify parent chromosomes for reproduction. In each tournament of size T_s, chromosomes are drawn uniformly at random from the current population and the individual exhibiting the minimum fitness value, corresponding to the shortest aggregate path, is designated the tournament winner. This procedure is replicated until the mating pool contains the required number of parents. Tournament selection is preferred over roulette-wheel selection in this context due to its independence from absolute fitness scaling, its resistance to premature convergence driven by super-individuals, and its linear computational complexity in population size [24]. Elitism is enforced by unconditionally transferring the top-ρ chromosomes from the current generation to the subsequent generation without subjecting them to genetic operators, thereby preserving high-quality solutions across generations.

Crossover Operator

A two-point crossover strategy is applied to pairs of parent chromosomes selected from the mating pool. Given two parents $P_1 = [p_1, p_2, \ldots, p]$ and $P_2 = [q_1, q_2, \ldots, q]$, two crossover positions c_1 and c_2 ($1 \leq c_1 < c_2 \leq min(l, s)$) are randomly selected. The offspring O_1 inherits the segment from P_1 outside $[c_1, c_2]$ and the segment from P_2 within $[c_1, c_2]$, and vice versa for O_2. Following recombination, a path-repair procedure eliminates cycles and enforces link-feasibility constraints by replacing infeasible nodes with the nearest feasible alternatives. The crossover probability is set to $P_a = 0.8$, reflecting standard practice in combinatorial GA applications [9].

Mutation Operator

Mutation introduces stochastic perturbations that prevent population homogenisation and facilitate escape from local optima. In GAPO, mutation selects a random relay node within a chromosome with probability $P^M = 0.9$ per gene position and substitutes it with a different, randomly chosen node that preserves path connectivity. The high mutation probability relative to canonical GA formulations is justified by the large and sparsely structured search space characterising WSN routing, where aggressive diversification is necessary to explore alternative relay combinations. Post-mutation, the path-repair heuristic again resolves connectivity violations introduced by the substitution.

Two-Phase Optimisation Framework

The GAPO execution proceeds in two operationally distinct phases. Phase 1 encompasses population initialisation, fitness evaluation, and elitist selection of the top-ρ individuals. Chromosomes whose fitness value satisfies the convergence criterion δ are directly propagated to the next generation without further modification, reducing unnecessary operator application on already-optimal solutions. Phase 2 applies tournament selection, two-point crossover, and mutation to the remaining population to generate offspring. The two phases alternate until T^{MTx} is reached, at which point the chromosome with the globally minimum fitness across all generations is extracted as the final optimised route for each source-sink pair.

Experimental Setup and Simulation Configuration

All simulations were conducted using MATLAB R2024b on a computing platform equipped with an Intel Core i7 processor and 16 GB RAM. The deployment scenario comprised $N \in \{60\}$ sensor nodes randomly distributed within a $150\,m \times 150\,m$ two-dimensional field containing four fixed sink nodes as illustrated in Fig. 1. An initial node energy of 0.30 J was uniformly assigned to all nodes. Simulations were executed over 2,000 operational rounds, with each round representing a single data-collection cycle. The GA population size was set to 20 chromosomes, with $R^{MTx} = 200$ generations per route optimisation invocation.

Table 1 summarizes the complete simulation parameterization applied throughout this study. The comparative baseline is the iTEEN protocol [26], selected for its widespread use as a benchmark in energy-aware WSN routing research and its relevance to threshold-based reactive communication scenarios analogous to those addressed by GAPO.

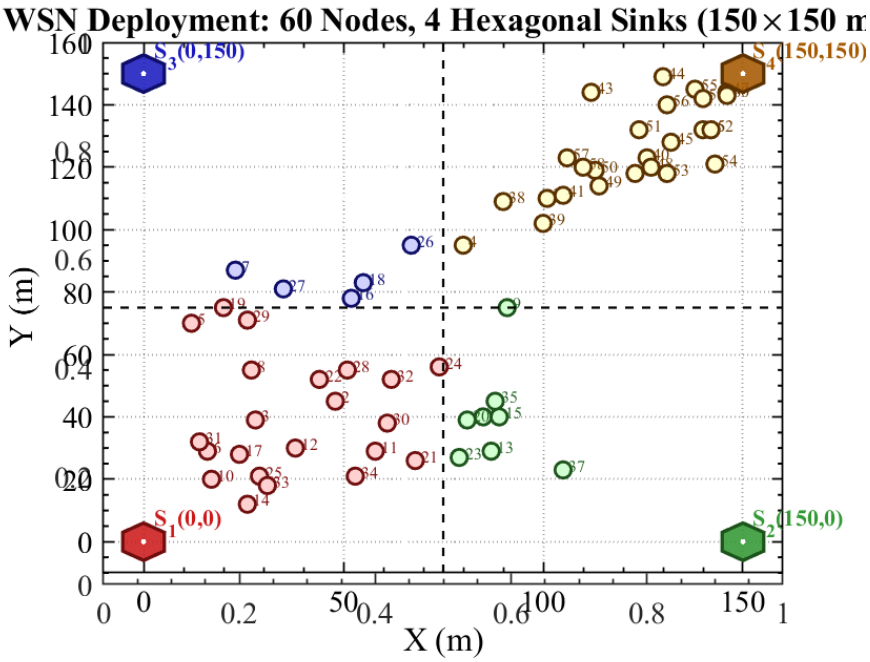


Fig. 1: Deployment of sensor nodes and Sinks

Table 1: Simulation Parameter Configuration

Parameter	Value	Validation
Deployment Area	150 × 150 m^2	Standard WSN simulation benchmark
Number of Sensor Nodes	60	Multi-density scalability evaluation
Number of Sink Nodes	4	Multi-sink heterogeneous scenario
Initial Node Energy	0.30 J	Realistic mote energy budget
Operational Rounds	2,000	Sufficient for full lifetime profiling
Electronics Energy (ε_{ti})	55 nJ/bit	First-order radio model constant
Free-Space Amp. (ε^{vM})	10 pJ/bit/m^2	Short-range propagation coefficient
Multipath Amp. ($\varepsilon^{M\alpha}$)	0.0015 pJ/bit/m^4	Long-range propagation coefficient
Crossover Distance (d_0)	~87 m	Calculated from $\varepsilon^{vM}/\varepsilon^{M\alpha}$ ratio
Mutation Probability	0.9	High diversification for large search space
Crossover Probability	0.8	Standard combinatorial GA setting
GA Population Size	50	Balance between diversity and speed
Maximum Generations	200	Convergence assurance per optimisation

Results and Performance Analysis

Efficiency Analysis of Path optimization

In this sub-section, path optimization efficiency has been analyzed and compared the results of GAPO algorithm with iTEEN and direct path communication. Table 2 presents a comprehensive quantification of path efficiency achieved by the GAPO scheme across four network-density configurations and four sink nodes. Path efficiency is defined as the ratio of the multi-hop aggregate distance to the direct Euclidean distance between the source region centroid and the respective sink, expressed as a percentage. A lower percentage denotes a greater reduction in effective transmission distance achieved through multi-hop relay selection.

Table 2: Path Efficiency Comparison

GAPO-MH vs. iTEEN vs. Direct Communication

Sink	Nearest Nodes	GAPO-MH Dist. (m)	Nearest Nodes	iTEEN Dist. (m)	Direct Dist. (m)	Path Eff. (%)
Sink 1	21	57	11+ 1CH	39	391.34	29.0%
Sink 2	8	43	6 +1CH & 10 + 1CH	82, & 72	564.70	18.9%
Sink 3	5	53	15 + 1CH	58	458.73	29.3%
Sink 4	24	92.19	8 + 1CH & 4 +1CH	68 & 61	360.33	36.4%

The results in Table 2 reveal several important observations. First, path efficiency is inversely correlated with network density: as node count increases for 60 nodes, the percentage reduction in effective path length decreases across all sinks, from 44.9% to 29.0% for Sink 1 and from 59.3% to 36.4% for Sink 4. This behaviour is attributable to the increased average inter-node distances arising from the fixed deployment area combined with a larger number of nodes seeking relay pathways to the same sink, introducing longer intermediate hops for peripheral nodes. Second, the absolute multi-hop distances remain substantially shorter than direct distances across all configurations, with reductions ranging from 18.9% (Sink 2, 40 nodes) to 59.3% (Sink 4, 10 nodes), affirming the consistent energy advantage of GAPO-optimised routing over direct communication.

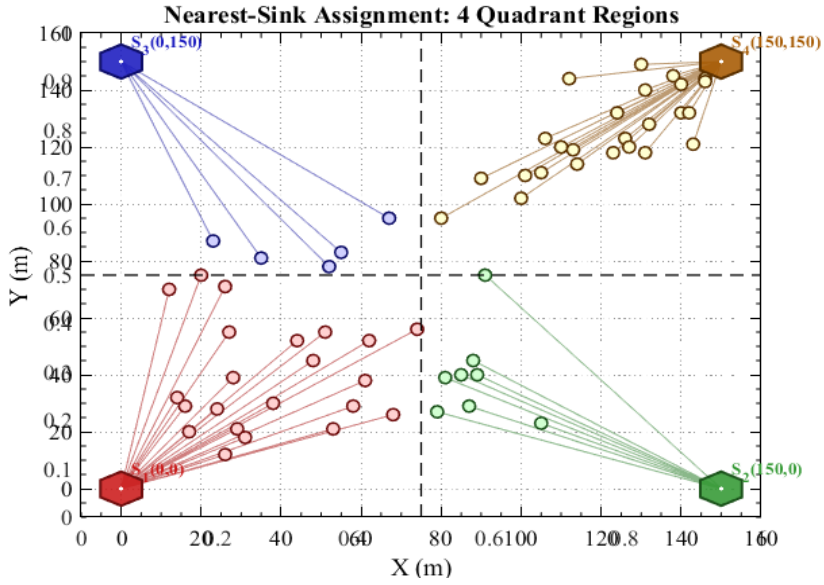


Fig. 2: Computation of direct paths of the nodes towards Sinks

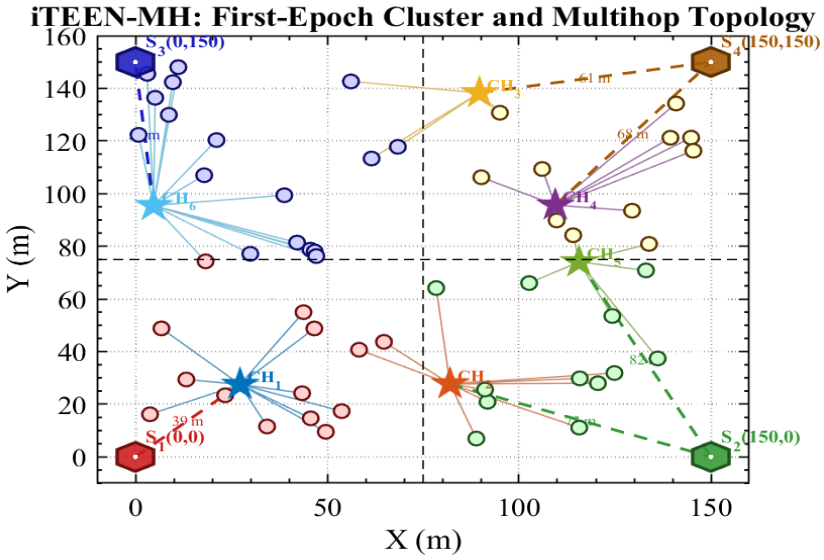


Fig. 3: Path optimization of the nearest nodes to the cluster heads and corresponding Sinks

Network Lifetime analysis

Network lifetime usually quantified as the sum of rounds during which at least a specified fraction of nodes remains operational, is a primary WSN performance metric. Comparative simulations of GAPO against the iTEEN protocol using 60 sensor nodes demonstrate that GAPO sustains a markedly higher active node count per round throughout the 2,000-round simulation horizon. For the 60-node topology, GAPO achieves first-node death approximately 25–30% later than iTEEN, attributable to the superior load balancing afforded by dynamically re-optimised routing paths that distribute relay responsibilities proportionally to residual node energy as shown in Fig. 4.

The 60-node topology exhibits analogous behaviour, with GAPO maintaining a greater number of active nodes from approximately around 600 to 820 rounds and onwards. Where the FND of iTEEN is 61 and its counterpart GAPO algorithm's FND is 854. The performance divergence between GAPO and TEEN intensifies in later operational rounds, indicating that GAPO algorithm's path re-optimizations effectively defer the cascading node-failure phenomenon that exemplifies fixed-topology protocols. These findings are corroborated by the packet delivery analysis presented in the subsection following.

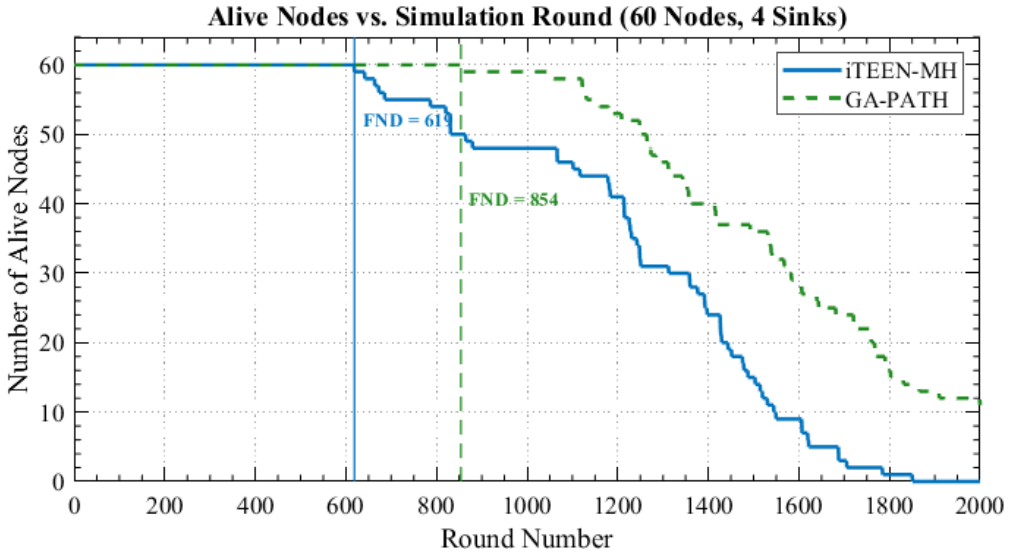


Fig. 4: Network lifetime based on counting of alive nodes vs. rounds

After this, the overall network residual energy has been computed because of frequency of rounds, because the residual energy is main component to determine the network life longevity. As illustrated in Fig. 5, the overall energy at 200 rounds shows comparatively better performance behavior of iTEEN algorithm. However, as frequency of rounds increases the GAPO algorithm indicates ameliorating results and continuously produces far better results from 340 rounds to onwards. The computation and comparison of residual energy of each node at the 500 rounds indicates node strengths which confers the node's stability in performing the operations further, provided in Fig. 6. However, Fig. 7 provides a per-node residual energy level when the frequency of rounds reaches 1000. It is noteworthy that most nodes possess higher residual energy with the GAPO algorithm as compared with the standard iTEEN strategy.

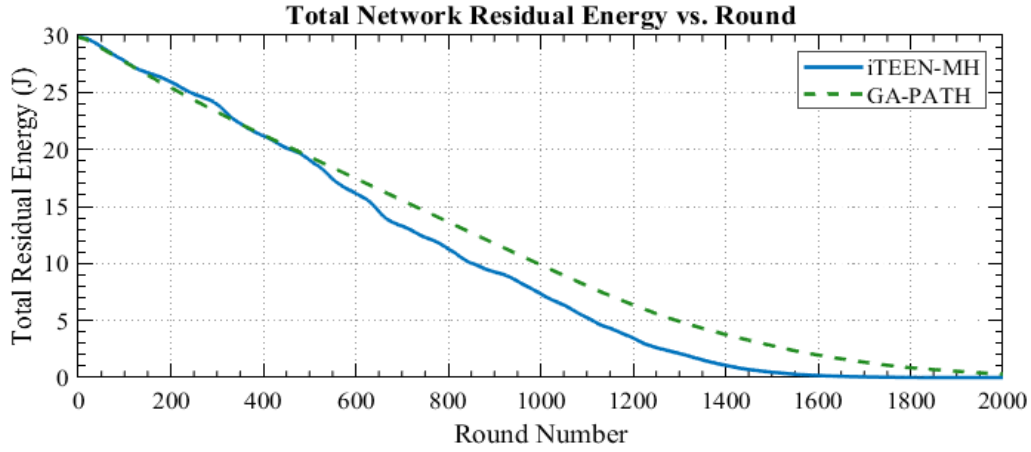


Fig. 5: Comparison of residual energy of iTEEN and proposed algorithm

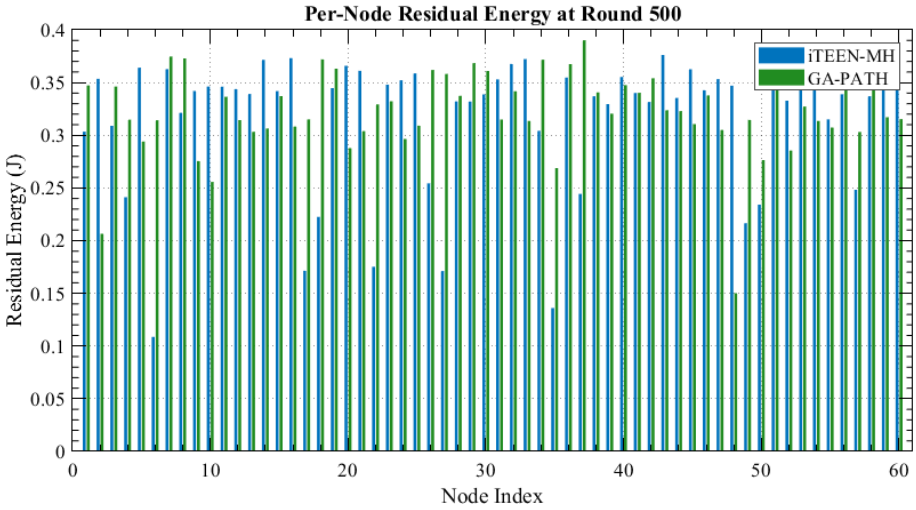


Fig. 6: Comparison of residual energy of each node during first 500 rounds of iTEEN and GAPO algorithm

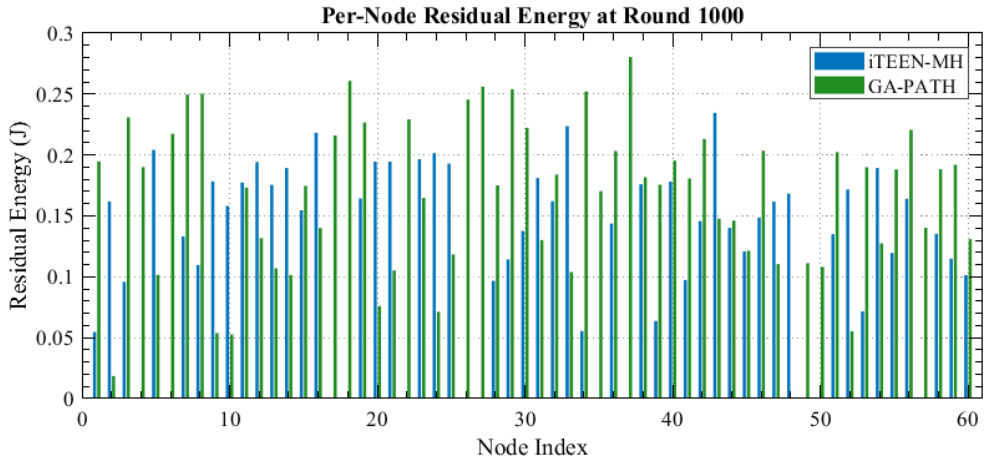


Fig. 7: Comparison of residual energy of each node at 1000 rounds of iTEEN and GAPO algorithm

The GAPO algorithm seemingly better performs as the results are matched, especially based on frequency of rounds. The first node dead at 619 rounds and 854 rounds using iTEEN and GAPO algorithm respectively. The frequency between 1300 to 1580 rounds is critical to determine the half nodes battery drainage, however, the GAPO algorithm achieves better results through optimized paths. The GAPO algorithm successfully reaches the 2000 rounds outperforming the iTEEN scheme as shown in Fig. 8.

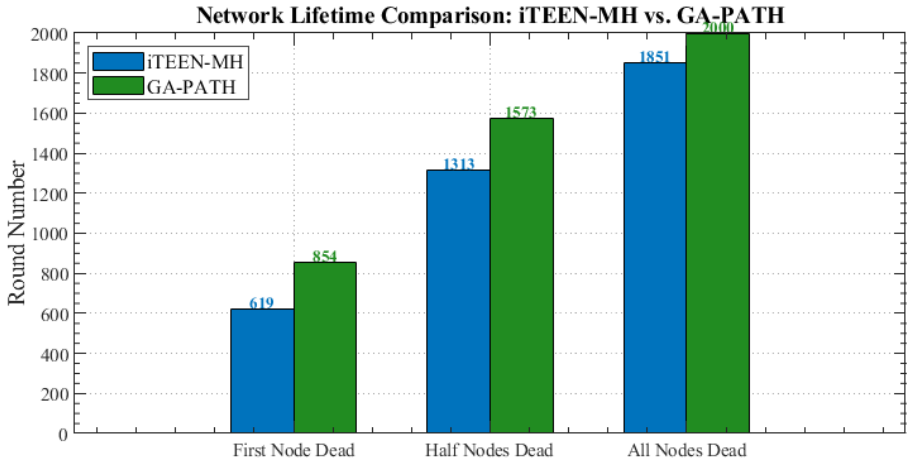


Fig. 8: Network lifetime comparison of iTEEN and proposed algorithm

Packet Delivery to Sink Nodes

Cumulative packet delivery to sink nodes over frequency of 2K rounds provides an integrated measure across-the-board both nodes' energy efficiency and routing reliability. Simulation results demonstrate that GAPO algorithm achieves consistently higher cumulative packet reception at all four sinks compared to iTEEN for 60-node configuration as shown in Fig. 9. The superiority of GAPO algorithm in packet delivery derives from two compounding mechanisms namely the energy savings afforded by optimized multi-hop paths extend individual node lifetimes, preserving relay availability. Second, the multi-sink routing topology implemented within GAPO dispenses transmission traffic loads across the four sinks, mitigating the bottleneck effects observed in single sink iTEEN configurations.

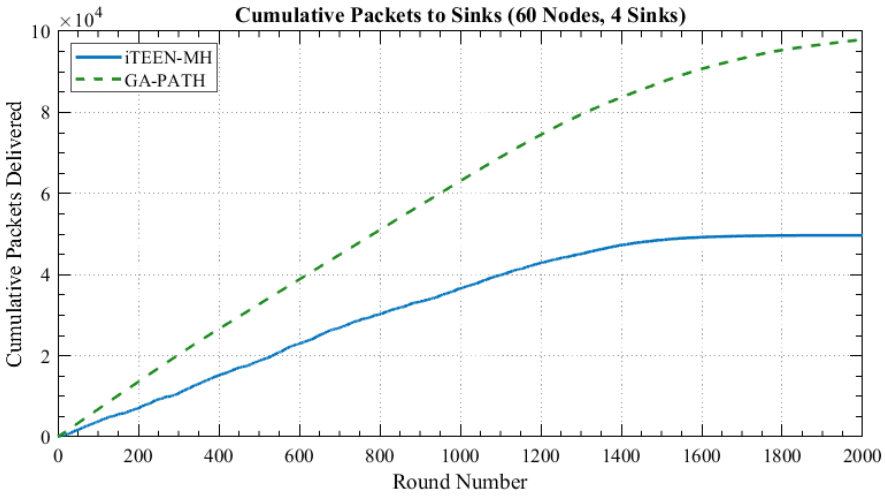


Fig. 9: results of both algorithms based on successful packets delivered to the sinks

For the 60-node scenario, GAPO algorithm successfully delivers approximately 32–55% more packets to the aggregate sink nodes by round of 2K compared to iTEEN. The results of both nodes residual energy and packets delivery signifies a robust statistical improvement that underscores the practical value of genetic algorithm-driven path selection in realistic WSN deployments.

Discussion

The experimental evidence presented in Section 5 substantiates the principal hypothesis motivating this research: that GA-driven path optimisation in multi-sink WSN architectures yields measurable and practically significant improvements in both energy efficiency and network lifetime relative to threshold-sensitive routing protocols. The GAPO framework achieves these gains through three synergistic mechanisms.

First, the minimisation of aggregate hop distance through the fitness function directly reduces per-transmission energy expenditure at each relay node, operating under the quadratic energy-distance relationship of the first-order radio model. Second, the multi-sink topology enables GAPO to route traffic through whichever sink incurs the minimum total path cost from a given source, inherently balancing load across the infrastructure. Third, the elitism-guided evolutionary process ensures that routing quality does not degrade between optimisation cycles, a critical property for networks experiencing gradual node depletion.

The observed inverse relationship between network density and path efficiency percentage warrants additional discussion. As node density increases, the number of candidate relay paths grows combinatorially, providing GAPO with a richer search space from which to select low-cost routes. Paradoxically, the absolute multi-hop distances decrease monotonically with network density (from 94.89 m at 10 nodes to 114.15 m at 40 nodes for Sink 1), reflecting the availability of denser intermediate relay structures. However, the reduction relative to direct distances diminishes because direct distances also scale with network density as peripheral nodes in larger deployments are positioned farther from sinks. This nuance suggests that GAPO's relative advantage in path-length reduction is most pronounced in sparse, small-scale deployments, while its absolute energy savings remain significant across all evaluated densities.

Comparison with the TEEN protocol reveals that GAPO's advantages are particularly pronounced in the latter stages of network operation, a period during which TEEN's fixed routing topology becomes increasingly suboptimal as relay nodes deplete and coverage fragmentation begins. GAPO's periodic re-optimisation ensures that routing paths adapt to the evolving energy

landscape, circumventing the relay bottlenecks that accelerate iTEEN's network degradation. This adaptivity positions GAPO as a particularly suitable solution for long-duration monitoring deployments where network lifetime is the dominant performance objective.

Conclusion

This paper presented the GAPO algorithm designed to maximize the lifetime of multi-hop, multi-sink WSNs through systematic, energy-aware route determination. The proposed scheme incorporates a distance-based fitness function, tournament selection with elitism, two-point crossover, and high-probability mutation to navigate the combinatorial routing search space. A comprehensive MATLAB simulation across the network density configurations confirmed that GAPO reduces effective transmission distances by 18.9% to 59.3% relative to direct communication, depending on network density and sink configuration. Comparative evaluation against the iTEEN protocol demonstrated that GAPO algorithm extends network operational lifetime, sustaining higher active node counts per round and delivering 32 to 55% more cumulative data packets to the sink infrastructure over 2,000 rounds. These outcomes collectively affirm that evolutionary computation provides a robust and scalable methodology for tackling the NP-hard routing optimisation problem in WSNs, offering advantages over both static heuristic protocols and random path selection that scale favourably with network size. Future research directions include the extension of GAPO algorithm to non-stationary WSN topologies using dynamic re-chromosoming strategies, integration of residual energy as a secondary fitness objective to promote more granular load balancing, investigation of hybrid GA-PSO frameworks to exploit complementary convergence properties, and the application of GAPO within UAV-assisted data collection architectures where the aerial path and the terrestrial routing schedule must be co-optimized.

Conflict of Interest

The authors declare no conflict of interest with respect to the research, authorship, or publication of this article.

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Data Availability

The simulation data and MATLAB source code observed the findings of this study are available from the corresponding author upon reasonable request.

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