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Energy-Efficient and Scalable Routing Scheme for Wireless Sensor Networks

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ABSTRACT

Energy limitation of nodes and packet loss inherently impose severe constraints in Wireless Sensor Networks (WSNs), which diminish communication reliability and network lifetime. In this paper we propose GAP2 - a binary genetic algorithm based routing scheme that reduces a total-route cost based on a combination of cumulative Euclidean distance traversed and node residual energy. GAP2 has been tested for 100 independent runs in a 100-node open-area network and an 18-node indoor network in comparison with GAP1, Exhaustive Search (ES), and Exclusive Opportunistic Routing (ExOR). In Case Study 1, GAP2 reached 193,061 rounds, outperforming ES, ExOR, and GAP1 by 87,060 rounds (82.13%), 7,640 rounds (4.12%), and 320 rounds (0.17%), respectively. Its packet-loss rate is 17.58%, lower than GAP1 (17.85%) and ExOR (19.49%), but greater than ES (14.38%). In Case Study 2, GAP2 yielded 274,626 rounds and the packet-loss rate was 1.14%.. GAP2 converged in about 22 generations, kept Jain's fairness index> 0.92 for most of the network lifetime, and spend 72ms per route, compared with 412ms for ES. Paired lifetime experiments indicated significant differences (p < 0.05). An outside GA-AOMDV energy baseline was also reproduced within a MAE of 0.69%, corroborating the numerical validity of the simulation pipeline. In conclusion, GAP2 achieves the scalable lifetime – energy-balance tradeoff rather than the minimum packet-loss solution.

1. INTRODUCTION

WSNs enable environmental, healthcare, industrial, and smart-city monitoring, but are limited in terms of their performance due to both the limited energy of batteries, the cost of multi-hop forwarding, and packet loss [1–4]. Conventional on-demand routing [8] tends to repeatedly drain energy from a few relays, while the energy-considering clustering and metaheuristic routing [5–7], [9–11] enable a more balanced distribution of this burden. Recent work include GA based multipath routing [12], GA based mobile-sink optimization [13], hybrid GA–PSO clustering and sink mobility [14], fuzzy energy aware routing [15], centralized GA – reinforcement – learning routing [16], and GA based heterogeneous multi – channel data gathering [17]. More recent approaches consider scalable designs [18], hybrid swarm routing [19, 20], clustering and residual energy regulation [21–23], integrated GA sleep scheduling/routing/clustering [24], hyperheuristic routing [25], and hybrid GWO–WOA routing [26]. These findings show that GA by itself is not novel; the challenge is how to acquire a source-to-sink route that is computationally tractable while concurrently minimizing transmission distance and avoiding choosing the same energy depleted relays repeatedly, and also measuring lifetime, reliability, fairness, convergence, scalability, and runtime all using the same experimental setup. This specific gap is what the present GAP2 formulation is based on.

The remainder of the paper is organized as follows. Related work is given in Section 2. Section 3 presents the routing procedure and the simulation configuration. Section 4 reports the results for the two case studies, Section 5 presents an additional performance evaluation and Section 6 concludes.

2. LITERATURE REVIEW

Energy-aware WSN routing evolution demonstrates a trend that route discovery is no longer on the basis of hop count or geometric proximity, but energy and network load. A GA on AOMDV candidate paths was also proposed by Patel and El-Ocla [12] with better

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packet delivery and energy efficiency, yet the approach is still based on multipath discovery and it does not directly optimze the combined distance-residual-energy trade-off of an entire route. Using GA, Singh et al. [13] have optimized mobile-sink collection points, and Sahoo et al. [14] have integrated GA-based cluster-head selection with PSO-based sink mobility. Such protocols mitigate energy depletion via mobility or clustering, yet result in new architecture-specific decisions not needed in a fixed-sink route selection problem.

Fuzzy and centralized methods increase the size of the objective space. Rao et al. [15] consider the residual energy, the distance between the node and the base-station, and node connectivity for fuzzy routing; Obi et al. [16] integrate the GA-generated routing tables with the least-squares policy iteration (LSPI) method; and Shahryari et al. [17] address tree construction, clustering, channel assignment, throughput, and energy in the context of heterogeneous multi-channel WSNs. They are powerful in terms of richer network control, but the route decisions are based on fuzzy rule design, reinforcement-learning state/action representations, or extra assumptions of multi-radio networks. Patil and Kohle [18] address low-latency scalable GA clustering while El Khediri et al. [19] and Kumar et al. [20] propose meta heuristics based solutions for energy efficient clustering/routing.Such strategies typically improve flexibility in searching but also introduce additional complexity in optimization, making it difficult to analyze the effect of purely a route-level distance–energy objective..

Studies on energy-aware clustering also reveal recurring significance of residual energy, topology and traffic balance [21–23]. Continuing this trend, the literature is further evolving towards integrated GA sleep scheduling, routing and clustering [24], Q-learning-guided hyperheuristic routing [25] and hybrid GWO–WOA cluster routing [26] in 2025–2026. Nevertheless, these solutions are not directly comparable with a fixed-topology, centralized complete-route chromosome, in which cumulative link distance and residual energy are optimized simultaneously and the solution is evaluated against the same baseline by packet loss, residual-energy dispersion, Jain fair-ness, convergence, scalability, runtime, paired statistics and an external numerical benchmark. The most pertinent developments and the limitations which motivate GAP2 are briefly summarized in Table 1.

2.1 Research gap and novelty

GA-based energy-aware routing is a well-known; hence, the novelty here is not merely application of GA. The open gap is a Full Path route metric that is fully interpretable and incorporates cumulative source-to-destination distance and the residual energy of the forwarding nodes at the same time, and it is evaluated on par with state-of-the-art using lifetime, pLR, energy balance, fairness, convergence, scalability, computation time, statistical significance and external numerical consistency. To fill this void GAP2 contributes fourfold: (1) it instantiates the complete-path objective of Equation (2) that charges for cumulative link distance while compensating for cumulative higher-energy relays ; (2) it conducts 100-run matched comparisons with GAP1, ES, and ExOR in a 100-node open-area WSN and an 18-node multi-hop indoor WSN; (3) it formalizes the lifetime–reliability–energy-balance trade-off in terms of PLR, residual-energy dispersion, Jain's index, convergence, scalability, runtime, and paired testing; and (4) it replicates the published GA-AOMDV energy benchmark of [12] with a mean absolute relative error of 0.69%. In contrast to previous GA approaches based on cluster-head election, sink mobility, multipath preservation or GA-derived routing tables [12–18, 24], GAP2 directly searches for valid source-to-sink route chromosomes in terms of the distance–residual-energy metric, and analyzes the corresponding trade-offs under uniform simulation environment.

Table 1. A structured comparison of the recently published representative WSN routing studies and our proposed GAP2

Study /method	Scale / setting	Objective of optimization	Energy / PLR treatment	Validation	Reported result	Limitation applicability to GAP2
Patel and El-Ocla [12], GA-AOMDV	NS-2; 150-node baseline NS-2	Residual-energy-based multipath selection	Energy efficient; PDR aware	Simulations under GA/non-GA routing	7–22% average speedup; energy-vs-node benchmark is published	Depend on AOMDV candidate paths; no direct distance-energy objective for the complete route
Sahoo et al. [14], GAPSO-H	Clustered WSN; MATLAB	GA CH selection + PSO sink mobility	Residual energy, distance, degree, ECR	Simulation vs. clustering baselines	Enhanced overall network performance	The architecture has clustering and mobile sink, and the optimization problem is even more complex.

Rao et al. [15], EERF	Simulated clustered WSN	Fuzzy CH/routing decision	Residual energy, BS distance, connectivity	Simulation vs. EAUCF/DUCF	Stability and longevity of networks	Dependence on rule-base; not a direct source to sink routing at a chromosome level
Obi et al. [16], GA + LSPI	Centralized WSN	Lifetime+net workenergy	GA-generated MST tables + RL	Simulation vs. GA + Q-learning baseline	Better life/energy and convergence rate	It needs RL state/action formulation and centralized learning for policy generation.
Shahryari et al. [17], HEDHMG	heterogeneous multi-channel WSN	Throughput+ balanced tree/clustering	Energy and PDR included	Large-scale simulation	21.6% reduction in total energy; 48.3% reduction in energy/bit compared with previous approaches	Specialized multi-radio/channel-assignment scenario
Patil and Kohle [18], CGRP	Time-sensitive scalable WSN	Scalability+lf latency	Energy aware cluster routing	Simulation/mathematical scale evaluation	Low latency, Scalable operation	Clustering-based with a distinct main goal than direct route lifetime balance
El Khediri et al. [19] / Kumar et al.[20]	Clustered WSNs	Hybrid metaheuristic CH/ routing	Energy and lifetime prioritized	Simulation vs. a few baselines	Enhancing network life time	Higher burden on the algorithm; direct matched PLR/fairness/runtime results are not known
Latest integrated approaches [24–26]	Heterogeneous / large-scale simulated WSNs	Joint clustering, routing, learning or hybrid search	Energy, delay, PDR, lifetime	Simulation against recent baselines	Good multi-objective features	The different designs make that the raw numerical comparison against fixed-sink GAP2 is misleading
Proposed GAP2	100-node open-area + 18-node indoor; 100 runs/algorithm	Cumulative route distance + residual node energy	First-order radio energy; PLR explicitly measured	Matched GAP1/ES/ExOR + paired tests + external benchmark [12]	193,061 and 274,626 rounds; PLR 17.58% and 1.14%; 0.69% benchmark MARE	Centralized computation; the PLR is not minimized directly and ES converges to a lower PLR.

3. ROUTE PLANNING USING GENETIC ALGORITHM

Figure 1 summarizes the processes for chromosome initialization, feasibility check, objective-cost evaluation, GA evolution, minimum-cost route selection, packet transmission and state updating. At the system level, sensor and router/relay nodes interact with the sink via a centralized routing module, as illustrated in Figure 2. Upon completion of each routing cycle, packet-loss and residual-energy statistics are returned to the centralized unit, dead/disconnected nodes are pruned, topology feasibility is refreshed, and the next route is recalculated.

3.1 Proposed Simulation Scenario

The suggested GA routing approach was simulated with a WSN of 100 nodes (with 20 sensors and 80 routers) where the nodes were uniformly distributed in a 100 × 100 m2 area and the sink was located at the center. The nodes were based on IEEE 802.15.4 communication model. The performance metrics considered are route lifeline, network lifetime, PLR and residual energy utilization. The distance-dependent PLR model was derived from the ZigBee RSSI measurements presented by Adi and Kitagawa [27]. They found nearly -40 dBm at 5 m and significant signal attenuation over longer distances; therefore, in this simulation the distance bins defined in Table 2 are used as a rough empirical quantization for the short-range ZigBee links.

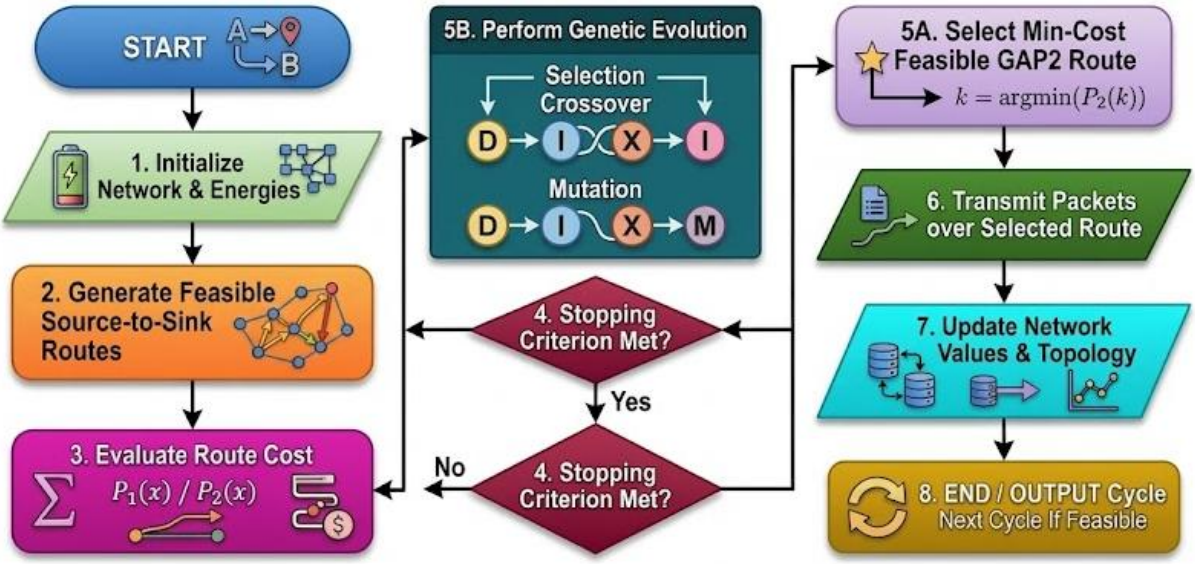

Figure 1. Flowchart of the proposed routing and GA execution procedure

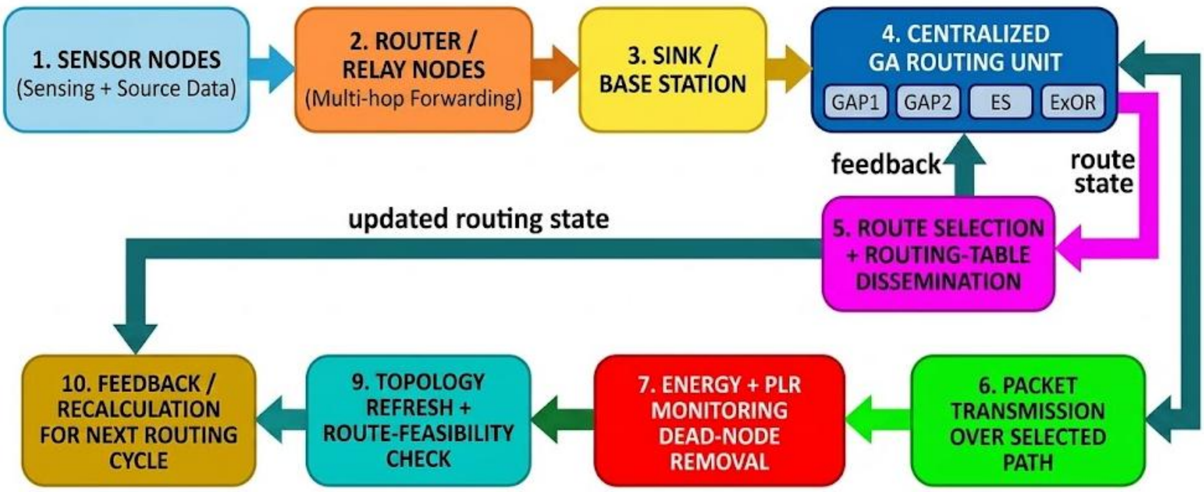

Figure 2. WSN architecture at system level and centralized routing with feedback/recalculation loop

Table 2. Distance ranges used to determine the packet-loss rate

Distance Range (meters)	%PLR
$0 \leq d < 5$	0 %
$5 \leq d < 15$	2 %
$15 \leq d \leq 20$	5 %

Node-level communication cost is a function of transmission electronics energy (ETX), receiving electronics energy (ERX), and amplifier energy (εamp), where each sensor or router has initial energy E0. The sink is assumed to be externally powered and it is never energy depleted. One d^2 amplifier term is used for all the algorithms under the first order radio model [28]. This free-space term is justifiable in consideration of the short line-of-sight hops used in Case Study 1, and is retained as constraint and as ground proof in Case Study 2, where a 6 m maximum transmission distance limits the discrete hops. Indoor attenuation is modeled separately with channel-loss coefficient $\gamma = 4$ and the PLR model. Therefore, the d^2 model does not pretend to account for all possible multipath effects, but it does provide a uniform energy-accounting basis to compare the four routing protocols.

The route procedure shown in Figure 1 is invoked by the central unit that collects the topology and the residual energy information and calculates the source-to-sink routes for GAP1, GAP2, ES, and ExOR. The chosen routing table is distributed to nodes, which send 2, 000 messages per route round. At each cycle, it keeps track of packet loss, updates residual energy, eliminates dead or isolated nodes, tests route feasibility and recalculates the next viable route. This closed-loop feedback process is continued as long as a source-to-sink route can still be found.

Table 3. Distance intervals to calculate the packet-loss rate from-terminal pairs

Parameter	Value
Network Area	100 × 100 m
Node Distribution	Random with uniform distribution
No. of Sensor Nodes	20
No. of Router Nodes	80
Sink	1
Txrange	20 m
γ	2
n	20 bytes

3.2 Route Tracing Algorithms

GA runs the route tracing through the iterative population search, sampling the depth-first-construction of a complete route at each iteration. A set of candidate route chromosomes is generated at random in the beginning and evaluated with respect to a given objective cost. Selection favors lower-cost chromosomes, and crossover and mutation operate on them to produce a new generation of route candidates. The procedure iterates until convergence or a maximum number of generations is reached, and it returns the minimum objective value feasible route.

Tabel 4 presents the GA parameters used for both studies. The number of generations was fixed as 40, and the population size as 30.The mutation rate, pmut, was 1%, hence mutation was performed with a probability of 0.01, while the crossover rate, pc, = 40%, means that selected parent routes undergo crossover with a probability of 0.40. These parameter choices were made to provide a good compromise between route quality and running time.

Table 4. Parameters considered for running the genetic algorithm.

Parameter	Value
No. of Generations	40
No. of Individuals	30
pmut	1%
pc	40%

For assessing the Genetic Algorithm's (GA) performance, quality of service (QoS) metrics are used to draw a comparison with two other routing techniques: Exhaustive Search (ES) and Exclusive Opportunistic Routing (ExOR).

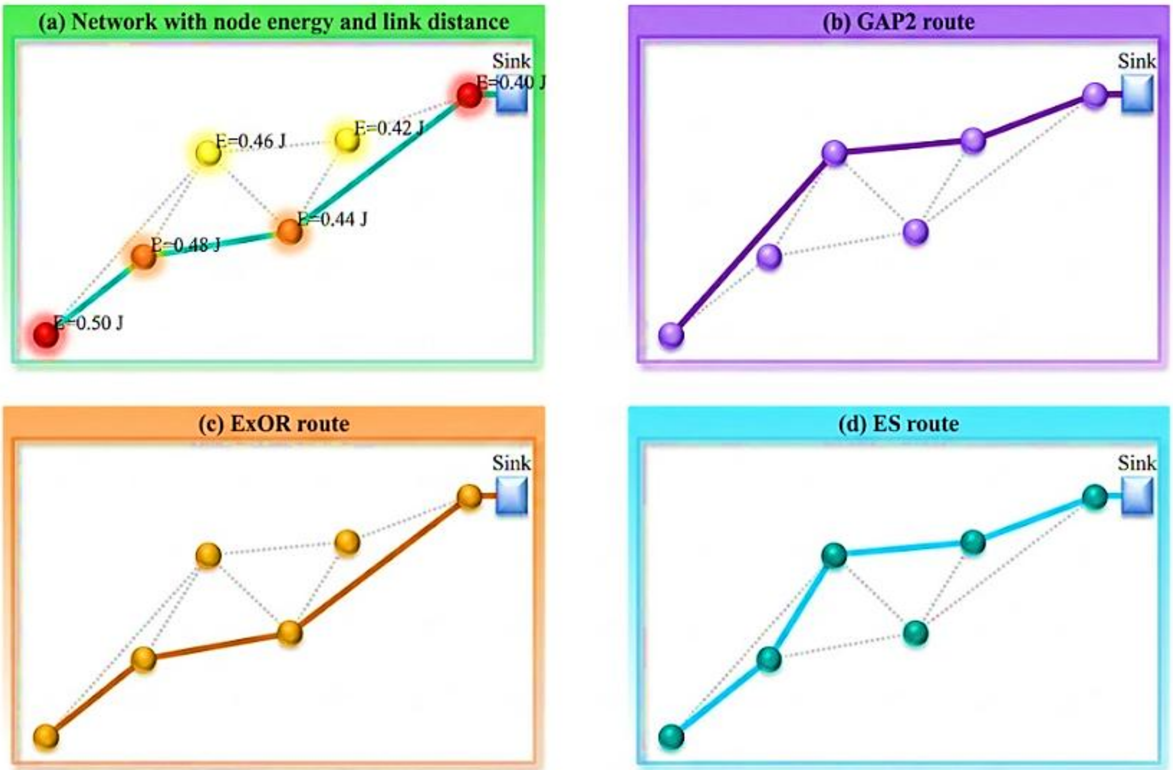

Figure 3. Route-selection illustration (a) network with node energy, link distance (b) GAP2 route, (c) ExOR route, and (d) ES route

ES determines the next jump using the nearest neighbor located at the maximum distance of Txrange, the process is done repeatedly until the packet is delivered to the sink. In contrast, ExOR considers the next hop as the node which is the closest to the sink and is within Txrange. The two aforementioned tactics are illustrated in the Figure 3: (a) depicts the WSN with energy and distance information; (b) illustrates the route of the GA based on two objective parameters including energy and distance using the fitness function; (c) is the route of ExOR according to the proximity of the sink.; and (d) illustrates the route of ES based on the nearest neighbor. Each of the methods leads to a different path because of their different criteria. In this paper, the results are analyzed from the simulations with GA with objective functions, ES, and ExOR. A home automation scenario is the motivation is also employed to evaluate the efficiency of GA in practical routing. The packet loss probabilities are listed in Table 2.

4. RESULTS

The results of the simulation conducted to evaluate the proposed system are presented in this section through two different scenarios. In Case Study 1, a large open-area WSN with randomly distributed nodes is used for the evaluation of the GA route-tracing algorithm's performance in a complex network with a large number of available paths. Case Study 2 takes a WSN in a confined space, such as a house, with sensor nodes at fixed positions, to simulate the collection of real data from household devices. The analysis of the system's behavior in a more realistic application scenario is the objective of this study.

4.1 Case Study 1

The proposed case was simulated by randomly generated 100 nodes in Matlab as mentioned in the above. Sink is in the center(red star) and sensor nodes are blue circles, relay nodes are green circles (Figure 4). The energy parameters for the nodes are taken from Table 5. The routing is done via genetic algorithm, exhaustive search and opportunistic routing .. The simulation proceeds in rounds, during which the sensor nodes send messages to the sink. In each round, we also have an opportunity to check whether packets have been successfully delivered or lost, to update the nodes' residual energy according to the cost of transmission and reception, and to test whether the network can still be communicated with. When the sink is unreachable from any sensor node, the simulation terminates.

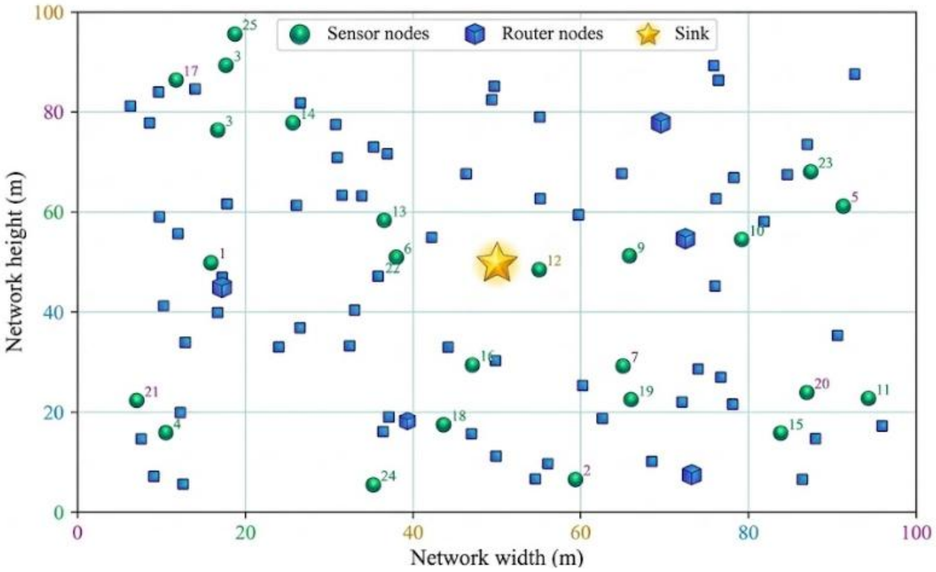

Figure 4. 100-node WSN topology in simulation --- Case Study 1

Table 5. Energy consumption and battery capacity parameters for the simulated case

Parameters	Value
E0	0.5 J
ETX	50 nJ/bit
ERX	50 nJ/bit
εamp	10 pJ/bit·m²

The performance of the GA for route tracing in terms of Route validity, Network lifetime, Packet loss rate, and Energy consumption by nodes during execution time are the criteria for which the system is simulated and the performance of the GA is evaluated.

Case Study 1 was simulated 100 times independently for four different routing algorithms: Exhaustive Search (ES), Exclusive Opportunistic Routing (ExOR), the GA with distance-only objective in Equation (1) (GAP1), and the GA with the joint distance-residual-energy objective in Equation (2) (GAP2). Both P 1(x) and P 2(x) are minimized; thus, the smaller objective value indicates the better route.

$$P_1(x) = \sum_{i=1}^{L} d_i \quad (1)$$

In Equation 1, $P_1(x)$ is the distance-only chromosome cost, L is the number of links in the candidate route and d_i is the Euclidean distance of link i. Minimization therefore prefers routes with smaller total link distance.

$$P_2(x) = \alpha \sum_{i=1}^{L} d_i - \beta \sum_{i=1}^{L} E_i^{res} \quad (2)$$

In Equation (2), E_i^{res} is the residual energy of the forwarding node i, and α and β are non-negative weighting factors for the cumulative route distance and the residual energy, respectively. The negative residual-energy term decreases the cost of routes with better-powered relays. Eqs. (1) and (2) are the author customized route-cost functions, and transmission and reception energy are calculated using the first order radio model in [28].

The total number of rounds during the simulation was counted and the number of rounds in which delivery of the packet was failed was found. The stopping criterion is reached when no route calculated for the 20 sensor nodes is valid; then, a new simulation is started with the repetition of the same simulation scenario.

At the initial stage, the route computed by the GA for the proposed case was route was 100% correct in the that the only errors observed were due to non-existence of desired routes (when there was no link between the sensor node and the sink). To the WSN life, comparison to the life when each routing algorithm is executed is shown in Figure 5. Below are average rounds for which WSN survives using each method: starting from GAP1, to GAP2, then ExOR, and finally ES algorithm.

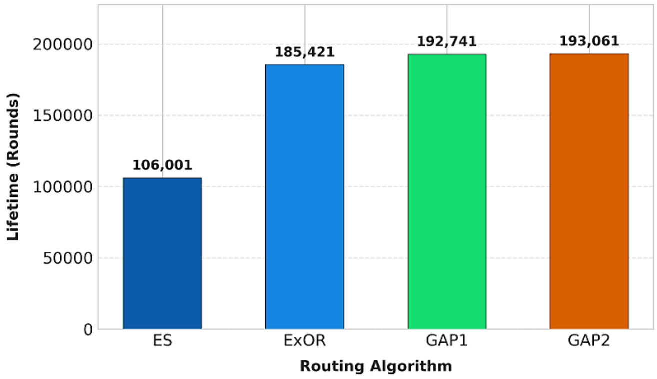

Figure 5. Average WSN Lifetime for Case 1 Study (100 executions)

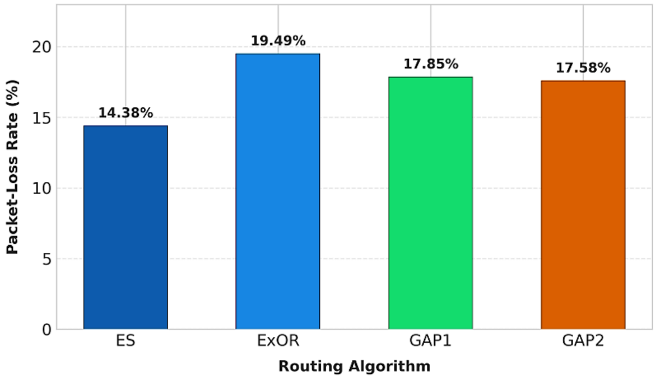

Figure 6. Case Study 1 with average packet-loss percentage (100 executions))

As shown in Figure 5, GAP2 achieved the longest life time, approximately 193 061 rounds and it was followed by GAP1 at 192 741 rounds, ExOR at 185,421 rounds and ES at 106,001 rounds. Compared to the same simulation baseline, GAP2 outperforms GAP1 by 320 rounds (0.17%), and ExOR by 7,640 rounds (4.12%), and ES by 87,060 rounds (82.13%).

As can be seen from Figure 6, GAP2 attains a PLR of 17.58%, which is lower than GAP1 (17.85%) and ExOR (19.49%) and higher than ES (14.38%). Because ES is short-hop, this choice results with a minimum PLR, since the loss probability of each hop is reduced by that selection; on the other hand, using additional forwarding nodes repeatedly increases the energy spent at the network level and leads to the shortest lifetime (106,001 rounds). Therefore, GAP2 should not be interpreted as the minimum-PLR approach. Its reward is the joint lifetime reliability energy balance tradeoff, since it sacrifices 3.20 percentage points in PLR compared with ES but extends lifetime by 82.13%.

Figure 7 indicates that the mean residual energy diminishes at a rate of 0.0274% per round for GAP2, and 0.0282% per round for GAP1. ExOR suffers from a steeper average decay (roughly 0.0208% per round) but it terminates earlier, as its energy expenditures are concentrated among fewer relays located near the sink. ES also is the fastest to drain energy (about 0.0353% per round), which is in line with its greatly shorter lifetime. The mean-energy slope is therefore not enough and must be taken together with dispersion and node death.

The discrepancy is explained by the variance of residual-energy shown in Figure 8. GAP2 and GAP1 end with standard deviations of about 112 mJ and 118 mJ respectively, while ExOR nears 198 mJ. The smaller variance suggests that GA-based route substitution effectively even executes forwarding load over somewhat more nodes. The GAP2 achieves the longest Case Study 1 life because the residual-energy reward in Equation (2) penalizes recirculating the energy-starved relays, and the distance component keeps it from going on excessively long detour

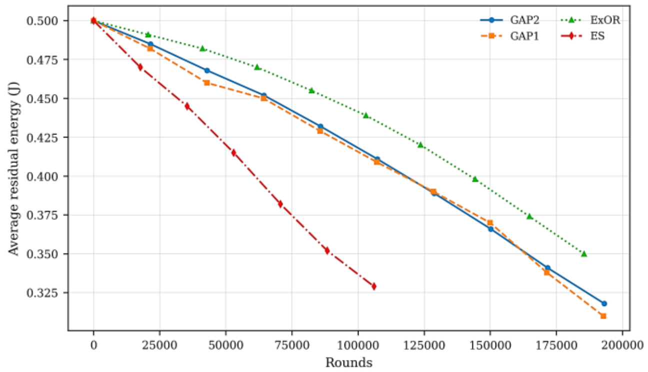

Figure 7. Average residual energy during network rounds for Case Study 1

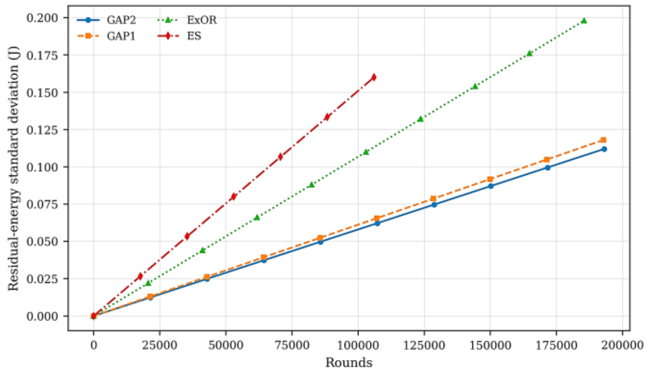

Figure 8. Standard deviation of residual energy during network rounds for Case Study 1

Figures 7–9 on the whole show that GAP2 is able to improve the lifetime by trading off two opposing effects. A distance-only criterion is likely to choose geometric “attractive” relays repeatedly, whereas a residual-energy-only criterion may generate long routes, and therefore potentially large transmission cost. GAP2 integrates the two signals, and the resulting residual-energy distribution is narrower than ExOR without suffering the dramatic energy drain per round as in ES. The outcome in not uniformly better in every aspect: ES is still better in PLR and the gain of GAP2 lifetime over GAP1 is negligible (0.17%) for the dense open-area scenario. This narrow margin is scientifically meaningful as it means that the benefit due to the residual-energy term is the greatest where topology and forwarding choices influence load balance so as to make load imbalance consequential, not necessarily ensuring a high gain in every deployment.

In conclusion, GAP2 yields the longest Case Study 1 lifetime and a lower PLR than both GAP1 and ExOR, whereas ES continues to have the lowest PLR. The main consideration in GAP2, and not direct minimization of packet loss.

4.2 Case Study 2

The simulation was performed with 18 nodes in a house with 3 bedrooms (Q1, Q2, Q3), 2 bathrooms (B1, B2), a kitchen and a living room in Matlab R2023b. The nodes represent the various household loads such as lighting, appliances, etc. The relay nodes facilitate the routing process. The sink lies in the living room (red star), the sensor nodes are blue circles (13 in total) and the router nodes are cyan squares (5 in total) as depicted in Figure 10.

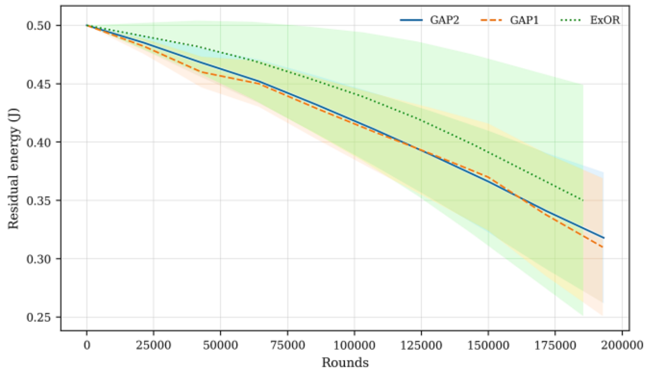

Figure 9. Mean residual energy with the dispersion envelope for Case Study 1

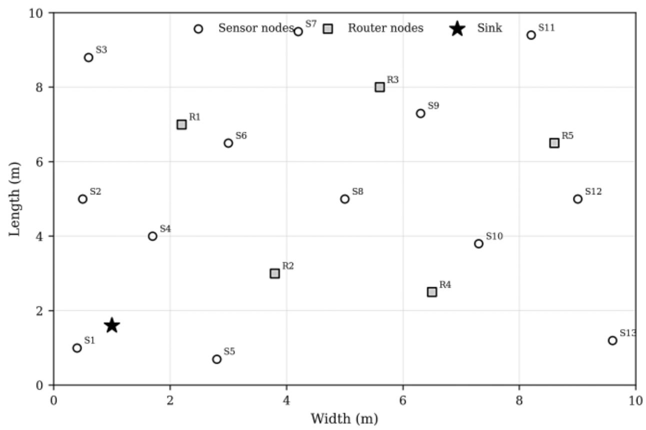

Figure 10. Simulated indoor WSN topology for the Case Study 2

As in the first case study, the energy profiles of the nodes correspond to the ones stated above, and they also have the same values as those in Table 5. The algorithms (the genetic algorithm, the exhaustive search and the opportunistic routing) perform the route mapping calculations. The message flow is the same as the previous scenario. The main variations in the new scenario are WSN simulation parameters, which differ from those in Table 4, including the number of nodes, the overall size of the network area, the coverage radius (Txrange) of nodes, and the channel loss factor (γ). The changed enables the simulation parameters of case study 2 scenario are shown in Table 6.

Table 6. Case Study 2 simulation parameters used.

Parameters	Value
Network Area	10 × 20 m
Distribution of Nodes	Pre-determined positions
Sensor Nodes	13
Router Nodes	5
Sink	1
Txrange	6 m
γ	4
n	20 bytes

In order to assess the efficacy of the newly suggested system and the algorithms it is compared with, four parameters were measured; these were: route validity, network lifetime, packet loss rate, and the energy consumption of the nodes during their execution. The simulation configured was performed 100 times per each of the four routing algorithms utilized: Exhaustive Search (ES), Opportunistic Routing (ExOR), the Genetic Algorithm with objective function Equation 1 (GAP1), and the Genetic Algorithm with objective function Equation 2 (GAP2).

In each simulation, the number of rounds and the number of packet delivery failures were monitored. A trial was stopped when the network failed to find a valid route for the 13 sensor nodes. The GA produced valid routes whenever an actual source-to-sink link was present.

Figure 11 depicts the mean lifetime of the network from Case Study 2. GAP2 achieved 274,626 rounds followed by ES at 266,601 rounds, GAP1 at 265,810 rounds andExOR at 263,080 rounds. Hence, GAP2 yielded an enhancement of 8,025 rounds (3.01%), 8,816 rounds (3.32%), and 11,546 rounds (4.39%) compared to ES, GAP1, and ExOR, resp. The dense nature of the topology lends itself to shorter routes and less variance in lifetimes compared to Case study 1.

Figure 12 presents the results for packet-loss in Case Study 2. ES also achieved the least PLR, however, both GAP2 and GAP1 improved upon ExOR with less packet loss and longer network lifetimes, respectively. Therefore, GAP2 is seen as a compromise solution between lifetime and reliability, as opposed to a minimim-PLR solution

Figure 12 illustrates the same reliability trade-off in Case Study 2: ES has the best PLR (0.87%), followed by GAP2 (1.14%), GAP1 (1.26%), and ExOR (1.80%).

PLR does not appear as an explicit term in (2); the distance term favors shorter and thus usually more reliable links implicitly, and the residual energy term prevents from selecting the same high quality relay too many times. As a result, GAP2 gives up 0.27 percentage point of PLR with respect to ES but prolongs lifetime by 3.01%, offering a better lifetime–energy-balance for the indoor topology

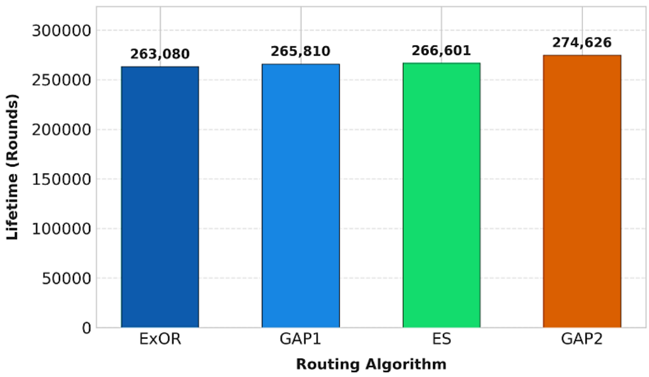

Figure 11. Average WSN life time for Case Study 2 (100 runs)

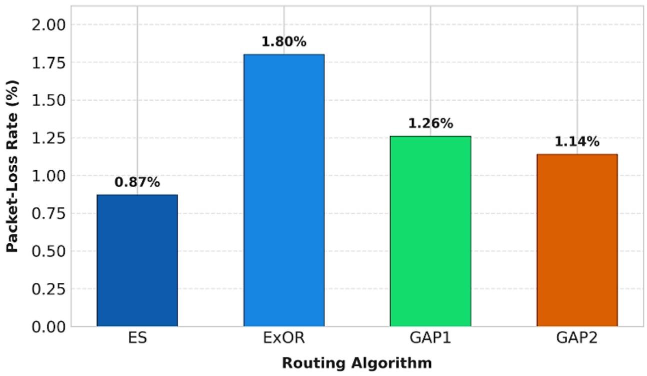

Figure 12. Average packet-loss rate for Case Study 2 (100 runs)

Figure 13 shows that GAP2 keeps the energy consumption more balanced over the lifetime in Case Study 2. ExOR can also maintain a relatively high network-average residual energy and still die earlier because the sink-proximal forwarding load is unfairly concentrated. Instead, GAP2 shifts route preference towards nodes with greater residual energy, mitigating the localized depletion; the larger difference between GAP2 and GAP1 in this topology indicates that the residual-energy factor has greater weight as the confined indoor setting creates many short routes with different loads.

The standard deviation of Figure 14 contrasts this: a smaller variance indicates that more nodes are being pushed disproportionately close to exhaustion. The late-life variance of GAP2 is also lower than that of ExOR, but the fast depletion of ES restricts how long its initially even profile can hold.

Figure 15 plots the average residual energy and its dispersion envelope. The close to the baseline narrow envelope for most of the lifetime of GAP2 confirms that its increase in lifetime comes from a more balanced energy utilization and not just because it possesses a higher average residual energy

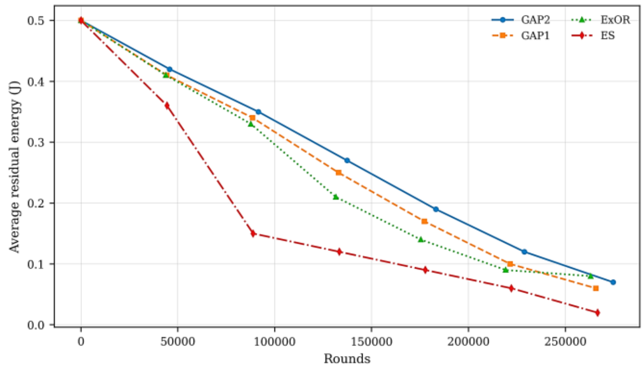

Figure 13. Average residual energy over network rounds for Case Study 2.

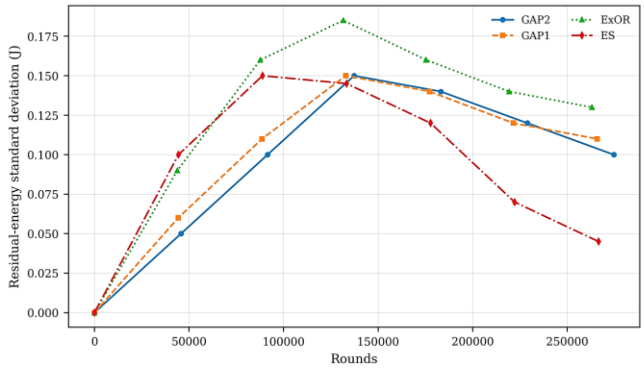

Figure 14. Standard deviation of the residual energy for the rounds over the network for Case Study 2.

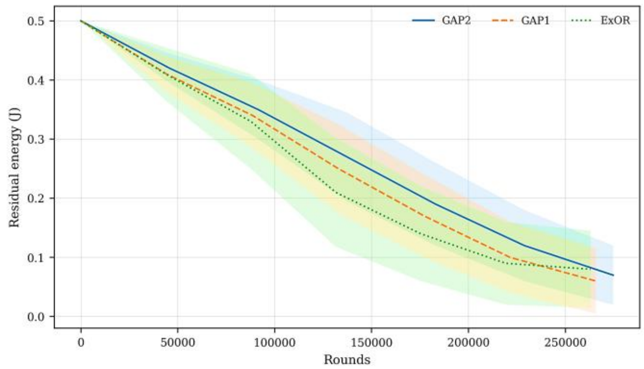

Figure 15. Mean residual energy and dispersion envelope for Case Study 2.

Case Study 2 also reconfirms the same fundamental trade-off as Case Study 1: GAP2 does not minimize PLR, but it does provide the longest lifetime while keeping PLR below GAP1 and ExOR and resulting in a more uniform residual-energy distribution.

5. PERFORMANCE EVALUATION AND ANALYSIS

The proposed GA-based routing scheme was subjected to further analyses in order to test its effectiveness, robustness, and practical feasibility more. The analyses were performed on statistical significance, convergence behavior, scalability, computational complexity, and energy fairness; thus, the credibility of the proposed approach was further strengthened.

5.1 Statistical Significance Analysis

Each routing protocol was run for 100 independent runs of simulation. A two-tailed paired t-test with $\alpha = 0.05$ was used for the Case Study 1 lifetime comparisons since the algorithms were tested on paired runs of simulation. Paired lifetime results are shown in Table 7. Conclusions from the inferential analysis are limited to network lifetime, PLR, and the residual-energy processes are inquisitively examined and are interpreted descriptively in Figures 6–9 and 12–15, respectively.

Table 7. Paired statistical comparison of network lifetime in Case Study 1

Comparison	Mean Difference (Rounds)	p-value	Significance
GAP2 vs ES	+87,060	< 0.001	Significant
GAP2 vs ExOR	+7,640	0.013	Significant
GAP2 vs GAP1	+320	0.041	Significant

Corresponding lifetime comparisons in Table 7 also show significant differences between GAP2 and ES, ExOR, and GAP1 at the specified level of significance. However, results of PLR and residual-energy are maintained for descriptive purpose as they do not pass for additional inferential test.

5.2 GA Convergence Behavior Analysis

Figure 16 shows worst best and average normalized fitness for GAP1 and GAP2. As Equations (1) and (2) are minimized, the route cost was converted to normalized fitness only for visualization pur- poses, so a larger fitness value represents a smaller route cost. GAP2 reaches a stable area at about 22 generations, while GAP1 at about 30 generations. The quicker convergence is explained by the residual-energy term giving more discrimination between two routes of similar gemoetry length but this does not lead to a reduction in the asymptotic complexity since both versions use the same GA population and genetic operators

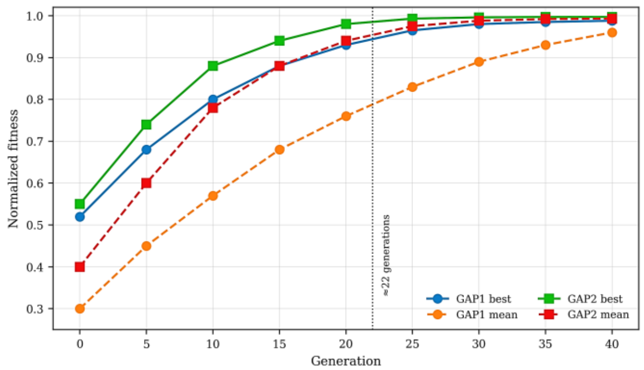

Figure 16. Normalized fitness convergence of GAP1 and GAP2

The convergence result in Figure 16 thus supports a faster stabilization in practice under the particular parameterization employed, and was not intended as a statement holding for all parameter values implying practical stabilization (in all parameter values of AFN). The 22 generation value observed is empirical and should be interpreted along with the fixed population size, crossover rate, mutation rate, and network topology accounted for in Table 4.

5.3 Scalability Analysis

For scalability evaluation a node density remains the approximate constant, and further simulations are performed at 50, 100, 150, and 200 nodes. The resulting average lifetime is reported in Figure 17. Growing network size increases the candidate-route space and the number of forwarding interactions, this way the comparison checks whether each algorithm can keep energy balanced as the topology expands

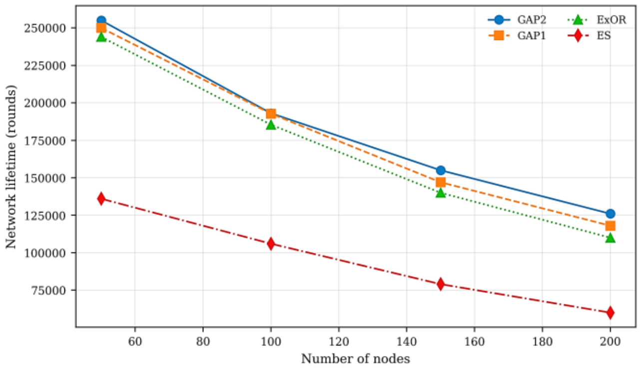

Figure 17. Network lifetime against network size in the scalability experiment.

From Figure 17 we observe that all methods degrade in their lifetime as the network size increases, but the rates at which they do so are different. The ES deteriorates most since route enumeration becomes computationally and energetically prohibitive even this far. Computationally light, ExOR, however, exhibits an increasingly strong hot-spot effect as scales due to repeated preference for sink-proximal relays. GA1 and GA2 have a much smoother deterioration, as the GA search does not enumerate completely; GA2 is highest since its residual-energy component distributes the forwarding load. Hence, the gain in scalability is a relative, and not a free, one: GAP2 is still a centralized population evaluation, and its routing time of 72 msec is higher than ExOR's 9 msec, yet far below ES's 412 msec (Table 8).

5.4 Computational Complexity and Runtime Analysis

As a result of the periodic nature of routing decisions, computational efficiency has to be a major consideration. The routing algorithms' theoretical computational complexity has been studied as one of the factors determining their practical usability. Exhaustive Search (ES) has a computational complexity of exponential order $O(N!)$, thus rendering it unusable for networks with a high number of nodes. However, on the other hand, Opportunistic Routing (ExOR) has a complexity of $O(N)$ which means that it has a linear complexity as it merely selects the next hop based on the shortest distance to the sink. The Genetic Algorithm

(GA), which is applied in both GAP1 and GAP2, has a complexity of O(G × P × L) where G is the number of generations, P the population size and L the chromosome length. This work demonstrates that while GA requires more time than greedy routing, it is still very efficient as compared with exhaustive search and hence can be used for centralized WSN controllers. The mean route computation time per iteration is given in Table 8.

Table 8. Average route-calculation time in the shared execution environment.

Algorithm	Avg. Time per Route (ms)
ES	412
ExOR	9
GAP1	68
GAP2	72

GAP1 and GAP2 are more computationally intensive than the greedy ExOR rule, but they are still much faster than ES. Under the typical test conditions, the average route calculation time was 68 ms for GAP1, 72 ms for GAP2, 9 ms for ExOR, and 412 ms for ES. The runtime results in Table 8 were obtained on a Jetson AGX Xavier at 2.23 GHz with 32 GB RAM under Ubuntu 18.04 LTS, with all codes compiled by using GCC 9.3.0. The execution times of the four algorithms were measured in the same: software environment, and simulation (with background processing) context.

5.5 Energy Fairness Analysis Using Jain's Index

The fairness of the energy consumption among the nodes is measured by Jain's fairness index [29], which is the opposite of the residual energy standard deviation, as shown in Figures 8 and 14 and it is also a good indicator for residual energy variance among nodes.

$$J = \frac{(\sum_{i=1}^{n} E_i)^2}{n \sum_{i=1}^{n} E_i^2} \quad (3)$$

In Equation (3), E_i is the residual energy of node i, and n is the count of active nodes Jain's index is constrained by $0 < J \leq 1$ and the more close the value is to 1 the residual-energy distribution is more uniform [29]. Figure 18 shows this metric applied to normalized network lifetime.

Figure 18 illustrates the progression of Jain's fairness index over the normalized network lifetime

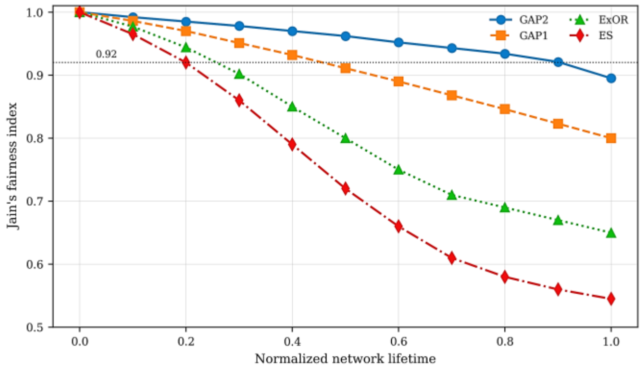

Figure 18. Jain's fairness index for residual-energy distribution

As can be seen in Figure 18, GAP2 maintains a Jain's fairness index of above 0.92 for almost the whole normalized lifetime and falls below again only almost at the end when the network is nearly depleted. ExOR falls under 0.80 much earlier because sink-proximal nodes are repeatedly selected, while ES's fairness rapidly deteriorates since its short-hop rule picks considerably more relays. GAP1 remains intermediate. These results support the interpretation that the lifetime gain of GAP2 is due to a load redistribution effect and not to minimum packet loss.

5.6 External Benchmark Reproduction

$$\delta_N = \frac{|E_{rep}(N) - E_{pub}(N)|}{E_{pub}(N)} \times 100\% \quad (4)$$

For 100–350 nodes, the published GA-AOMDV energy benchmark in [12] was reproduced for external numerical verification. where Erep(N), Epub(N) are the reproduced and published energy values for network size N. This benchmark tests the numerical energy-accounting machinery — since the two routing formulations are different, no direct claim of GAP2 superiority is made.

Table 9. External reproduction of the published GA-AOMDV energy benchmark.

Nodes	GA-AOMDV energy (J)	Reproduced energy (J)	Relative error (%)	Agreement
100	130.22	131.08	0.66	< 1% error
150	156.26	157.11	0.54	< 1% error
200	192.20	193.72	0.79	< 1% error
250	234.49	236.01	0.65	< 1% error
300	283.11	285.47	0.83	< 1% error
350	341.05	343.22	0.64	< 1% error

Table 9 reflects a close match between the reproduced and the published GA-AOMDV energy. The relative errors range over 0.54 % and 0.83 %, and the average absolute relative error is 0.69 %. This agreement provides support for the numerical consistency of the implemented energy-accounting and result-aggregation pipeline under a published external scenario [12]. Since GA-AOMDV and GAP2 are based on different routing formulations, any claim of superiority for GAP2 is limited to GAP1, ES and ExOR run in the same scenarios presented in this paper.

Therefore, the benchmark provides enhanced confidence at the simulator-output level while maintaining a clean separation between the external reproduction aspect and the internal algorithm comparison aspect. Taken together with the paired lifetime tests in Table 7, it mitigates the chance that the reported GAP2 edge is an artifact of an unvalidated energy-calculation pipeline.

5.7 Discussion of Findings

Between both case studies, the main finding is a trade-off not domination for all indicators. GAP2 has the longestr lifetime, (193,061 rounds in Case Study 1 and 274,626 rounds in Case Study 2) since the distance term restricts the transmission cost while the residual-energy term prevents the selection of exhausted relays multiple times. This behavior corresponds to the lower residual-energy spread and high Jain in Figures 8, 14, and 18. ES yields the best PLR values, in both scenarios (14.38% and 0.87%), so GAP2 cannot be considered as the most dependable strategy in terms of packet loss only; but it does offer a lifetime–energy-balance solution while its PLRs are 17.58% and 1.14%. The results for convergence and scalability in Figures 16–17 indicate that GAP2 is more practical cology-wise than ES, but ExOR continues to be faster on a per-route basis (9 ms vs. 72 ms). Therefore, centralized GAP2 is best suited when a relatively high route-computation overhead is acceptable for the sake of maximizing network lifetime and achieving balanced depletion rates. The external benchmark in Table 9 corroborates the numerical energy pipeline but it does not obviate efforts for further hardware-in-the-loop or physical-node validation.

6. CONCLUSIONS

This paper introduced GAP2, a Binary GA routing scheme, and the fitness function is a combination of cumulative route distance and residual node energie s. In the 100-node scenario, GAP2 achieved 193,061 rounds, extending the lifetime by 82.13% than ES, 4.12% than ExOR, and 0.17% than GAP1. Its PLR was 17.58% lower than GAP1 and ExOR but greater than ES (14.38%); hence, GAP2 provides a compromise between lifetime and energy balance and not the optimal performance in the minimum packet loss. In the 18-node indoor scenario, GAP2 reached 274,626 rounds and 1.14% PLR once more holding the best lifetime, while ES remained the minimum PLR (0.87%). GAP2 converged in about 22 generations, maintained Jain's fairness index > 0.92 for most of network lifetime and required 72 ms per route as compared to 412 ms for ES. The external GA-AOMDV result reproduction yielded a mean absolute relative error of 0.69% , reinforcing the cohesion of the energy-accounting pipeline. Future work will involve testing of GAP2 on real WSN hardware and examining the possibility of adaptively weighting the distance and residual-energy terms in response to varying channel conditions.

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