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An Effective Genetic Algorithm-Based Approach to Improve Wireless Sensor Network Fault Tolerance for Multi-hop Surveillance Applications

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ABSTRACT

Fault tolerance in wireless sensor networks (WSNs), used for multi-hop surveillance systems, is defined as the capability to maintain functionality despite node failures, whether in sensor or interconnection nodes. One approach to improve fault tolerance is to extend the number of available alternative paths. This can be achieved by dividing the deployed interconnection nodes into disjoint subsets, or paths, each capable of delivering collected data to the base station. Maximizing the number of these alternative paths significantly improves both fault tolerance and network resilience. The problem of maximizing alternative paths can be formulated as a Disjoint Set Paths (DSP) problem, which is known to be NP-complete. Due to the exponential time complexity of exact solutions, heuristic and meta-heuristic algorithms are commonly employed for such optimization problems. This paper proposes a genetic algorithm-based approach (GADSP) to solve this problem. The algorithm was implemented in Java and tested on networks of varying sizes and sensing ranges. Simulation results demonstrate that the proposed algorithm can achieve near-optimal solutions, consistently within a quality gap $Q \leq 6\%$ for 100-node networks and approach the upper bound, while maintaining polynomial computation time. Computation times did not exceed 0.6 seconds, confirming polynomial-time efficiency. Compared to the theoretical upper bound, GADSP demonstrates strong reproducibility and resilience improvements. The proposed approach can be applied to large-scale surveillance WSNs where fault tolerance is critical. Future work may extend the model to heterogeneous sensor deployments and energy-aware optimization.

KEYWORDS

fault tolerance, genetic algorithm, wireless sensor network, disjoint set paths

1. INTRODUCTION

A wireless sensing node can be considered a combination of several units that acquire, store, send, receive, and process data. These units communicate with each other to form a wireless sensor network (WSN) used for data collection or surveillance tasks. Each sensor node typically incorporates a low-power radio frequency (RF) communication unit and a digital signal processing unit, both connected to a small energy source [1][2][3]. Figure 1 presents the in-node interface.

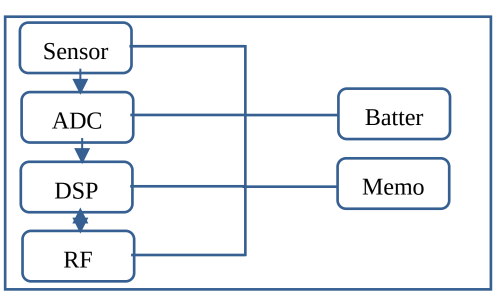

Figure1: The in-node interface

According to the different layers of the sensor network's protocol stack [4], the wireless radios allow sensor nodes to communicate with each other and with a base station (BS). The BS serves as a destination where the collected data can be processed, visualized, analyzed, and stored. Figure 2 illustrates the overall WSN topology.

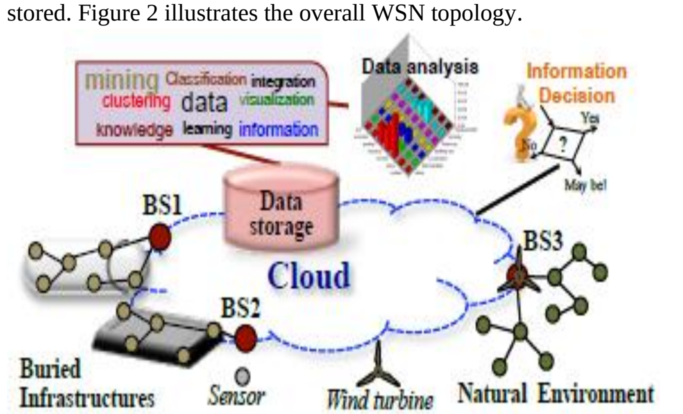

Figure 2: The overall WSN topology [39]

Recently, WSNs have been increasingly applied to a wide variety of daily life systems, which come with more diverse requirements and characteristics. Applications include environmental monitoring [5, 6, 7], industrial infrastructures [8], military operations [9], medical and healthcare systems [10], transportation and mobile networks [11], and the Internet of Things (IoT) [12]. Figure 3 illustrates these common applications.

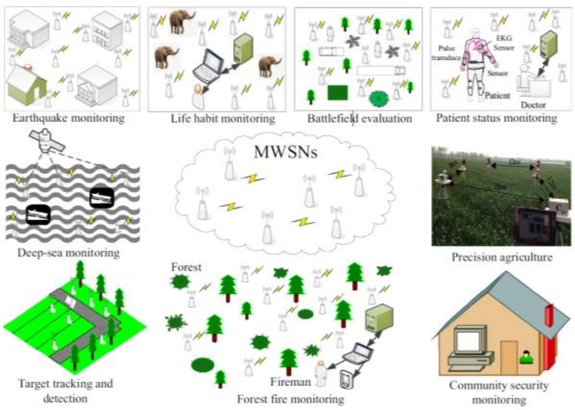

Figure 3: The most common applications [13]

It is worth noting that this wide scope of applications has introduced many significant challenges, prompting extensive efforts to develop appropriate solutions. Intensive research has addressed issues such as coverage, deployment and allocation, sensor relocation and mobility, node density, connectivity, communication and access range, adaptability, energy and lifetime, fault tolerance, reliability, and many more [14–24].

In any WSN, a limited number of wireless sensing nodes are deployed for the surveillance of specific targeted objects or fields, and the collected data must be transmitted to static or mobile base stations. The (x, y) coordinates of each node in the two-dimensional space should be specified. Therefore, the ability of a sensor node to communicate with other sensor nodes depends mainly on its deployment and coverage range r. A sensing node i can communicate with any sensing node j if the distance d_{ij} between them is less than or equal to r. Figure 4 presents ten sensing nodes randomly deployed in a $10\ x10$ field with $r\ =\ 1.5$.

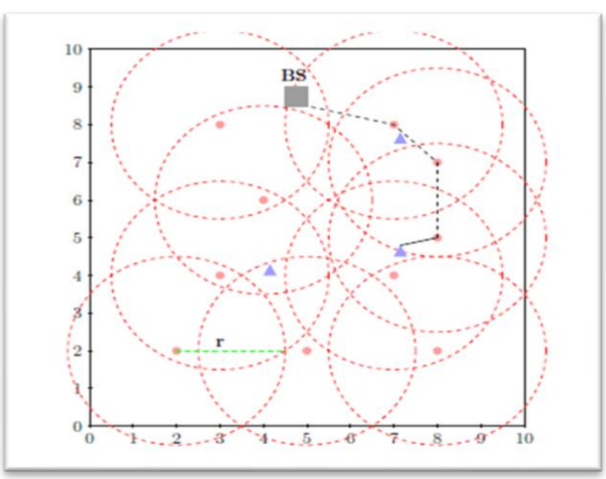

Figure 4: Ten sensor nodes were randomly deployed [3]

Notably, regardless of the communication protocol used to send the collected data to the base station or end user, the data cannot be delivered in the event of a path failure. Such failures, as noted in [25], can stem from noise, interference, environmental conditions, node malfunctions, or excessive distance. Self-adaptivity, as defined in [26], refers to a system's ability to adjust to its environment or maintain its objectives despite changes. Consequently, the self-adaptive property of wireless sensor networks can be directly linked to the stages of the proposed approach based on the genetic algorithm. As illustrated in Figure 5, the four stages are the following:

- **Monitoring**: corresponds to sensing node status and detecting path failures, providing the raw input for GA evaluation.
- **Analyzing**: maps to the fitness evaluation of candidate disjoint paths, where the algorithm assesses connectivity and fault tolerance.
- **Planning**: aligns with GA operators (crossover, mutation, and selection), which provide a new path configuration to improve resilience.
- **Executing**: represents deploying the best chromosome/path set to maintain reliable communication with the base station.

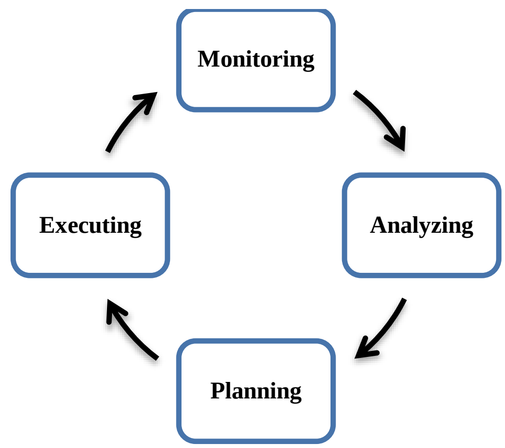

Figure 5: The most common stages

Clearly, Figure 5 shows that the GA-based DSP approach is not only a heuristic optimization method but also part of a broader self-adaptive design strategy for WSN fault tolerance.

Fault tolerance ensures a WSN remains continuously operational despite failures, thereby enhancing its reliability, availability, and overall dependability. When a sensor node cannot be repaired, designing a fault-tolerant system from the outset is crucial. This involves considering potential faults and their impact on WSN performance during the design phase, as discussed in [27, 28]. Various fault-tolerance approaches have been proposed, including graph domination of the wireless sensor network (WSN) with parallel scatter search [29], Topology Control Scheme for Fault Tolerance [30], optimized machine learning for fault detection [31], and 3D Virtual Biomimetic Network Topology [32]. Dynamic simulations such as Monte Carlo have also been used to estimate reliability [33] and resiliency [34]. However, these approaches do not directly tackle the NP-complete Disjoint Set Paths (DSP) problem, which is central to maximizing multipath routing diversity. In fact, multipath routing is critical because it ensures that data can still reach the base station even when individual paths fail. The novelty of the proposed Genetic Algorithm-based DSP approach (GADSP) lies in explicitly formulating DSP maximization as an optimization problem and solving it with a GA framework. Unlike prior works [29–34], GADSP achieves quantified near-optimality (quality gap $Q \leq 6\%$) and maintains polynomial computation time, thereby filling a distinct gap in the literature by directly enhancing fault tolerance through multipath maximization.

More precisely, multipath routing is a common fault tolerance approach where multiple alternative paths are established between source nodes and the base station [35]. Determining and maximizing these paths is a complex optimization problem, evaluated by the computational time and resources needed for its solution. Optimization problems are categorized as polynomial (P), non-deterministic polynomial (NP), NP-complete, and NP-hard [36]. For NP problems, finding an exact algorithm that guarantees a globally optimal solution within acceptable time and resources is often impossible. Consequently, numerous heuristic algorithms have been developed to find near-optimal solutions efficiently. Heuristics quickly generate acceptable quality solutions but don't guarantee optimality [37]. The Genetic Algorithm (GA) stands out as a widely implemented evolutionary computational search method.

Maximizing the number of available alternative paths is an NP-complete Disjoint Set Paths (DSP) problem [38], typically addressed using heuristic and meta-heuristic algorithms. Recognizing that increased multipath enhances fault tolerance, this paper proposes a Genetic Algorithm-based approach to find a near-optimal solution for this NP-complete optimization problem within a reasonable computational time.

The rest of this paper is organized as follows: the next Section 2 presents the proposed method. Section 3, presents the main results and discussion. Finally, Section 4 concludes this paper.

2. THE PROPOSED METHOD

In a WSN with a set Y, sensors: $s_1, s_2, \ldots, s_y$ deployed to monitor a set of targets or field surveillance, a senior s_i could communicate with a sensor s_j or the BS if s_i or the BS lies within the sensing area of sensor s_i. The DSP problem, could be defined as follows:

Definition: (Disjoint Set Paths Problem)

Given a set Y of subsets of a finite set S, find the maximum number of disjoint paths for S. Each path P_i is a subset of Y ($P_i \subseteq Y$), such that every element of S belongs to at least one member of P, and for any two paths P_i and P_j, their intersection is empty ($P_i \cap P_j = \varphi$).

And thus:

- any path P_i provides a data path to the base station
- any sensor s_i could be included in one path at max

The fault tolerance in WSN can be improved by determining the maximum number of disjoint set paths (DSP). This problem is solvable by transforming it into a disjoint set theory problem.

Specifically, a sensor s_i is represented by a subset P_i within the collection Y, where $S_j \in S_i$ if and only if S_j lies within the sensing region of sensor s_i. Thus, Y is a collection of subsets representing sensors, and a path P_i represents a path from a source to the BS.

As shown in Figure. 6, s_1, s_2, s_3, s_4, and s_5 are five sensors and a BS with the possibility of direct communication. It is notable that each sensor network may be represented as a bipartite graph G(V,E), where V represents S and BS, $e_{ij} \in E$ if s_i can directly communicate with s_j or the BS.

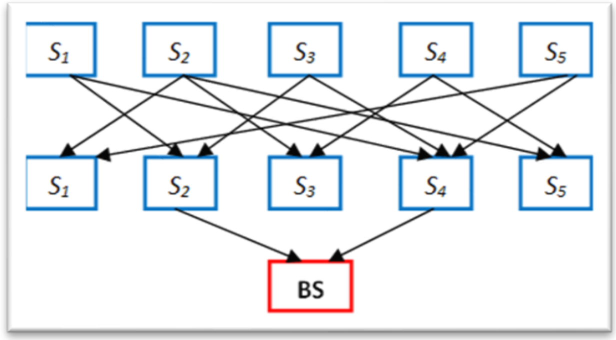

Figure 6: Five sensors and BS direct communicate

Figure 7 depicts the bipartite graph for Figure 1. In this example, it is applicable for each sensor to be a source. For s_1 as source, $P_1 = \{s_1, s_2, BS\}$, $P_2 = \{s_1, s_4, BS\}$, $P_3 = \{s_1, s_4, s_3, s_2, BS\}$, $P_4 = \{s_1, s_4, s_3, s_5, s_2, BS\}$, and many more. One could find two DSPs which is the optimum number of disjoint paths in this case.

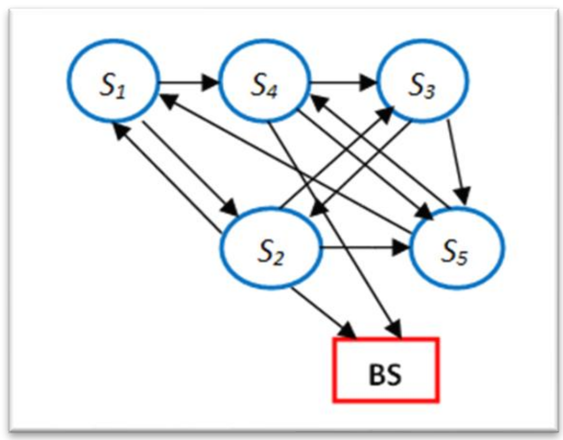

Figure7: The bipartite graph

This paper proposes a Genetic Algorithm-based approach for Maximizing Disjoint Set Paths. For any GA, the chromosome representation is a key design concept, along with the crossover, mutation operator, and fitness evaluation.

A. Chromosome Representation

Initially, sensors are randomly assigned to predefined groups, forming candidate DSPs. A group constitutes a valid path if it connects a source to the BS. Chromosomes are integer-encoded, where each gene corresponds to a sensor and its value indicates the assigned group. For example, Figure 8 shows group 1 containing S_1 and S_3, while group 2 contains S_2, S_4, and S_5. Gene values range from 1 to the total number of specified groups.

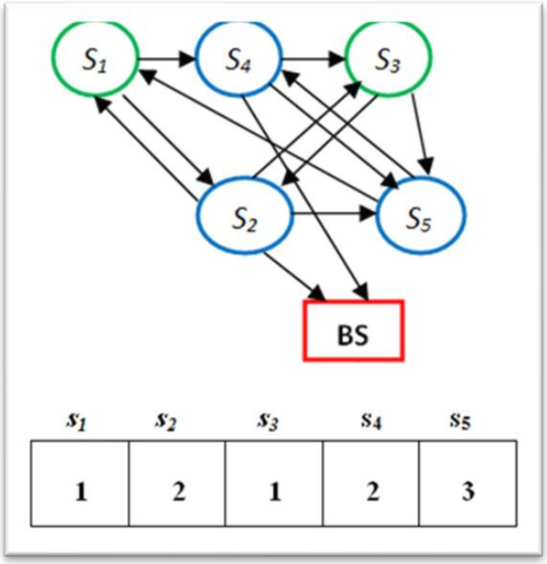

Figure 8: Group 1 contains S_1 and S_3, while group 2 contains S_2, S_4, and S_5

The number of candidate paths should be limited to the maximum possible number of paths. Considering that if the BS is accessible by only *k* sensors, and given the DSP constraint that prevents the sensor from joining two paths simultaneously, it is impossible to exceed *k* paths. Therefore, the maximum number of expected paths, which is determined by the number of sensors that can access the BS (as illustrated in Figure 9); is used as an upper bound (UP) in this work.

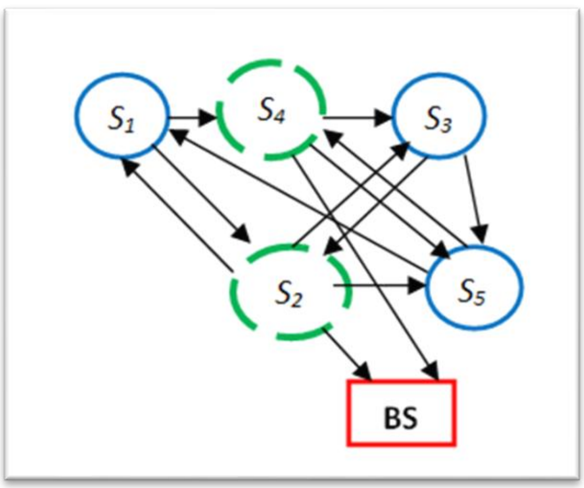

Figure 9: The number of sensors that can access the BS

B. The Objective Function to be Optimized

The objective function can be formulated as the number of fit chromosomes and DSPs that can be found by the grouping combination through the GA iterations.

C. Fitness

The fitness function is used as a constraint that must be satisfied, and the fit chromosome is the candidate DSP that can provide a source to the BS connection through the GA iterations.

D. Crossover

In general, crossover was used to generate the new population in GA from selected parents. In this approach, single-point crossover was used to generate the next generation for all populations, taking every two members as parents.

E. Mutation

Mutation aimed to enhance the inherited value of solutions. In this approach, the gene value is a digit from 1 to up, and the current value of a randomly selected gene could be changed accordingly.

F. GA Algorithm Implementation

To ensure clarity and reproducibility, the complete genetic algorithm framework used in this study is summarized below.

Algorithm 1. GADSP_GA
Input: Sensor set S, Base Station BS **Output**: Maximum number of disjoint set paths (DSP)
Step1: Initialize population of chromosomes (size = 100)
Step2: For each chromosome:
• Encode sensors into groups (candidate paths) • Evaluate fitness (valid source-to-BS connection)
Step3: Repeat for 500 generations or until termination criterion:
• a. Select parents using tournament selection • b. Apply single-point crossover (rate = 0.8) • c. Apply mutation (rate = 0.05) • d. Evaluate fitness of new population • e. Update best solution if improved
Step4: Return best chromosome representing maximum DSPs

Furthermore, Table 1 summarizes the specifications of the experimental environment and the setup parameters used in evaluating the GA-based method.

Table 1: Experimental environment and GA hyperparameters

Parameter	**Setting**
Computer Properties	
Processor	Intel Core i7 (HP EliteBook 8770w Workstation)
RAM	16 GB
OS	64-bit Windows 10
Programming language	Java
GA Hyperparameters	
Population size	100
Number of generations	500
Crossover rate	0.8
Mutation rate	0.05
Termination criterion	Algorithm stops when either 500 generations are reached or no improvement is observed in the best fitness value for 50 consecutive generations
Parent selection	Tournament selection employed to ensure diversity and avoid premature convergence

3. EXPERIMENTAL RESULTS

This section presents the experimental results of the proposed GA-based approach on Java programs for various instances. The approach was applied to wireless sensor networks (WSNs) with different configurations, sizes, and sensing ranges

To illustrate the proposed approach, a simple numerical example will be given, consisting of a WSN with 5 sensing nodes and a BS with a sensing range of $r=4$ randomly deployed in a $20x20$ area, is used to illustrate the approach. The (x_i,y_i) coordinates for each sensor s_i were randomly generated as shown in Table 2.

Table 2: Randomly deployed

s_i	1	2	3	4	5	BS
x_i	1	7	4	0	9	9
y_i	4	8	8	2	4	9

Accordingly, the Access Relationship Matrix (ARM) is illustrated as follows.

$$ARM = \begin{pmatrix} & 1 & 1 & 1 & 0 & 0 \\ 1 & & 1 & 0 & 1 & 1 \\ 1 & 1 & & 0 & 1 & 1 \\ 1 & 0 & 1 & & 1 & 0 \\ 0 & 1 & 1 & 0 & & 0 \end{pmatrix}$$

Therefore, considering s_1 as the source, only $s2$ and s_3 are reachable, resulting in a maximum of two disjoint shortest paths (DSPs). Thus, the set of possible paths, Y, is $\{p_1, p_2\}$, where $p_1=\{s_1, s_2, BS\}$ and $p_2=\{s_1,s_3,BS\}$.

For a WSN with 100 sensing nodes and sensing ranges $r=\{10, 20, 30, 40, 50, 60, 70, 80, 90, 100\}$, randomly deployed in a $20x20$ area, with s1 as the source and the BS centrally located, Table 3 presents the upper bound (up) and the maximum number of paths found by the proposed GA for all configurations.

Table 3: The maximum number of paths found for a WSN with 10 to 100 sensing range

sensors	range *r*	up	GADSP	Q
100	10	17	7	0.00
100	20	24	23	0.04
100	30	29	28	0.03
100	40	36	34	0.05
100	50	44	42	0.04
100	60	53	50	0.06
100	70	60	57	0.06
100	80	68	64	0.05
100	90	72	68	0.05
100	100	81	76	0.06

* Q represents the quality of solution (up-GADSP)/up.

The proposed approach, GADSP, has found a near-optimal number of DSP for all 100 sensing node configurations with sensing range from 10 to 100.

The GADSP approach achieved a near-optimal number of DSPs for large-scale WSNs, specifically for 1000 sensing nodes with ranges from 10 to 100. This was demonstrated in a $20x20$ area with 1000 randomly deployed nodes (r = {10, 20, 30, 40, 50, 60, 70, 80, 90, 100}), as shown in Figure 10.

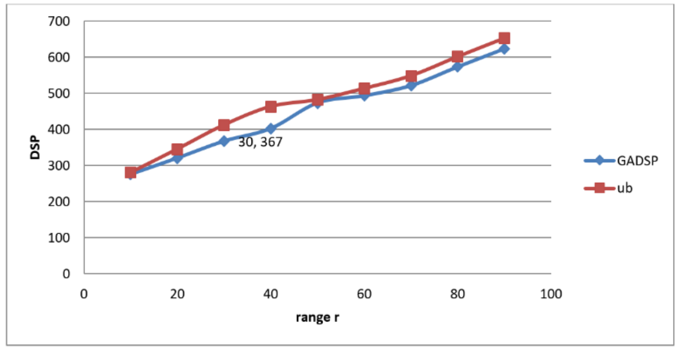

Figure 10: The maximum number of paths found for a WSN with 1000 sensing node

The GADSP approach achieved a near-optimal number of DSPs for all 100 sensing node configurations, with node counts between 10 and 100. This was demonstrated in a 20x20 area using randomly deployed sensor sets (S) of 10 to 100 nodes, each with a sensing range (r) of 10, as shown in Table 4.

Table 4: The maximum number of paths found for a WSN with a sensing range of 10

sensors	range *r*	up	GADSP	Q
10	10	3	3	0.0
20	10	5	4	0.2
30	10	6	5	0.18
40	10	8	6	0.25
50	10	9	9	0.00
60	10	11	10	0.09
70	10	13	11	0.15
80	10	16	13	0.18
90	10	19	16	0.15
100	10	21	19	0.09

* Q represents the quality of solution (up-GADSP)/up.

Furthermore, our proposed GADSP approach yielded a near-optimal number of DSPs for all 100 to 1000 sensing node configurations. This was observed in a 20x20 area where sensor sets (S) of 100 to 1000 nodes, each with a sensing range (r) of 10, were randomly deployed, as shown in Figure 11.

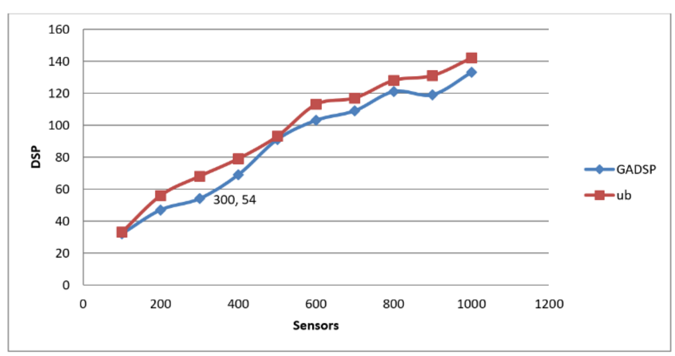

Figure 11: The maximum number of paths found for a WSN with 100 to 1000 sensing nodes

The results shown demonstrate that GADSP consistently achieves solutions very close to the theoretical upper bound, with quality gaps Q typically below 0.06, and a computation time of no more than 0.6 seconds for all results. These findings confirm the near-optimality of the GA framework and validate its polynomial-time efficiency.

4. CONCLUSION

This paper addressed the challenge of enhancing reliability in wireless sensor networks (WSNs) by proposing a genetic algorithm-based approach for maximizing disjoint set paths (DSPs). By formulating DSP maximization as an NP-complete optimization problem and solving it using the GADSP framework, the study has demonstrated that fault tolerance can be significantly improved through increased multipath availability. The proposed method was evaluated across a wide range of WSN configurations, and the results consistently showed that GADSP achieves near-optimal solutions relative to the theoretical upper bound, with quality gaps typically below 0.06. Furthermore, computation times did not exceed 0.6 seconds, confirming the polynomial-time efficiency and practical applicability of the approach.

While the proposed GADSP approach demonstrates near-optimal performance and polynomial-time efficiency, several limitations must be acknowledged. First, the performance of the algorithm depends on the careful tuning of GA parameters such as population size, crossover rate, and mutation rate, which may vary across different network scenarios. Second, the current model assumes static and uniformly deployed sensor nodes, whereas real-world WSNs may involve heterogeneous, clustered, or mobile deployments. Third, the study focuses solely on maximizing disjoint paths without incorporating energy consumption, network lifetime, or load-balancing considerations, which are critical factors in long-term WSN operation.

Future work will address these limitations by extending GADSP to heterogeneous and mobile WSN environments, integrating energy-aware and lifetime-optimization objectives, and evaluating performance under more realistic deployment conditions. These enhancements will further strengthen the applicability of the proposed approach in large-scale, real-world surveillance and monitoring systems.

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