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Energy-Efficient Path Optimization Using A Genetic Algorithm (GA)

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Abstract

Wireless sensor networks (WSNs) have remained a hot field of research for the last three and a half decades. WSNs comprise small-sized sensors having small batteries, so energy depletion is a significant problem, resulting in a short lifetime of the WSNs. Since the WSNs work as application-centric they have the capabilities of data gathering and transmission to the base station. Therefore, a significant amount of sensor networks' energy is spent during data collection and transmission operations if the route is not optimized. In this study, an efficient optimization routing scheme for multiple hops is proposed to enhance the lifetime of the network. In this regard, a meta-heuristic genetic algorithm plays a vital role in finding the optimized route.

The genetic algorithm is modified by tuning its parameters for better optimization results so that the best route can be selected among all possible routes and will save the wireless sensor networks' energy. All information is routed towards the sink via intermediate neighbor nodes, which only relay the data without performing any computation or operation. The genetic algorithm determines the route information to all nodes and sinks. Then, the data takes the most optimal route for data transmission. The simulation results of 10 sensor node deployments indicate that the path efficiency, namely 44.9% and 59.3%, is achieved through optimal paths to the nearest sinks towards sink1 and sink4, respectively. While the 20 sensor nodes deployment resulted in considerable path efficiency to the nearest sinks towards sink1 with 38.8%, sink2 with 41%, sink3 with 52.3%, and sink4 with 52.2%. Thus, this study proved a considerable saving of energy and resulted in substantially efficient optimized paths.

Keywords: Wireless Sensor Networks, Energy efficiency, GA, Network routing, Multiple hops.

Introduction

Recent developments in micro-electro-mechanical systems, or MEMS have resulted in the development of miniature, low-power, and cost-effective motes or sensors. Such sensors are able to sense and collect data from their environment, process raw data, and then transmit the information to a central base station through a radio link or wireless connection for a comprehensive analysis [1-5]. Generally, data transmission typically employs either of the two methods: direct and multi-hop transmissions. In direct communication, every node sends the data by using its energy. In this way, it is better for the nodes nearer to the sink nodes, but it is very costly for the farther nodes. In a multi-hop transmission scheme, data is transmitted through adjacent nodes. For example, the green-colored nodes and yellow-

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colored nodes send the data to their neighbor nodes until data is transmitted by other nodes to the sink, as shown in Fig. 1 [1]. These sensors are to be used in various environments to track and monitor. When large numbers of such sensors are put in a certain area and can communicate wirelessly, they work together to make a Wireless Sensor Network (WSN). Nevertheless, these sensors have a relatively short battery life, which will be consumed if the computations for the tasks happen frequently. This means that the longevity of the WSN has to be improved for the network to work for more extended periods for optimal monitoring and tracking [6], [7].

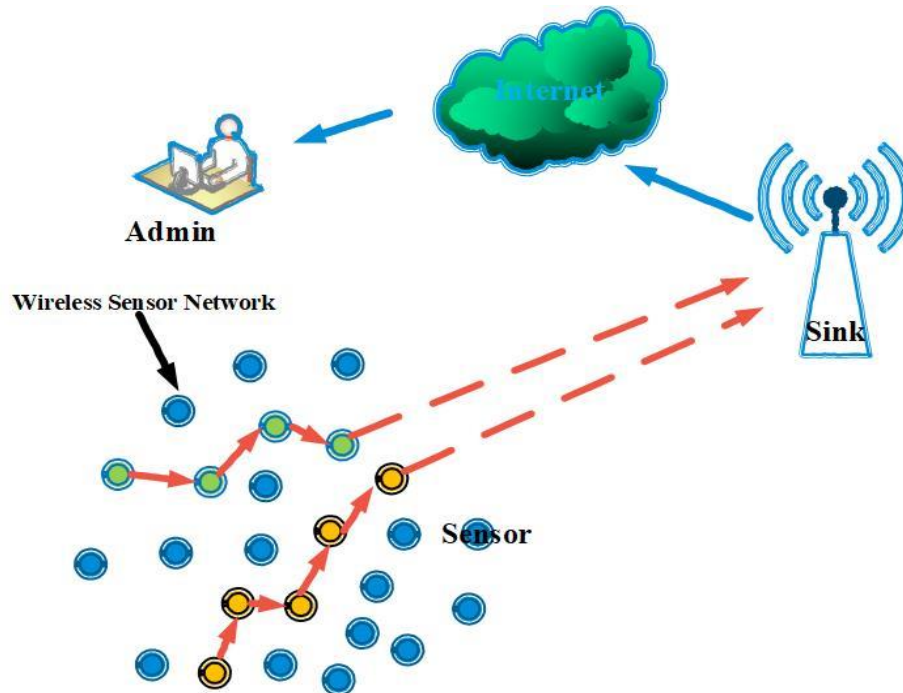


Figure 1: An example of a multi-hop routing scenario of wireless sensor networks [1].

The most critical reason for rapid battery drainage is the failure to identify a reasonable but optimized routing path. For this problem, we are using a genetic algorithm (GA) for path determination for the routing of data [8-14]. We utilize the multi-hops and direct transmission approaches to allow for data to pass between nodes. We then apply the Euclidean distance formula for calculating distances at the first hand, and then determine the path using the GA. We also check the additional energy loss by using the maximum distance between nodes and the sink due to the scheme being direct or multi-hop. In comparison, we opt for a robust routing scheme of path estimation to optimize paths from the source node to the sink. Therefore, the main contributions of this study are to devise an efficient routing scheme by determining optimal paths to route the data. This routing scheme not only prevents unwanted energy consumption but also increases the network lifetime.

This research proposes a novel GA based approach for path determination and optimization toward reliable communication and minimum energy wastage. A comparison of the achieved results with those of standard algorithms is done for validation of the proposed scheme's effectiveness. This research paper is broken into five sections; Section 1 presents the introduction, and Section 2 incorporates the research background. Further, the genetic algorithm and its operators are defined in Section 3. Section 4 commences with simulation results, discussions, and the conclusive remarks are provided in Section 5.

1. Background

In the recent past, several researchers have emphasized resource utilization and power consumption as key factors contributing to maximizing network lifetime [10-13]. Various algorithms have been proposed for improving optimization and prolonging network lifetime. Energy wastage generally occurs when sensors communicate data through a longer route instead of a shorter route. Optimization of routes in the network may significantly increase network lifetime with minimum energy consumption. Genetic Algorithm (GA) optimization was found to be a promising means of selecting the most efficient routes from all those available. Hence, research and scholarly communities have shown high interest in such energy-efficient routing schemes that might reduce energy loss. A more detailed review of various data routing techniques that emphasize energy-efficient use can be accessed in [14, 15]. Such energy-efficient routing strategies are the key to ensuring maximum operational time for wireless sensors and WSNs. Research in [16] presents a data-centric routing scheme within currently available WSN routing protocols. Furthermore, evolutionary and heuristic algorithms have been efficient in finding shortest paths in WSNs. Additionally, in [17-27], the average transmission path for data packets is discussed using a methodology intended to reduce that path. [2] presents a Genetic Algorithm (GA) for optimizing routing paths in Wireless Sensor Networks (WSNs) with multiple sinks, enhancing energy efficiency and data delivery by determining a novel routing and scheduling method using GA. Furthermore, it contributes as the optimized path for energy-saving data transmission to sinks via optimal hops from sensor nodes to the nearest sink, thus prolonging network longevity.

The lifespan of the sensors plays a crucial role in determining the performance of the network, as does the chosen route for data transfer. Therefore, it's essential to establish optimized pathways for data transmission that minimize energy consumption, ultimately enhancing the longevity of the wireless sensor networks.

2. Genetic Algorithm

Genetic Algorithms (GAs) are motivated by biological processes and simulate natural selection. They work according to mechanisms of stochastic search and have been used in several studies for probabilistic and optimization problems. The literature indicates that GAs work well on pathfinding and determining optimal routes in a relatively short time. The GA works based on several components: selection, crossover, mutation, and a fitness function. It starts with considering a group of people as a population that has data regarding the energy level of each individual. It then chooses individuals from the higher energy levels for the purpose of crossover. After crossover, the mutation operator is applied, with the probability selected as 0.8. Finally, after all the specified parameters are met, the ideal route for the exchange of data is determined. The sensor node then forwards the data along the optimal path towards the nearest neighbor. A GA can be broken down into two phases. Phase 1 involves the initialization of the population and the evaluation of each individual's fitness level. If the individual's fitness level meets the criteria, it is not subjected to further processes. If the criteria are not met, these selected individuals go through tournament selection, crossover, and mutation operations. For this study, the GA uses the following operators:

a. Initial Population

This is the first step in the GA process, where all sensor nodes are generated randomly. Here, all of these sensor nodes are referred to as individuals or alleles. This evolutionary generation starts at 0; from this initialization, the communication radius or threshold establishes itself as shown in Fig. 2.

b. Fitness Function

It measures the fitness of every individual in terms of their energy level. Checking energy levels is the primary purpose because, for identifying such individuals, these are going to extend the lifetime of the WSN. A certain number of criteria determine the fitness of an individual, such as elitism.

$$FF_{E_{individuals}} = \sum_{i=1}^{N-1} dist_i^2 \quad (1)$$

Where $FF_{E_{individuals}}$ estimates the energy level of each sensor node, and comprises the overall population N . The $dist_i$ indicates the Euclidean distance of the node from all the other nodes.

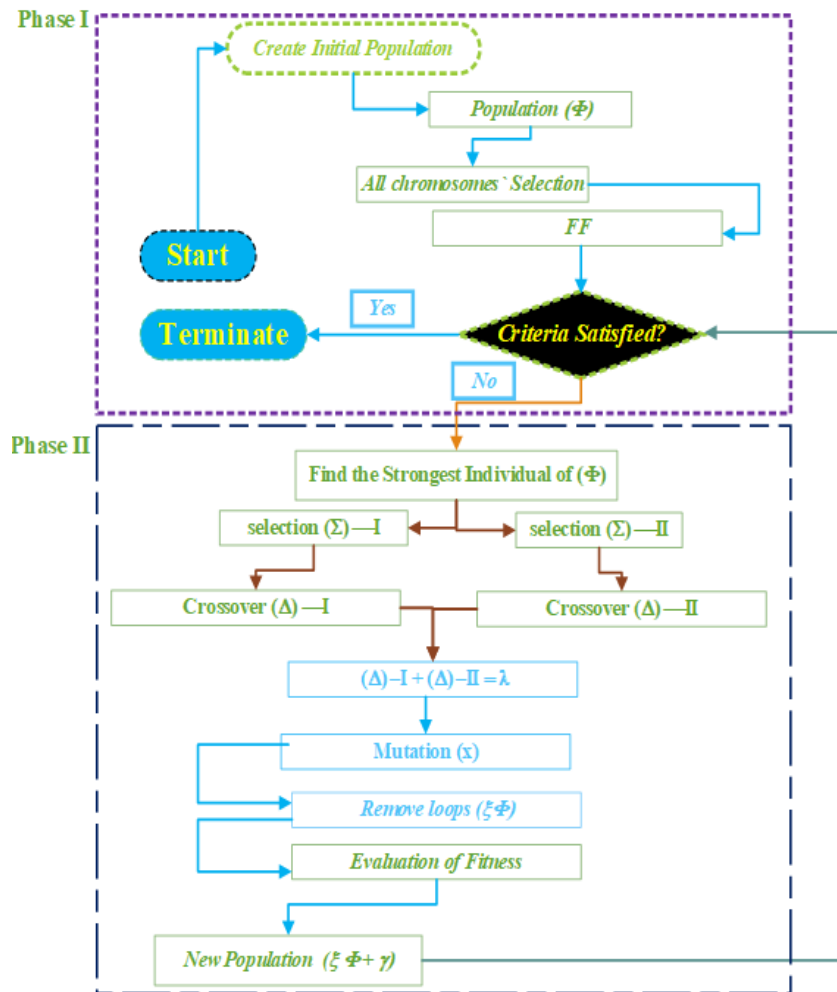


Figure 2: Working diagram of the Improved-Genetic Algorithm.

c. Selection

After testing the fitness of the individuals, the selection operator retrieves the best-performing members. This operator deploys tournament selection and maintains the mating pool, containing individuals with a fitness level greater than the threshold. The strongest and fittest members are selected and subjected to later processes, such as crossover.

d. Crossover

After the selection process, crossover is called for generating new individuals by combining parent and child individuals. For this study, the two-point crossover method is used, wherein each individual of the population becomes a parent in order to produce a child individual. This child is created through the copying of characteristics from the two parent individuals.

e. Mutation

After the crossover operation, the mutation operator is applied to refine the results of the individuals by creating copies of the sensor nodes. The mutation probability is set at 0.9 to enhance evaluation and achieve robust results. In GA, generally there is no fixed mutation rate; instead, it's a probability parameter that determines the likelihood of a change occurring in an individual's genes, typically set at a low value such as 0.001 to 0.01. The purpose of this rate is to prevent the GA from getting stuck in local optima by introducing new genetic material, but if it's too high, the algorithm can degenerate into a random search. The optimal mutation rate is often problem-dependent and can even be adapted during the GA run. Loops are removed, and the resulting solutions are combined with the previously fit individuals to ensure that no effective individuals are lost, ultimately improving outcomes as shown in Fig. 2.

3. Performance and Simulation Results

The experimentation and simulation were conducted with the use of MATLAB R2024b platform by conceptualizing experimental parameters as indicated in Table 1. The scenario of the simulation was implemented in a $100 \times 100m^2$ area with four sink nodes at four vertices and 10 and 20 sensor nodes deployed randomly. First, the direct distance is assessed in two rounds, e.g., round 1 having 10 sensors, and round 2 for 20 sensor nodes as represented in Table 2. Then we ran the GA to determine all possible paths of all sensor nodes towards the base station. As the GA is performing the route determination, all the route information are conveyed to each sensor node in such a manner that any source will be able to forward the data to the nearest neighbor node.

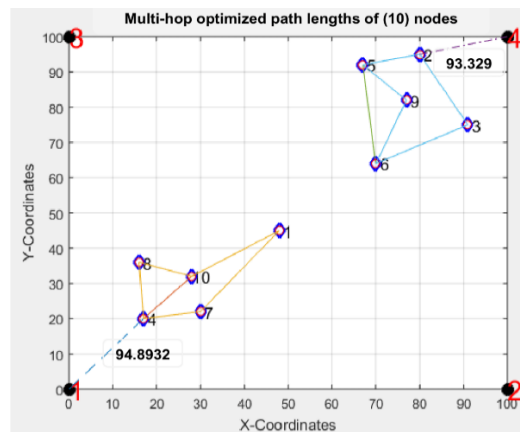
Table 1: Parameter Settings

Parameters Attributes	Brief description
WSN Area Size	$100 \times 100 m^2$
No. of nodes	10, 20
Energy level	0.10 J
Frequency of trials	4000
Energy Dissipation	55 nJ/bit
$d_i < d_j$	10 pJoules/bit/m
$d_i > d_j$	0.0015 pJ /bit/m

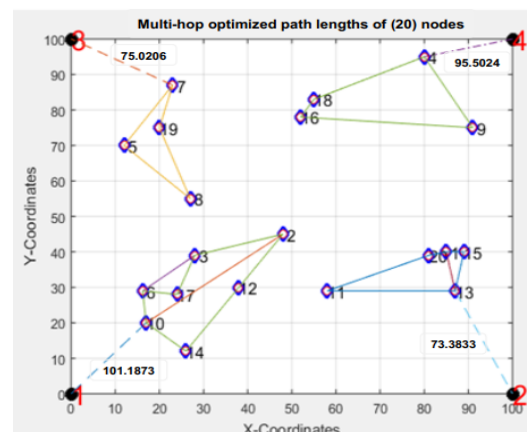
As the sensor node collects data, neighboring nodes relay this information until it reaches the base station, as illustrated in Fig. 3. This research targets the use of multiple sinks that exchange routing and location information with every sensor node and utilize GA. The results are compared to the prevailing TEEN algorithm [19]. Herein, the GA identifies possible paths, from which an efficient path is chosen. This strategy not only saves energy but also reduces the costs of transmitting data.

Table 2: Computation of the direct distance of the nodes towards all sinks.

	Sensors	Towards Sink 1	Towards Sink 2	Towards Sink 3	Towards Sink 4
Round-1	N1	93.9415	42.7200	104.0433	61.8466
	N2	65.7951	68.7677	73	75.6902
	N3	48.0104	81.8841	67.1193	94.3663
	N4	124.1974	97.0824	80.1561	20.6155
	N5	71.0211	112.4455	32.3109	92.9731
	N6	33.2181	88.6760	72.8247	109.8337
	N7	89.9889	116.1809	26.4197	78.0897
	N8	61.2698	91.4002	52.4786	85.7555
	N9	117.9237	75.5381	94.3716	26.5707
	N10	80.9197	64.4049	78.4092	61.2209
Round-2	N11	64.8459	51.0392	91.6788	82.4924
	N12	48.4149	68.8767	79.6492	93.5094
	N13	72.8011	41.2311	100.4988	80.6226
	N14	28.6356	74.9667	91.7605	114.9783
	N15	97.5756	41.4849	107.3359	61
	N16	93.7443	91.5860	56.4624	52.8015
	N17	36.8782	80.9938	75.8947	104.6900
	N18	99.5691	94.4139	57.5674	48.1041
	N19	77.6209	109.6586	32.0156	83.8153
	N20	89.8999	43.3820	101.4002	63.8905



(a)



(b)

Figure 3: Multi-hop distance optimization (a) Path optimization of 10 nodes (b) Path optimization of 20 nodes

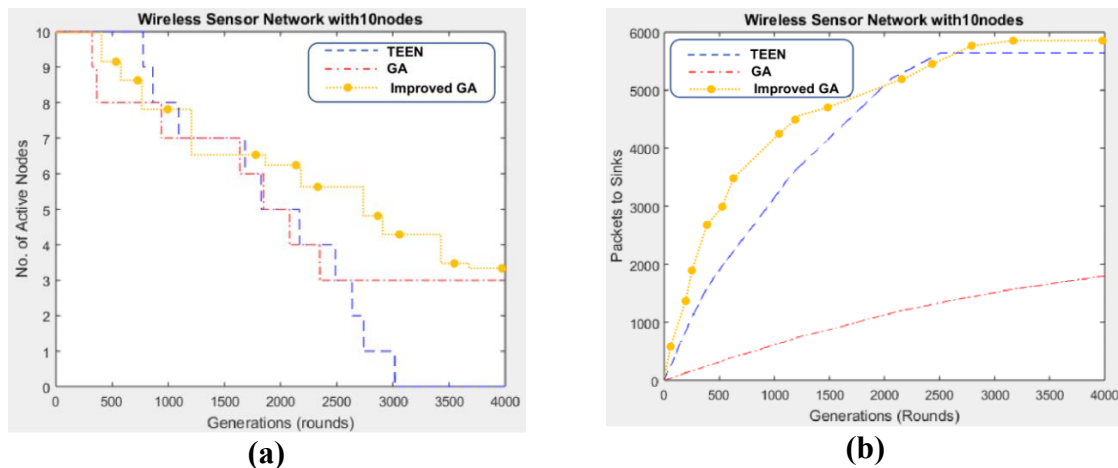


Figure 4: Path optimization results of the TEEN, GA and Improved-GA algorithms with 10 sensor nodes (a) Evaluation of active node (b) Results of packets transmission.

The performance of the scheme developed is compared with the traditional TEEN algorithm. The results prove that there is considerable improvement in the utilization of paths, which contributes to higher energy savings for the WSNs, as shown in Fig. 4. As illustrated in Fig. 4(b), packets are delivered to the closest sinks during 4,000 rounds, and the scheme performs better than the TEEN algorithm. Both techniques achieve their maximum number of packets of data at the sink within the same number of rounds. But the improved-GA scheme outperforms in delivering the maximum packets while costing the lives of a few sensors.

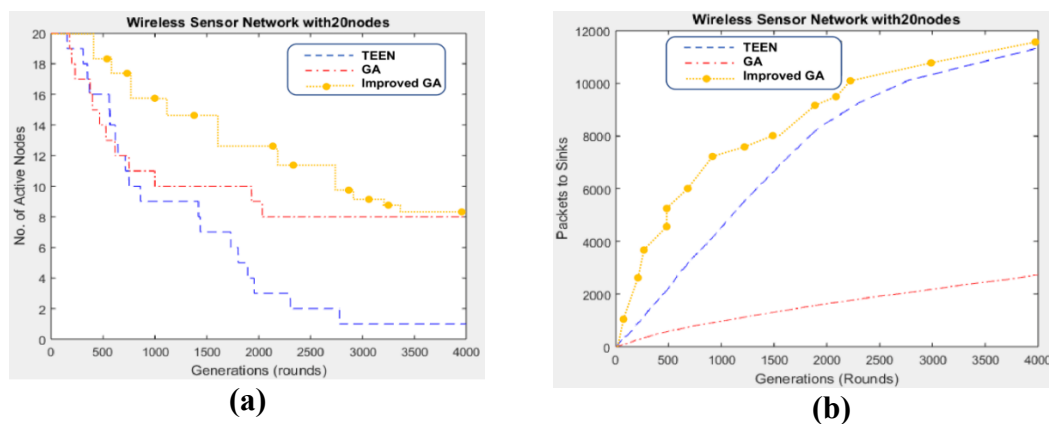


Figure 5: Path optimization results of the TEEN, GA and Improved-GA algorithms with 20 sensor nodes (a) Evaluation of active node (b) Results of packets transmission.

Similarly, the results of deploying 20 sensor nodes are computed as their direct distance and then the multiple-hops distance is evaluated as shown in Table 2 and Fig. 3 (b), respectively. In Fig. 3 (b), the routing paths from a source node to the sink node as determined by the improved-GA can feasibly be selected among all the possible paths.

The energy levels are crucial in determining the life of the nodes. In other words, the active nodes per round are based on their energy and operation levels. That is, the number of sensor nodes can transmit the data to several rounds. Thus, the number of rounds is set at 4K for both the proposed scheme and the standard TEEN algorithm. The proposed scheme gives very compromising results against the TEEN and GA algorithms when compared in terms of active or alive nodes during the operation of the WSNs, as depicted in Fig. 5 (b). An effective

routing path is a prerequisite for ensuring the optimal utilization of the WSNs' lifetime as well as optimized routing of the data. Energy consumption of sensor nodes and sink nodes is estimated and compared against the TEEN algorithm, which is depicted through Figures 4 (b) and 5 (b). This evaluation presents the packet transfer from the sensor nodes to the sink.

4. Discussions

This research presents an efficient routing scheme for the WSNs to maximize the lifetime of the network. The routing scheme is determined with the help of GA. All of the sensor nodes are deployed in the $100 \times 100 m^2$ area randomly. We set 10 sensor nodes randomly and determined paths among them using the GA. Each node knows the location and distance of the other nodes, and only the data is shared with the closest node.

In our proposed scheme, the simulation is performed through a variable number of nodes, namely 10 and 20 sensor nodes as well. First, we assumed WSNs with 10 sensor nodes deployed in an ad hoc manner at different positions. The distance between the nodes is calculated using the Euclidean distance matrix for the sake of knowing all the possible distances and the minimum one towards the nearest sink. The total distance of all sensors to sink1 is 211.1621 meters, while all sensor nodes route data towards sink4 with 157.2098 meters, as shown in Table 2. When each node routes the data, the energy consumption may be higher due to the direct distance. However, we calculated and evaluated the distance with the help of GA through the multiple hops communication scheme. As shown in Fig. 3 (a). Where sensor nodes 1, 7, 4, 10, and 8 are sending the data towards sink1, and nodes 6, 9, 2, 5 and 3 are sensing the data towards sink4. The multiple hop scheme, as shown in Fig. 3 (a), for the data route to the nearest sink through the relay nodes. The total distance towards the sink1 is 94.8932 meters, which is efficient 44.9% than the direct distance, up to 55.1% of the total path, as shown in Table 2. Whereas, the total distance of the nodes towards sink4 is 93.329 meters, which is an efficient path for routing the data, 59.3% better than the direct distance, saving up to 40.7% of the total route, as shown in Table 3.

After these calculations of the direct and multiple hops distance, we compared the results with the standard TEEN algorithm [19] with an equal number of sensor nodes. The comparison was performed by considering the number of all active nodes and all dead nodes. The findings of the simulation show better performance of the proposed algorithm than [19]. The number of packets received by all sinks has been significantly better than [19]. Hence, the four sinks help in receiving the data more efficiently and effectively. After the experiment results using 10 sensor nodes, we increased the number of network nodes to 20 sensor nodes, randomly scattered in the WSNs field. Where the nodes found nearest towards sink1 are 2, 12, 3, 17, 14 and 6 with the total distance of 260.9523 meters. Sink2 has the nodes connected, namely 11, 13, 1, 20 and 15, with a total distance of 178.6261 meters. The total distance of nodes 8, 19, 5, and 7 towards the sink 3 is 143.2248 meters directly. The direct distance of the sensors to sink4, namely 10, 18, 16, 9 and 4 is 182.742 meters. Whereas, distance with the help of GA gives a very significant reduction in the path towards each sink. The path length through multiple hops is 101.1873, which covers 38.8% of the total direct distance. While sinks have 73.3833 meters of path from the nodes, which is 41% of the total direct distance, as displayed in Table 3.

The sensor nodes having distance through multiple hops towards sink3 is 75.0206 meters with an efficiency of 52.3% of the total direct distance. The nodes route towards Sink4 by multiple hops is 95.5024, which results in 52.2% efficiency compared to the direct distance, as revealed in Table 3. The results of the proposed approach are compared with [19]. The proposed technique outperforms [19] in terms of active and dead nodes. Successful

transmission of the data packets towards the sinks is significantly greater than the [19] scheme. Every exponential variation in the number of sensor nodes gives the exponent number of solutions. In other words, as the number of sensor nodes increase in WSNs, the possible routes for routing the data through optimal paths increase. This optimization gives the advantage of selecting the best and optimal route towards the nearest sinks. The simulation was done by comparing the proposed technique with [19]. The results indicate that the energy consumption and performance of all nodes are limited by the number of active and dead nodes, which outperforms the standard algorithm [19]. Furthermore, the packet reception at the side of the sink is significantly better than that of [19].

Table 3: Performance Evaluation

No. of Nodes	10 Nodes	20 Nodes
No. of nearest nodes towards Sink 1	5	6
Direct Distance (meters)	211.1621	260.9523
Multi-hop distance (meters)	94.8932	101.1873
Path efficiency %	44.9%	38.8%
No. of nearest nodes towards Sink 2	0	5
Direct Distance (meters)	-	178.6261
Multi-hop distance (meters)	-	73.3833
Path efficiency %	-	41%
No. of nearest nodes towards Sink 3	0	4
Direct Distance (meters)	-	143.2248
Multi-hop distance (meters)	-	75.0206
Path efficiency %	-	52.3%
No. of nearest nodes towards Sink 4	5	5
Direct Distance (meters)	157.2098	182.742
Multi-hop distance (meters)	93.329	95.5024
Path efficiency %	59.3%	52.2%

5. Conclusion

The Wireless Sensor Network is an area of research that is spreading very fast and has vast implications for society. WSNs are composed of tiny sensors with a limited battery life, and therefore, energy exhaustion poses a serious problem. This leaves the networks with a limited lifespan. As WSNs are application-specific and can perform data acquisition and forwarding to a base station, a significant amount of power is utilized during these operations, particularly if routing is not efficient. This study focuses on optimizing routing through an improved-GA, which creates an efficient multi-hop routing scheme. The meta-heuristic genetic algorithm is crucial in identifying the optimal route. Our findings show that our approach outperforms the standard TEEN algorithm across various operational rounds, specifically 1500, 2000, 2500, 3000, 3500, and up to 4000 rounds, resulting in an extended network lifetime. In the future, we intend to design a model with a hybrid routing technique and improve energy harvesting and scheduling networks in order to save node energy and extend the lifetime of the network.

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Statements on compliance with ethical standards and standards of research involving animals

This article does not contain any studies involving animals performed by the author.

Disclosure and conflict of interest

The author has no conflict of interest.

Data availability statement

The data will be made available on reasonable request.

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