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Multi-Hop Path Optimization strategy by Genetic Algorithm for Wireless Sensor Networks

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Article Info

Abstract

Wireless Sensor Networks (WSNs) have been a key research area over the last three decades. WSNs are comprised of low-power sensors with limited battery capacity, and energy depletion is an essential issue that usually results in a short network lifetime for WSNs. To address this problem, this study proposes a multi-hop routing strategy to maximize the network lifetime and compare it with direct communication strategies. Most of the energy used in sensor networks is dedicated to data transfer and acquisition, particularly if non-optimized routing is employed. Thus, there is the usage of a meta-heuristic genetic algorithm to compute the most appropriate route. A variant of this genetic algorithm is used to optimize results further, enabling the choice of the optimal route from all available ones, thus preserving energy in the WSNs. Data is routed to the sink via intermediate neighbor nodes that act as pure relays and do not undertake any computational functions. The genetic algorithm determines the routing information for each node and the sink to allow data transmission through the most optimal path. The findings show that the multi-hop scheme is better than direct communication, greatly saving energy and extends network lifetime.

Keywords:

WSNs, Genetic Algorithm, Efficient routing scheme, path optimization, multiple hops and direct communication.

1. Introduction

Recent advances in micro-electro-mechanical systems (MEMS) have resulted in the creation of miniature, low-power, and cost-effective motes or sensors. These sensors can sense and collect data from their environment, process raw data, and transmit the information to a central base station via radio or wireless link for deeper analysis [1]. Generally, data transmission typically employs any of the two methods: direct transmission and multi-hop transmission. Fig. 1 (a) and 1(b) shows direct and multi-hop transmission schemes respectively. In direct transmission scheme, each node transfers its data to the sink node without disclosing the data to any of its neighboring node in the network. In multi-hop transmission scheme, data is transmitted through adjacent nodes [2]. For example, as shown in Fig. 1 (a). Node A will transmit the data to its neighbor node B. This node B will forward the information to node C, and so forth, until data will be transmitted by node E to the sink.

These sensors are designed for use in diverse environments for tracking and monitoring. When a larger number of such sensors are placed in a certain area and can communicate wirelessly, they together form a Wireless Sensor Network (WSN) [3], [4]. However, these sensors have a relatively short battery life, which will be consumed quickly if the computation tasks happen frequently. This implies that the longevity of the WSN has to be improved for the network to function effectively over extended periods for optimal monitoring and tracking.

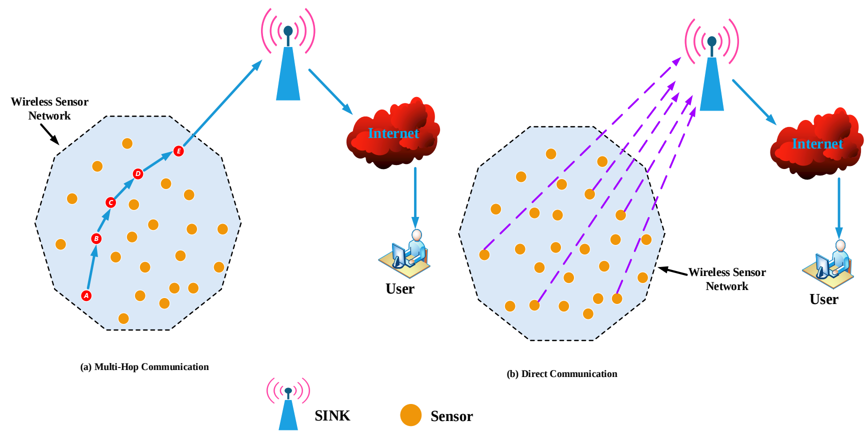

Fig 1: An example of routing schemes: (a) Multi-hop scheme. (b) Direct scheme.

The most critical reason for rapid battery drainage is the failure of identifying a reasonable routing path. To address this problem, a Genetic Algorithm for path determination of the message routing is utilized [5]. The multi-hops were utilized to allow for data to pass between nodes. Next the Euclidean distance formula is employed to calculate distances and determine the path used by Genetic Algorithm. Additional energy loss was checked by evaluating the maximum distance between nodes and the sink noting the scheme being direct or multi-hop [6], [7]. In comparison, a strong scheme of path estimation is required to optimize paths from the source node to the sink. Therefore, through this efficient routing scheme, unwanted energy consumption be decreased. This research proposes a novel GA-based approach for path determination and optimization toward reliable communication and minimum energy wastage. For validation of the proposed scheme's effectiveness a comparison of the achieved results with those of standard algorithms is conducted.

Research paper is divided into six sections; Section 1 presents the introduction; Section 2 incorporates the research background. Further, the genetic algorithm and its operators are defined in section 3. Section 4 commences with methodology, followed by results and discussions in section 5, with conclusion in section 6.

2. BACKGROUND

Several recent research studies have emphasized resource utilization and power consumption as key factors contributing to extending network lifetime [8-13]. 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 short route. Optimization of routes in the network may significantly increase network lifetime with minimum energy consumption. Genetic Algorithm (GA) optimization was found to be the most promising means of selecting the efficient routes from all those available.

Shanker et al. (2023) explores the benefits of energy consumption against routing efficiency in WSNs through GAs to provide optimal use of resources for enhanced performance of WSNs [7]. Rajkumar et al. (2024) extend this notion by employing evolutionary algorithms to identify both the shortest and most effective routes, directly contributing to enhanced performance within networks and minimized energy wastage [8]. The author discusses secure routing and energy optimization in IoT applications with diverse WSNs, focusing on data integrity and energy efficiency [9]. These studies are rooted in fundamental work on genetic algorithms conducted by Holland (1992), who introduced a powerful approach for solving challenging optimization problems in dynamic environments like WSNs. Additionally, Wang explored a data dissemination protocol based on a genetic algorithm and showed how it can significantly improve the overall performance of the WSNs by choosing the best possible path for sending data [11]. Hence, research and scholarly communities have shown high interest in such energy-efficient routing schemes that might reduce energy loss. Energy-efficient routing strategies are crucial for maximizing operational time in 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 the shortest paths in WSNs. Additionally, in [8-13], the average transmission path for data packets is discussed using a methodology intended to reduce that path. The lifespan of the sensors will largely determine the network's performance, as does the route taken in the data transfer pathways. Consequently, it is important to have optimized routes for data transmission that will use little to no energy, so that the lifespan of the wireless sensor networks is improved.

3. GENETIC ALGORITHM

Genetic Algorithms (GAs) are motivated by biological processes and simulate natural selection (10). They work according to mechanisms of stochastic research and have been used in several studies for probabilistic and optimization problems. According to the literature, GAs are very efficient in pathfinding and determining optimal routes in a relatively short time [2-7].

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 everyone [14-16]. 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 divided 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 [13]:

Initial Population

This is the first step in the GA process where all sensor nodes are generated randomly. Here, all 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.

Fitness Function

It measures the fitness of every individual regarding the 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.

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

Where 〖FF〗_individuals estimates the energy level of each sensor node, comprises the overall population N. The 〖dist〗_i indicates the distance of the node from overall nodes.

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.

Crossover

After the selection process, crossover is called for generating new individuals by combining parent and child individuals. For this study, a 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.

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. 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.

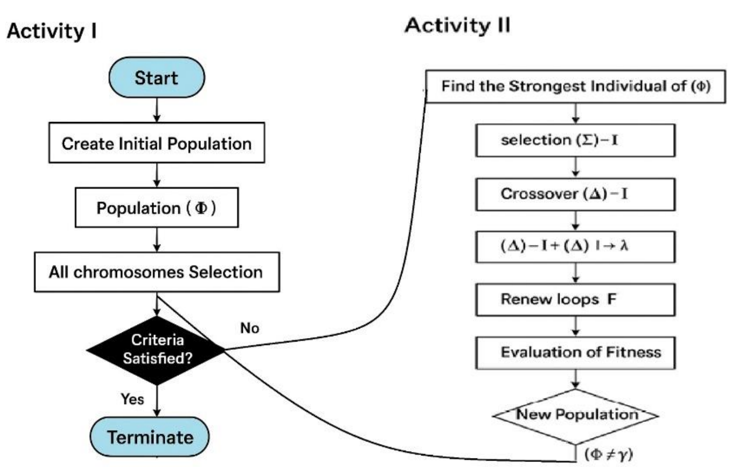

Fig 2: Operator utilization of GA

4. METHODOLOGY AND RESULTS

This research was carried out using MATLAB R2024b environment. The scenario has been set as the deployment of 10, 20, 30 and 40 sensor nodes randomly in a 100×100m^2 area. The GA was executed to determine all possible paths of all sensor nodes towards the base station. As the route determination has been done via GA, all route information is shared with each sensor node enabling any source to transmit the data to the nearest neighbor node.

Table 1: Parameters Setting

WSN area Size	No. of nodes	Energy level	Frequency of trials	Diss: of Energy	$d_i < d_j$	$d_i > d_j$
$100 \times 100\ m^2$	30, 40	0.10 J	4000	55 nJ/bit	10 pJoules/bit/m	0.0015 pJ /bit/m

As the sensor node gathers the data then all neighbor nodes relay the data until the data reaches the base station as shown in Fig. 4. This study is carried out by deploying multiple sinks which share route and location information with each sensor node with the help of GA. The results are compared with the standard TEEN algorithm [14].

Setting the parameters for the simulation

This section shows the basic parameters setting of the proposed study as given in Table 1. Using these parameters, simulation results were compared with the standard TEEN algorithm using 40 sensor nodes. This deployment of such a given number of sensor nodes shows that proposed scheme is beneficial for small-scale and large-scale sensor networks alike. The deployment of 40 sensor nodes is simulated in a 100×100m^2 environment randomly and every sensor node sends the data directly to the nearest sinks as shown in Fig. 3. However, the multiple paths are determined by the GA and the most efficient path is selected among all the possible paths. The nodes are finding the most efficient path towards the sinks from the rest of the available routing paths as illustrated in Fig. 4.

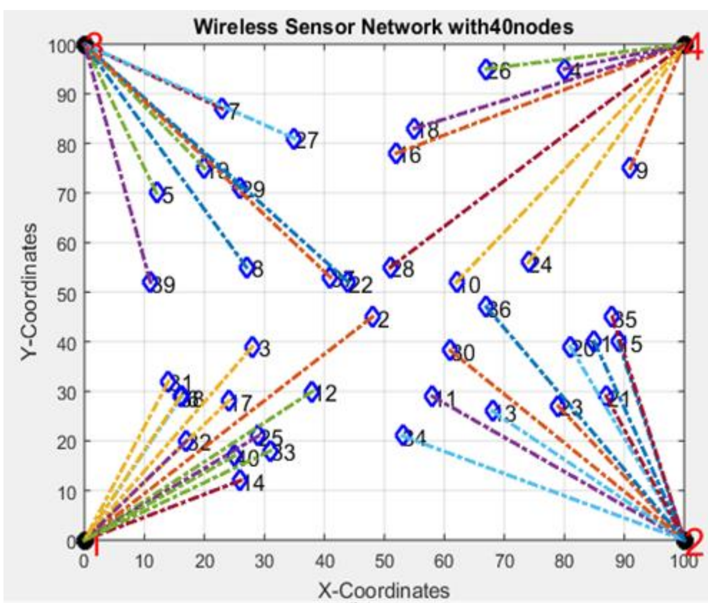

Fig. 3: Routing paths using 40 sensor nodes

The live 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. This scheme provided very compromising results against the TEEN algorithms when compared in terms of active or alive nodes during the operation of the WSNs as depicted in Fig 5.

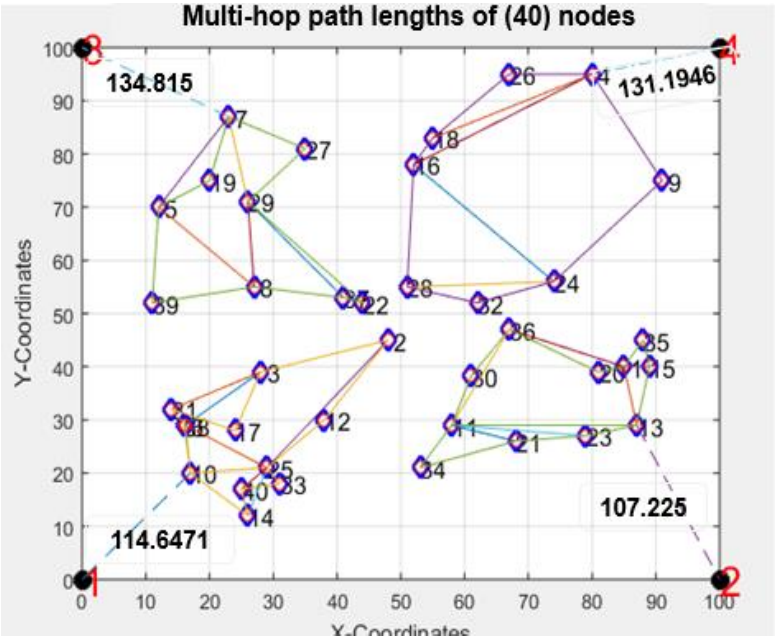

Fig. 4: Multiple optimized paths of 40 sensor nodes

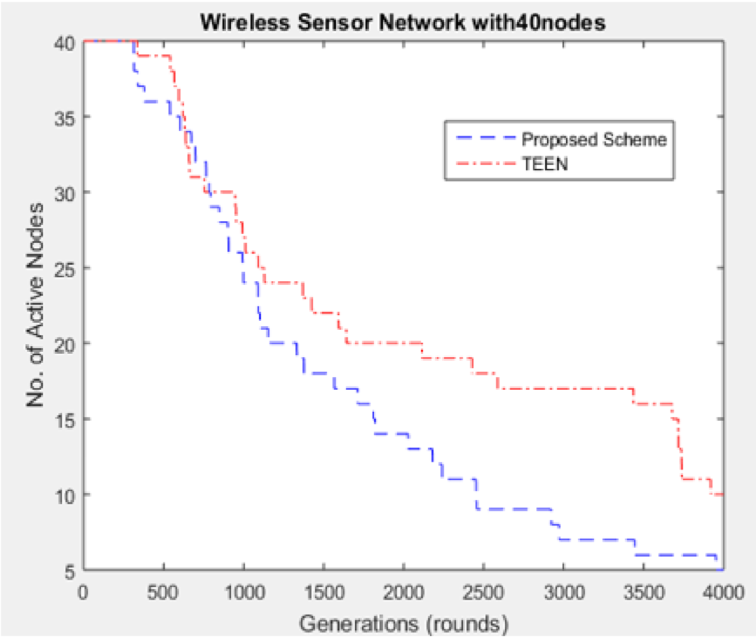

Fig. 5: Number of rounds vs number of active nodes

An efficient path is inevitable to opt for the lifetime maximization of the WSNs and data routing. The energy of the sensor nodes and sink nodes are evaluated and compared with the TEEN algorithm as shown in Fig 6. This indicates the transmission of the packets from the sensor nodes towards the sink's side.

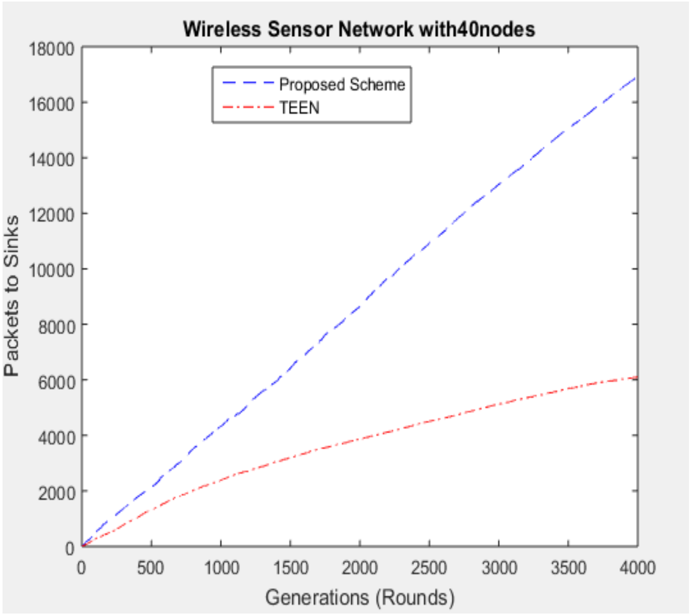

Fig. 6: Packets reception at sinks end vs number of rounds

5. 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 the sensor nodes are deployed in the 100×100m^2 area randomly. Eight (08) sensor nodes positioned randomly and paths among them were determined by the GA. Each node knows the location and distance of the other nodes and data is solely shared with the close by node. In the proposed scheme, the simulation has been performed using variable number of nodes specifically 40 sensor nodes. Initially it was assumed that WSNs with 40 sensor nodes deployed in an ad hoc manner at different positions. The distance of the nodes` has been calculated using the Euclidean distance matrix for the sake of knowing all the possible distances and the minimum one towards the nearest sink.

The simulation results with 40 nodes has been done through the calculation of the direct distance which has been 391.3397 with eleven sensors towards the sink1. The nodes which found the sink2 as the nearest sink are twelve sensors with the distance of 564.6962 meters. Similarly, sink 3 has been found nearest by 9 nodes with the total distance of 458.7276 meters. While, sink4 with the total direct distance of 360.3252 meters is nearest to eight nodes. Therefore, the distance determined by GA through all multiple hops is efficient than the total direct distance towards all sinks. The sink1, sink2, sink3 and sink4 are having the total optimized path from the nodes is 114.1471, 107.225, 134.815 and 131.1946 respectively. By comparing the direct distance with the multiple hops distance determined by GA considerable efficient percentage of reduction in total path has been achieved.

The path efficiency of the sensor nodes towards the sink1 is 29% of the total direct distance which is diminished up to 71% of the path length and gives considerable reduction in both terms path length and energy consumptions well. The sink2 with the optimized paths is 18.9% with the multiple hops and utilizing the GA. GA gives optimum route than the total direct distance, saving 81.1% resulting in paths and energy efficiency both. The sink3 and sink4 with the GA and multiple hops paradigm saves the path length up to 29.3% and 36.4% respectively as indicated in Table 2. This optimization gives the advantage of selecting the best and optimal route towards the nearest sinks. The simulation has been done by comparing the proposed technique with the (14). The results advocate the trivial energy consumption and performance of all nodes as the number of active and dead nodes, which outperforms the standard algorithm (14). Moreover, the packet reception at the sinks side is compromisingly better than the (14).

Table 2: Path efficiency calculation

No. of Nodes	40 Nodes
No. of nearest nodes to Sink 1	11
Direct Distance (meters)	391.3397
Multi-hop distance (meters)	114.1471
Path efficiency %	29%
No. of nearest nodes to Sink 2	12
Direct Distance (meters)	564.6962
Multi-hop distance (meters)	107.225
Path efficiency %	18.9%
No. of nearest nodes to Sink 3	9
Direct Distance (meters)	458.7276
Multi-hop distance (meters)	134.815
Path efficiency %	29.3%
No. of nearest nodes to Sink 4	8
Direct Distance (meters)	360.3252
Multi-hop distance (meters)	131.1946
Path efficiency %	36.4%

6. CONCLUSION

Wireless Sensor Networks (WSNs) are generally susceptible to failures owing to their small-sized batteries, which restrict their operational lifetime. Path optimization in WSNs is vital for proper data transmission. An improved routing scheme for multi-hop in this research aims at improving the network lifetime. A major amount of energy in sensor networks is wasted while collecting and transmitting data, particularly when the path is not optimized. A meta-heuristic genetic algorithm is used to determine the most energy-efficient routes. The genetic algorithm is intended to provide more optimized results, permitting the determination of the best route among all given ones, thus saving energy in wireless sensor networks. Data is forwarded to the sink via intermediate neighbor nodes, which merely forward the information without carrying out any sophisticated calculations or operations. The genetic algorithm assists in identifying the routing information for all the nodes and the sink so that data takes the most optimal path for transmission. This research shows considerable energy waste reduction, reflecting the benefits of the multiple hop scheme over direct communication approaches. As a result, the multiple hop scheme not only conserves energy but also works more effectively, ultimately increasing lifespan of the network. Research outperforms the baseline TEEN algorithm for several rounds of operations, that is, 1500, 200, 2500, 300, and 3500, and goes up to 4000 rounds. A model will be created using a hybrid routing approach for saving node energy and maximizing the lifetime of the network in the future.

Conflict of Interests

No potential conflict of interest is reported for this research.

Data availability statement

The data will be made available upon reasonable request.

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