Vol. 7, No. 1 | January – June 2024

Energy Efficient Strategy for Wireless Sensor Networks Lifetime Endurance using Genetic Algorithm

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Abstract: Wireless sensor networks have remained a hot field of research for the last three decades. WSNs comprise small-sized sensors having small batteries, so energy depletion is a major problem, resulting trivial lifetime of the WSNs. This study proposes an optimized routing scheme for multiple hops Wireless Sensor Networks to enhance the lifetime of the network. Since the wireless sensor networks work as application-centric having the capabilities of data gathering and transmission to the base station. Therefore, a significant amount of sensor networks` energy is spent during such operation of data collection and transmission if the route is not optimized. So, a meta-heuristic genetic algorithm plays a vital role in finding the optimized route. We will modify the genetic algorithm 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 neighbour 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. Thus, this study proved a considerably saved extra waste of energy.

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

I. Introduction

The technological advancement in micro-electro-mechanical systems (MEMS) resulted in small-sized, power-constrained, cheap motes or sensors. The sensors have the capability to sense or collect the information from the surroundings and partially process it and then transmit it towards the base station of admin through a radio link or a wireless connection for further operations on the data as shown in Fig 1. The sensors can operate in any environment for tracking and monitoring [1], [2]. A number significant of sensors deployed in an area working together wirelessly constitute a Wireless Sensor Network (WSN) [3]. Therefore, the sensors depend on their small-scaled battery life which gets depleted quickly during computational processes [4-6]. It is crucial to enhance the WSN's lifetime so that the network can perform for a longer amount of time for the desired outcomes of monitoring and tracking purposes.

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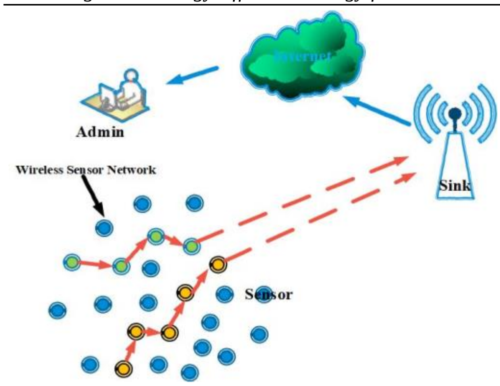


Fig. 1. Wireless Sensor Networks Multiple hops routing

One of the main reasons for the fast battery depletion is the non-determination of the routing path. To mitigate this issue, we use the genetic algorithm for routing path determination to transmit the data through multiple hops. In the multiple hops scheme, the source node will collect the information and it will it relay towards the nearest sensor node then the receiver sensor nodes will further relay the information until the information reaches the base station's end [7]. Therefore, an efficient routing scheme will give a solution to the problem of extra energy consumption.

In this way, this research provides a novel approach by suggesting genetic algorithm-based path determination and optimization for reliable communication and minimum energy dissipation. The obtained results are compared with the standard algorithm to validate the suitable applicability of our proposed scheme.

This research paper is broken into 5 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 and discussions and the conclusive remarks are provided in section 5.

2. Literature Review

Recently, several research scholars have carried out work focusing on the minimum utilization of resources and least power consumption, leading to the maximization of the network life span [10-13]. Also, different algorithms have been proposed for optimization and network lifetime enhancement. Mostly, the energy of the sensor is wasted if it transmits the data towards the long route rather than the nearer / short route. The route optimization techniques will increase the lifetime of the network and they can be relied upon for the minimum consumption of the energy. The optimization using GA is a promising scheme for selecting the most optimal among all the possible paths.

Therefore, routing schemes with energy efficiency have been gaining much attraction from research scientists and scholars on account of minimum energy waste. A summarized study on the various data routing techniques with energy-efficient utilization is provided in [14, 15]. The energy-efficient routing scheme is equally important for the wireless sensors and wireless sensor networks in order to operate maximum amount of time. A study in [16] sketches a data-centric routing scheme for the existing WSNs routing protocols. Notwithstanding, the evolutionary and heuristic algorithms are fruitful to utilize for finding an efficient path in WSNs. Similarly, an approach for reducing the average path in order to transmit data packets is proposed by [17-19].

The network depends upon the lifetime of the sensors and the path for the data transmission. It is essential to have an optimized route for data transmission so that minimum energy can be used, thus, it will increase the lifetime of the WSNs.

3. Genetic Algorithm

Genetic Algorithms (GAs) are inspired by the biological sciences and they mimic the natural selection process. The GA works on the mechanisms of stochastic search. Various studies have used Gas for probabilistic and optimization problems. Some research studies have shown that the GA has performed considerably well with the problems of path findings and optimal routes in a quick manner.

Usually, the GA works using its operators namely selection, crossover, mutation and fitness function. The GA initiate its operation by considering all individuals as a population. The GA will store the information on the energy level of each individual. Based on the acquired information, higher-level individuals will be selected further for the crossover process. After the crossover operator, the mutation operator invokes for the further process and we have set the probability at 0.7 as shown in Fig 2 and Fig 3. After all criteria are satisfied and then the route is determined which defines the optimal routes for data transmission. Then, the sensor node will route the data using the best optimal path towards the nearest neighbour node. We have divided The operation of GA is into two phases. Phase 1 starts with the initialization of the population and the determination of the fitness level of each individual. If the fitness level is satisfied then the individual does not go for the further process. If the criteria are not satisfied, then the selected individuals go for the tournament selection, crossover and mutation process. For this research, the GA uses the following operators:

a) Intitial population

This is the first and foremost step in the GA process, all sensor nodes or individuals say N are produced randomly. This evolutionary generation of individuals initiates with 0. These individuals are also called chromosomes or alleles in the population. With this initialization, the communication radius or threshold starts.

b) Fitness Function

The fitness function is applied to each individual to dig out energy levels. This energy level evaluation helps to find the individuals who can increase the WSNs lifetime. Therefore, the energy level of each individual is crucial for the network's lifetime. The fit individual is selected after applying certain evaluation criteria namely elitism.

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

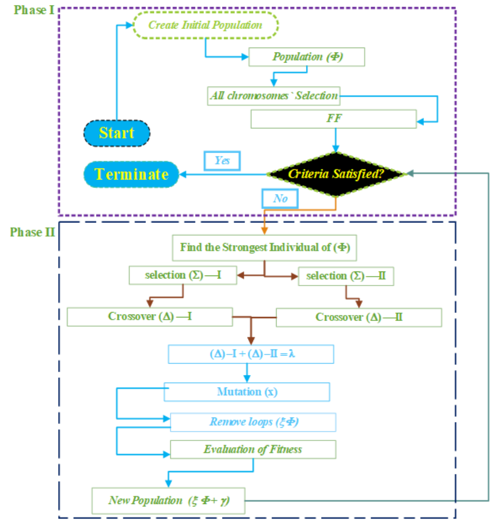
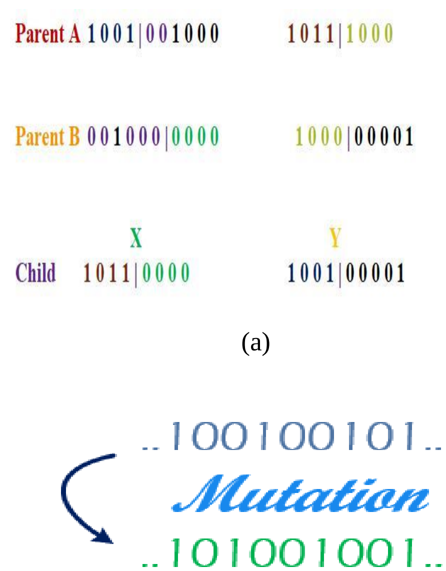


Fig. 2. Operator utilization of GA



(b)

Fig. 3. (a) Crossover Operator, (b)The Mutation Operator

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.

c) Selection

After evaluating the fitness level of each individual, the selecting operator is invoked to obtain the best of the best and fit individual. This operator uses the tournament selection, in which the mating pool of the individuals with the threshold level of fitness value is maintained. The strong and fit individuals are, then, selected for further operations namely crossover as shown in Fig.2.

d) Crossover

After the selection operator, the crossover operator is invoked to produce the new individuals by selecting parent and child individuals as shown in Fig 3(a). For this research study, we have utilized a two-point crossover by selecting each individual from the population as a parent to produce a child. This child individual is copied from the first individual to the second individual as depicted in Fig. 3(b).

e) Mutation

After the crossover operation, we invoke the mutation operator. This further refined the result of the individuals by making exact copies of the sensor nodes. We have set the mutation probability at 0.9 for better evaluation and robust results. Then, the loops are removed and the resulting solution is combined with the previous fit individuals. By doing this, we do not want to lose the fit individuals thus the result is much better.

4. Performance and Simulation

We have carried out this research by using MATLAB R2023b environment. The scenario has been set as the deployment of 8 and 10 sensor nodes randomly in a $100 \times 100m^2$ area. Then we run the GA 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 will be shared with each sensor node so that any source can transmit the data to the nearest neighbour node.

TABLE I. Parameters Setting

WSN Size	**Number of Nodes**	**Assigned Energy**	**Rounds**	**Diss: of Energy**	$\boldsymbol{d_i < d_j}$	$\boldsymbol{d_i > d_j}$
$100 \times 100\ m^2$	8, 10	0.8 J	4000	50 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 the route and location information with each sensor node with the help of GA. The results are compared with the standard TEEN algorithm [8].

a) 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, we have compared our simulation results with the standard TEEN algorithm using 8, and 10 sensor nodes [8]. This deployment of such a given number of sensor nodes shows that our proposed scheme is beneficial for small-scale and large-scale sensor networks alike. The routing paths using 8 sensor nodes deployed randomly in a $100 \times 100m^2$ environment. These sensor nodes are assumed to send the data to the closest sink nodes as shown in Fig 4. Therefore, the paths are determined by the GA and the most efficient path is selected among all the possible paths. This not only saves energy but also reduces the transmission cost of the data.

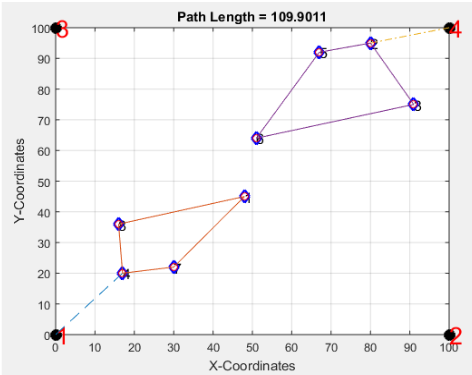


Fig. 4. Routing paths using 8 sensor nodes

The results of the proposed scheme are compared with the standard TEEN algorithm. Additionally, the results advocate considerable efficient path utilization which results in saving the energy of the WSNs as shown in Fig 5.

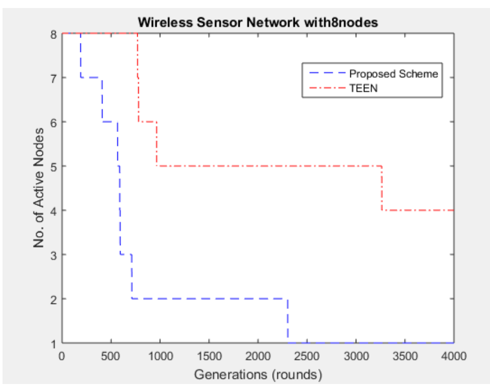


Fig. 5. Number of rounds vs number of active nodes

In Fig. 6, the data packets are sent to the closest sinks using 4K rounds. Where the proposed scheme leaves behind the TEEN algorithm. The maximum number of data packets is reached at the sink end in a given amount of rounds for both the TEEN algorithm and our proposed scheme.

Another, deployment of 10 sensor nodes is simulated in a $100 \times 100m^2$ environment randomly as shown in Fig. 7. The 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. 7.

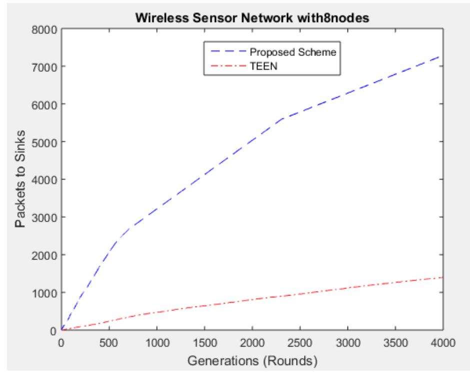


Fig. 6. Packets reception at sinks end vs number of rounds

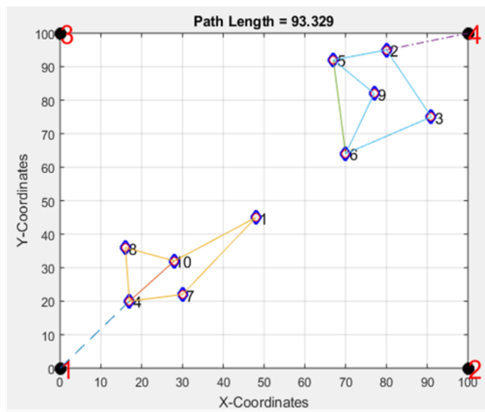


Fig. 7. Routing paths using 10 sensor nodes

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. Our scheme gives 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 8.

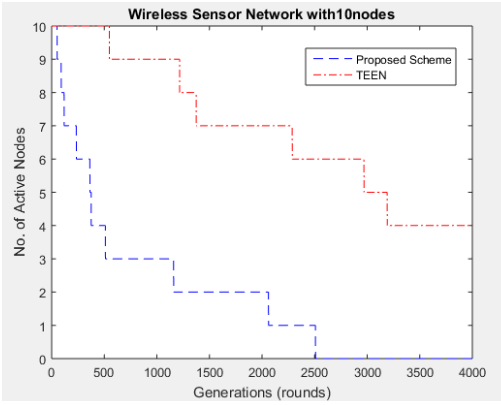


Fig. 8. Number of rounds vs number of active nodes

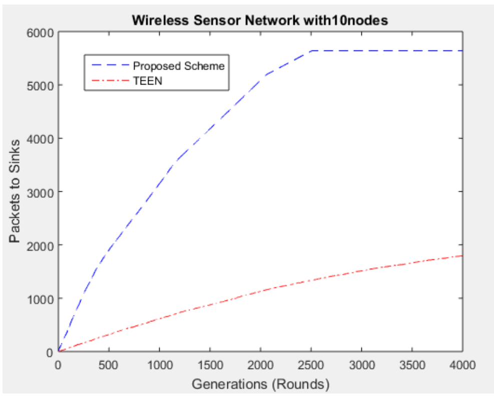


Fig. 9. Packets reception at sinks end vs number of rounds

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 9. This indicates the transmission of the packets from the sensor nodes towards the sink's side.

5. Result 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 $100 \times 100m^2$ area randomly. We set 8 sensor nodes randomly and determined paths among them by the GA. Each node knows the location and distance of the other nodes and only the data is shared with the closest node.

First, we assumed a WSNs with 8 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. As shown in Fig: 4. Where sensor nodes 3, 2, 5, and 6 can transmit the data to the Sink4. Other nodes 1, 4, 7, and 8 can send the data towards the Sink1. When each node routes the data, the energy consumption may be higher due to direct distance. However, we calculated and evaluated the distance with the help of a Genetic Algorithm (GA) through the multiple-hops communication scheme. The multiple hop scheme using 10 sensor nodes is shown in Fig: 7, the sensor nodes 2, 3, 5, 9, and 6 are transmitting the data towards the Sink4, where the data is routed to the nearest relay nodes. The total distance towards the Sink1 in which the efficient 44.9% than the direct distance. Whereas, the total distance of the nodes toward sink4 is 93.329 meters which is an efficient path for routing the data.

6. Conclusion

In this study, an optimized and energy-efficient strategy is proposed for the network lifetime maximization. We have simulated an environment with a different number of sensor nodes along with multiple sinks using the MATLAB platform. Each sensor node is responsible for the data transmission towards its nearest node. However, all routes are determined by a genetic algorithm. Therefore, the GA`s main operators are modified for better evaluation of the energy level of the individuals and path efficiency. The results are further compared with the standard TEEN algorithm. Our study outperforms the standard TEEN algorithm using the different number of rounds of operation namely 1500, 200, 2500, 300, 3500, up to 4000 rounds. In future, we will model an environment with a hybrid routing method to save the energy of nodes and network lifetime longevity.

CONFLICT OF INTERESTS

No potential conflict of interest is reported for this research.

ACKNOWLEDGEMENT

We would like to thank the University of Sindh, Jamshoro.

DATA AVAILABILITY STATEMENT

The data will be made available upon reasonable request.

FUNDING

No funding is received.

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