An Enhanced Genetic Algorithm (EGA)-based Multi-Hop Path for Energy Efficient in Wireless Sensor Network (WSN)

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***Abstract*—Wireless Sensor Networks (WSNs) encounter a number of issues in terms of performance. In WSN, the majority of the energy is utilized to transfer data from sensor nodes to a central station or hub (BS). There have therefore been many different types of routing protocols devised to help with the distribution of data in WSNs. Large-scale networks have been designed with minimal power consumption and multipurpose processing due to recent improvements in wireless communication and networking technology. For the time being, sensor energy remains a restricted resource for constructing routing protocols between sensor nodes and the base station, despite advances in energy collection technologies. For wireless sensor networks with far-flung cluster heads and base stations, direct transmission is a critical component since it impacts the network's efficiency in terms of power consumption and lifespan. A new approach for identifying an effective multi-hop routing between a source (CH) and a destination (BS) is investigated in this study in order to decrease power consumption and hence increase the life of a network (OMPFM). The suggested technique utilizes a genetic algorithm and a novel fitness metric to discover the best route. For selecting CHs and enhancing the speed and quality of created chromosomes, they suggest two pre-processes, which they call CH-selection and Chromosome Quality Improvement (CHI). The proposed method is evaluated and compared to others of its kind using MATLAB simulator. It has been found that using the proposed method outperforms other methods such as LEACH, GCA, EAERP, GAECH, and HiTSeC in terms of the first node die metric by 35%, 34%, 26%, 19% and 50%, respectively. It also outperforms other methods by 100% in terms of the last node die metric.**

Keywords—Cluster head; energy efficient; multi-hop path; enhanced genetic algorithm; wireless sensor network (WSN)

I. Introduction

The development of micro electromechanical system technology has made compact, low-cost nodes practical in networks. The nodes are responsible for sensing, processing, and communicating wirelessly. A lot of the nodes in wireless sensor networks (WSNs) run on batteries and are connected to a base station (BS). It acts as a middleman between the end user and the other nodes[1] like figure1 represents the WSN's basic architecture. In any of the supervised areas, WSNs ensure continuous monitoring (CM) or engage in event detection. WSNs need non-rechargeable batteries to power the sensor nodes, therefore modelling an energy-efficient routing algorithm is required. We need an energy-efficient routing strategy in places where battery recharging and replacement aren't an option. Energy is a big worry and as a result, there are several heuristics, however they all take longer to come into play. When it comes to WSN energy efficiency, clustering stands out as a viable option[2].

This probability-based clustering produces CHs, which can only communicate with other nodes in their immediate vicinity. So, multichip (MH) routing helps the network to route traffic beyond the communication range, which is limited by the energy factor. Multichip routing as an alternative, delay is reduced while energy consumption is increased, therefore the routing is more efficient. As a result, the researchers are working to create a better routing protocol that uses less energy[3]. MH transmission and direct transmission are the two most common conventional routing options (DT). Nodes in DT connect with the BS directly, but intermediate nodes in MH communicate with each other via subdivided communication distances, resulting in little energy and delay. Short-hop and long-hop routing are terms used to describe MH transmissions based on the number of hops. There are flat and hierarchical algorithm routing protocols in the literature that work to reduce the energy used by sensor nodes. This can be explained by comparing flat and hierarchical routing: in flat routing the communication takes place between nodes within the same communication range, while in hierarchical routing the communication takes place between a node and its nearest clustering hierarchy. Although hierarchical routing conserves energy, it places a heavy burden on the cluster's central hubs. To communicate outside of the regular radio range, all sensor nodes clamp themselves to a CH. This has an impact on QoS and performance[4],[33].

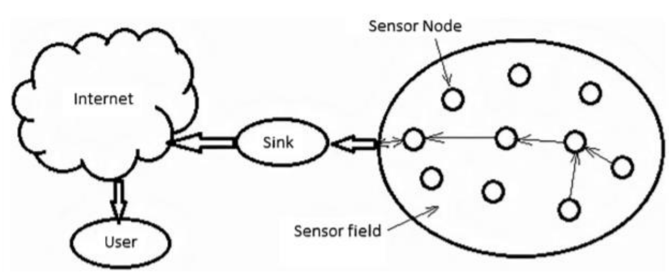

Fig. 1. The WSN's Basic Architecture.

A WSN is a network of micro-sensor-equipped nodes with a large number of spatially scattered communication infrastructures. These tiny sensors collect and interpret data from a specified area by sensing it and working together. A central station receives the data, which is subsequently processed. The relevance of WSNs in IoT-based goods and services is rising, but they have been around for a long. Things like health care, environmental monitoring, and smart cities will all need them in the future, due to the Internet of Things. [2, 3,5] It's easy to see that sensor networks have several orders of magnitude more nodes than ad hoc networks. Despite their extensive dispersion, sensor nodes have limited computing, memory, and power capabilities. The development of energy-efficient routing algorithms is a major problem in WSNs. It's impossible to delete or change sensor nodes after they've been set up in the network. Nodes' power usage and management have a strong impact on network performance. As the most energy-efficient systems in WSNs in recent years, hierarchical routing protocols have been frequently used [6]. Cluster heads operate as a go-between for the member nodes and the base station itself rather than having individual base stations for each member node [7]. Among the cluster's nodes, the CH utilises the least amount of network resources overall when gathering data, aggregating it, and transmitting it to the (BS).

It is the first hierarchically built protocol to use clustering for information routing (LEACH) [8]. When data are transported straight from the CHs to the BS, it is known as a single-hop routing protocol (SHR). It does, however, have significant drawbacks. In the first place, CHs positioned far from the BS lose more energy than those located nearby. As a result, populations in the furthest reaches of the galaxy are at greater risk of dying young. Large-scale networks can't employ LEACH's direct transmission method since it disrupts the distribution's load balancing and reduces the network's overall operating lifespan. It also depends on the relevance of the detected information at each point in time how often data is transferred between nodes. Due to the difference in activity, more active nodes die sooner than less active ones, causing an energy imbalance in the network[9].

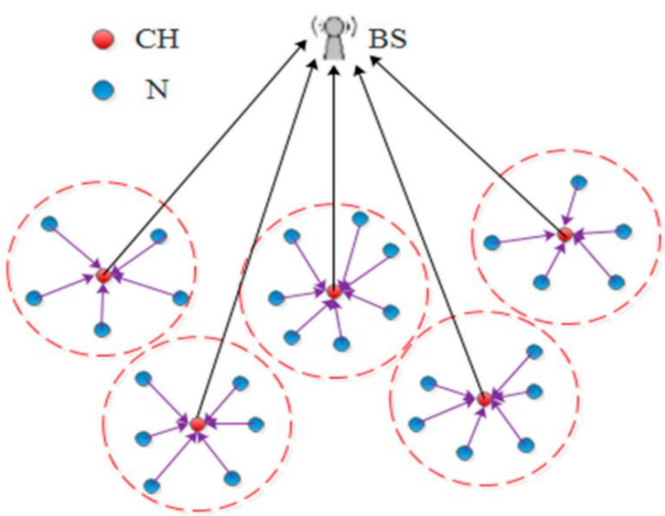

Fig. 2. The Wireless Sensor Network Architecture uses the Low Energy Adaptive Clustering Hierarchy (LEACH) Protocol.

Transmitting sensing data to the BS for analysis is critical in WSNs since this data helps the network meet its objectives. Making judgments that are in keeping with the network's aims is made easier with this strategy. With direct transmission, the LEACH protocol drains CHs quickly, especially if the distance between two CHs delivering data to BS is large. The additional energy used to transport data in a CH will have a negative influence on the network's overall lifetime factor performance. By determining the optimum route from a root CH to the BS, this research presents an improved way for increasing network lifetimes while using less power than the direct transmission process. The best transmission path is found using a genetic algorithm (GA). The proposed approach maximises the network's stability period during which all nodes are still operational. It also extends the network's lifespan in the event that all nodes fail. Maximizing the fitness function and improving the selection of cluster heads are two ways to accomplish this. The following is the paper's structure: It begins with a brief history of GA, followed by a discussion of similar works in Section 2, a detailed presentation of the proposed approach in Section 3, a quantitative assessment of the proposed method in addition to previous protocols in section 4, and a conclusion in Section 5.

II. Related Work

This section describes the LEACH and GA methods. Before discussing into GA optimization, let's take a look at the LEACH approach.

Wireless sensor networks have lately seen a slew of hierarchical routing methods [8,10,11–19]. To make the network last longer, several of them used multi-hop inter-cluster connection. WSN protocol LEACH [8,11] includes two phases: configuration and steady state operation. As a node is being set up, the distributed process employs a probabilistic method to assess whether or not it should be designated as a CH. Non-CH node will join the cluster based on the strength of the CH signal. The CH delivers the TDMA schedule to all cluster nodes at once to guarantee that it is received by all of them. Continuously sending one hop of data to the BS during the steady state phase is required. LEACH uses a CDMA coding to minimise inter-cluster interference. To maintain a fair distribution of burdens, the round concludes with a random rotation of CH. However, there are a number of disadvantages to using LEACH. During the CH election process, residual authority or position is not taken into consideration. Due to greater energy consumption and the death of remote CHs induced by direct data transfer from the sink node to the CH, this single-hop routing approach is unsuitable for large networks. With multi-hop communication between CHs and the BS, energy conservation and scaling were demonstrated to be higher [12, 20]. So, Zhang et al. [13] created the LEACH-WM WSN protocol, an intra-cluster multiple hop routing mechanism. In addition to the setup phase, LEACH contains an optimization phase. The BS receives data from the CH through a weight relay node during the final stage (WR). Because of its remaining energy and proximity to the backend server, this relay node is selected as a cluster member. Clusters located far away from the BS use their energy more quickly than clusters near to it, resulting in an uneven distribution of energy across the network.

Alnawaf et al. [14] employed a multi-hop approach to improve LEACH (MHT). CHs may be divided into two categories according on how far apart they are: internal and exterior. The CHs in the first group send data straight to the BS, whereas the CHs in the second group create a custom routing table to control data flow. CHs were distributed over two tiers while utilising the Improved MHT-LEACH protocol (IMHT). You can tell if you look at the distance between one CH level and the next by looking at how far one CH level is from BS. Despite the fact that these methods were developed to be as energy-efficient as possible, the majority of them solely consider the distance element when determining routes. Because data is always routed through the nodes nearest to the BS, those nodes use up their energy faster than the others. Defended routes cannot be changed for the network's whole operational life, affecting the network's ability to maintain a balanced load. Routing methods for WSNs will enhance load balancing by taking energy and distance into account when selecting the next hop. One way to increase the network's lifespan is to provide efficient data to the base station, as described by Biradar[15] et al. Each cluster has two means to connect with the others on the network, split into several clusters. Instead of using a backend server (BS), you may use a central hub (CH) to collect data from all cluster nodes and deliver it directly to the backend server instead (CHs). Second, the CH must use an inter-cluster channel to interact with both the BS and the CS, because it is located[16,17] in a remote location. When this occurs, it uses other CHs with a low hop count to deliver data to the BS. The optimal paths to the BS may be found using a multi-hop LEACH (MH-LEACH) protocol, according to Neto et al. [17]. Depending on the intensity of the received signal, each CH begins by sending an advertising message to create its routing table. However, the CH inspects the routes beforehand to make sure they won't cause a loop or send the incorrect way for individuals to go.

Wireless Sensor Networks (WSNs) may make use of EAACA, an ant colony algorithm that is energy-conscious and utilises the ACO to determine the most efficient route to the storage system's back end (sink node). When deciding on the next node, three factors are taken into account: the distance to BS, the remaining energy of the previous node, and the path's average power. Backward ants are used in the method to produce response packets in response to the legal routes built by forward ants. Using a lifespan aware routing method for wireless sensor networks, Mohajerani et al. developed a network topology where energy dissipation is uniformly spread among nodes (LTAWSN). When installing an energy-saving pheromone operator, it makes use of a phoney ant colony. When calculating the next step in the journey, a location function takes the distance to the destination into account, as well as nodes that are closer to the goal. Because they consume all of the network's energy, ACO's fat routing protocols require more energy than previous ACO versions and can quickly deplete the network's energy supply. In addition, they use two-step transmission systems, moving forward to investigate the route and returning to leave pheromones behind. As a result of increased transmission costs, nodes consume more energy.

Using the LEACH-C (LEACH-C) methodology was suggested in [14,20]. Centralized protocols have all choices made by a single node and then relayed to all sensor nodes. Some of their duties include electing the network's chief executives (CH) and supervising clusters. A well-balanced distribution of nodes inside clusters is one of the goals of the LEACH-C protocol. Lifespan is the goal of the LEACH-Deterministic Cluster Head Selection (LEACH-DCHS) technique [15,34]. As a result, two changes have been recommended. To begin, the threshold equation must be adjusted to account for the residual energy in the sensor nodes when selecting the network's CHs. As part of the second update, new network lifetime standards will be established. To better understand the Threshold-LEACH (T-LEACH) approach, [16,21] provided an overview of the basic theory. According to this protocol, the network's CHs are selected based on their energy thresholds. The CHs can only be utilised in a certain number of rounds at a time. As long as the CH's residual energy is less than the threshold energy, this situation will persist. That would necessitate the appointment of a new House Speaker. For a one-hop connection, a technique known as Unequal Clustering LEACH has been suggested by [17,22]. (U-LEACH). One hop delivers all of the CH's data directly to the BS. The old method utilises more energy in CHs placed distant from the BS because of their location. As we travel away from the BS, the U-LEACH predicts that cluster sizes will become more unequal and then drop. There were imbalanced clusters in the original LEACH protocol, thus the LEACH-B protocol was developed to address that issue. For the purpose of choosing CHs and creating balanced clusters, this protocol takes into account not just a desired percentage of cluster members, but also the residual energy those members have left over once the election process is complete. The MHT-LEACH protocol was proposed in [11, 23] as a way of reducing network transmission distances. It divides all of the CHs into two groups of equal size. For starters, there's the internal level, which includes all the CHs that aren't too far from the BS. Also included in this level are any CHs that are located outside of a certain threshold distance from the base station (BS). A suitable CH from the internal level receives data from any external CH and routes it to the BS[24,35].

A. The Leach Protocol

The LEACH protocol's goal is to reduce the amount of power used by WSNs while increasing their efficiency [14,21,25,26]. To that end, a random factor has been used in a rotation strategy for CH selection. Each round of the LEACH procedure [14,20,27] has two stages, the first of which is the steady-state set-up. Along with the CHs selection, clusters are also established in the first stage. Random numbers between 0 and 1 are generated by nodes in each cluster to choose a CH [14,28]. In order to compare the generated numbers to, we use T(n). As soon as the reference number is greater than the randomly generated number, the CH node becomes the active node for further calculations. Using Eq. (1), we can determine the value of the constant T(n).

$$\mathrm{T(n)} = \begin{cases} \frac{P}{1-P*(r mod \frac{1}{p})} & : if n \in G \\ 0: if n \in G \end{cases} \quad (1)$$

To illustrate, consider the graph below, where G represents a group of nodes that have not yet become CHs in the preceding 1/P rounds, and P represents the proportion of those nodes that have become CHs. All nodes in the cluster receive equal amounts of energy because of this. LEACH's power consumption is balanced across all nodes because the CH role is rotated, yet the protocol has significant drawbacks regardless of this benefit. The residual energy of a node, for example, is not taken into account by LEACH when choosing a CH. Equation (1) says that a node can become a CH at any time. All nodes have the same chance of becoming CHs after a certain number of rounds. Consequently, both high- and low-energy nodes are equally likely to become the CH. Another issue is the use of single-hop communications to transmit directly from a CH to a BS. This causes energy holes to form between CH and BS, making it impossible for isolated nodes to exchange data. When this is the case, network performance suffers as a result. As a result, an improvement to LEACH is proposed in this study to improve efficiency in the CH selection process and data transmission, as provided in the proposed mechanism, to address the issues raised above.

B. Genetic Algorithm Optimization Technique

GA is a solution-finding algorithm that mimics natural evolution by employing the same mechanisms as natural selection. GA is used to identify the best global solution to optimization and search problems. In GA, the most crucial techniques are selection [17,30], crossover and mutation. Starting with an initial sample of individuals, a random population is produced and each of those individuals is assessed according to their fitness level. Individuals with the best fitness values will be chosen from the initial population, and they will take part in the following generation [29,31]. An important part of GA is the objective function (fitness), which is used to assess the quality of individuals and pick the best contributors for future generations. By mixing the children of the parents, the crossover operator creates new ones, and these new ones will have a mix of qualities from both parents [18]. The new children are subjected to random swaps in the mutation operator, resulting in new solutions. When a certain condition is met, the algorithm comes to an end [8,19,25,26].

The crossover operation is demonstrated in Table 1. Pre-crossover chromosome presentation, followed by post-crossover chromosome presentation: that's how it works. The third position is designated as the crossing point. After that, a mutation operation depending on the mutation rate will be performed on one of the children, as detailed in the next section.

Given Table 2, when the mutation occurs at position 6, gene F in first part of table is not included in the old path (A D E F) and the new path is shown in the second part. The second offspring will be subjected to the same technique, and the fitness of the two new chromosomes will be determined. When the new offspring and their parents are compared to each other, a greedy selection is carried out to determine which has the highest fitness value. Chromosome fitness values are used in the selection process for future generations. Some are chosen for future generations based on the outcomes. In order to maintain a steady population size, chromosomes with lower fitness values will be picked for future generations rather than those with higher values. When the number of generations reaches a certain value, the process comes to a conclusion. Using a suggested OMPFM, crossover and mutation algorithms have been tweaked to prevent the formation of erroneous routes by efficiently choosing the CHs that are participating in the GA while also ensuring that they are easily available in the network. By adopting binary representation to address the OMPFM's multi-hop route problem, the CH will never be duplicated along the way. Using GA and other evolutionary algorithms to maximise network longevity, we'll look at routing protocols that have been utilised to improve the LEACH protocol going forward.

TABLE I. CROSSOVER OPERATION

Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Chr1	1	1	0	0	1	0	1
Chr2	1	0	0	1	0	1	1
Crossover Point↑							
Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Offs1	1	0	0	0	1	1	0
Offs2	1	0	0	1	1	0	1

TABLE II. MUTATION OPERATION

Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Offs2	1	1	0	0	1	0	1
Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Offs1	1	0	0	0	1	1	0

III. PROPOSED METHODOLOGY

The GA technique is used by OMPFM (optimal multi-hop path finding methodology) to discover the shortest path between two network nodes: the source CH and the BS. Because of its simplicity, the GA is utilized in this study as an optimization strategy to find the optimal solution. The sections that follow include a lot more details on this technique. With the new approach, each chromosome identifies which CH source gave rise to BS. Chromosomes can vary in length depending on how many CHs are involved, but no more than 100 CHs should be used in a single cycle. The newly suggested approach uses binary representation to represent each gene on a chromosome as a CH in the route. Routing pathways include CHs with gene values of 1 by default. Otherwise, their gene expression levels are zero, as seen in the table below. The source CH is the CH with ID 1, and there are seven CHs in total, each with an ID from 1 to 7. As shown in Table 3, there is a direct link between the chromosomal in issue and the BS. Table 3 shows the IDs of the CHs in the first row, and the path's CHs are listed in the second row. To illustrate, let's get from CH1 to the BS via the following path.

TABLE III. THE SELECTED PATH

CH1	CH2	CH3	CH4	CH5	CH6	CH7
1	1	0	0	1	0	0

CH1 → CH2 → CH5 → BS

The proposed technique reduces energy consumption while increasing network lifespan by sending data from a source CH to a destination BS. A fitness function determines the optimum course of action. With the OMPFM protocol, you may send only the data you want from one CH to another. For example, it may identify which CHs have the most energy to follow a particular path and then utilize important attributes to narrow the pool of choices. It was shown that using two pre-processing techniques, the GA optimization strategy performed better than the fitness function's proposed parameters for determining the optimum direct path from a source CH to BS. Both examine the GA's chromosomal quality and the suggested fitness function, as stated in the next subsections.

A. Filter Pre-processing

In the GA's first generation, the quality of the chromosomes used will be taken into consideration in the second revision of the formula. Before GA operations begin, the best CHs will be picked based on their energy levels via a filtering pre-process. We'll start by calculating the global average CH energy. CHs with higher energy levels will be needed to help create the second generation when the first is finished. By starting with the best chromosomes, the GA will be more efficient since it will have better chromosomes to work with. Additionally, by reducing the chromosomal length, this change enhances the GA's speed. When four CHs have more energy than normal, they will take part in the GA, and the chromosome will only be three instead of six in length (save for the source CH). The following paragraphs go into detail on how energy affects chromosomal quality. Due to optimal route discovery being an important component, it is necessary in the proposed transmission technique to take into account how many CHs there are in transmission path. There will be less average energy spent to transport data from one CH to another as the number of CHs in the transmission channel increases Eq. (2) gives the average amount of transmission-related CHs energy utilized.

$$\mathrm{Avg_{CET}} = (\textstyle\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{E_{Tx}(i)})/(\mathrm{N}) \tag{2}$$

To convey data from one CH to another through the transmission channel, you need a certain amount of energy called $\mathrm{E_{Tx}}$, whereas $\mathrm{Avg_{CET}}$ measures the average amount and N stands for the number CH involved. $\mathrm{E_{Tx}}$ can be calculated using the following formula [26].

$$E_{Tx} = E_{elec} * k + E_{amp} * k * d^m \tag{3}$$

Were n having a value of 2 in open space and a value of 4 in enclosed places where E_{elec} is the electronic energy and E_{amp} is the amplifier energy.

The same approach is used to determine the average amount of CHs consumed during the receiving process, which may be summarised as follows:

$$Avg_{CER} = (\textstyle\sum_{i=1}^{N} E_{Rx}(i))/(N) \tag{4}$$

Avg_{CER} is equal to the average energy necessary to receive data when N CHs are present in the transmission channel, where E_{Rx} is the average energy required to receive data from each CH. The energy model is used to determine E_{Rx} [26]:

$$E_{Rx} = E_{elec} * k \tag{5}$$

As a result of the calculations, the average CHs energy is as follows:

$$Avg_{RE} = (\textstyle\sum_{i=1}^{N} E_r(i))/(N) \tag{6}$$

Avg_{RE} is the average amount of remaining energy after all CHs have been spent in the current round? At the moment, the CH has an energy level of Er. The effects of energy on data transmission to the BS are shown in Equations (2), (4), and (6), which are all found in the source code. This means that reducing participation in the GA by CHs will make the transmission process more efficient. The following section delves deeper into the fitness function that has been proposed.

With the suggested method, the major objective is to reduce the amount of energy used in the data transfer procedure from a CH to BS. Several fitness function factors are taken into consideration in order to reach this objective. One of the parameters of the fitness function is the distance from the BS to each participant CH. As the number of CHs increases, so does the fitness function. As a result, another fitness function parameter is the ratio of proposed CHs to total CHs on the path. Number of members in a cluster is a critical fitness function parameter since it impacts how much energy cluster members consume. The number of participants in each suggested CH is the final fitness function parameter. It's true that the efficiency of transmission is maximised when the distance between the source and destination is as short as possible, but this comes at the cost of increased energy consumption.

Using the fitness function below, we can minimise the fitness function's values to discover the best route:

$$F(i) = D(CH_s, BS) + \left(\frac{N_{par}}{N}\right) + NO_{ofpart} + members \tag{7}$$

With respect to which, F(i) signifies the number of homologous regions on the i^{th}, average distance between the origin CH and the BS is represented by chromosomal D (CHs, BS)., as indicated in Chromosome homologs are represented by the letters N, P, and O, and the number of parts they play in the transmission process is represented by the letters No, P, and O, as described in the section on how they participate in the process [24,32].

In the first phase of the fitness function, the energy consumption is distributed across all CHs based on the distance between the source CH and the BS. It's important to note that this second section shows what percentage (really) of participants' CHs are actually employed in the transmission process. Because the suggested fitness function is a minimization function, when the percentage is low, the path's optimality improves. The optimality diminishes in direct proportion to the value. A CH that has engaged in the transmission process more than once would soon lose its energy, thus the third section shows the total number of CHs that have taken part in the transmission process along the way. In other words, when its value increases, the fitness function will become more valuable, and an inefficient path will result. The number of nodes in each clusteris the final consideration.

This is especially crucial because of its impact on energy usage.

IV. Result and Discussion

The decision was made to use a MATLAB simulation tool and the simulation parameters in Table 4 to test the fitness function. The effectiveness of the approach was evaluated by comparing the findings of the proposed technique with those of the LEACH process [26] and other comparable methods. Several tuning processes are used to specify the crossover and mutation rates after which the GA parameters provided in this paper are listed in Table 4.

The LEACH protocol is the most frequently used clustering method in the WSN community. As a consequence, referring to it as a guide is critical. On the other hand, the proposed OMPFM is pitted against several other protocols that are developed on top of LEACH. Before comparing the proposed OMPFM with the current methods, an assessment of the efficiency of the improved GA should be conducted in terms of chromosomal sizes and running time. This will indicate that the better GA is more efficient. A single round of comparison is shown in Figures 3 and 4 to demonstrate how conventional GA (NGA) compares to improved GA (EGA). For every additional round, the chart becomes increasingly jumbled; on the other hand, for every additional round less than ten, the comparison values get increasingly muddled. There will be a total of 10 rounds. Because all nodes in the selected rounds are still alive, the running time is precise and predictable, and the ideal chromosomal sizes have been attained. The chosen rounds are also the first ones. This is followed by ten tests in which the standard GA is compared to its upgraded counterpart (see Figures 3 and 4). Time required for 10 conventional GA rounds is shown in Figure 3, whereas time required for enhanced GA is shown in Figure 2. Figure 2 depicts the average chromosomal size throughout the first ten cycles. There is only one way to get the average chromosome size from the BS to each CH, thus the total number of CHs divided by the number of CHs each round gives the average chromosome size. Figure 3 demonstrates that the enhanced GA requires less time each round than the regular GA does. To improve efficiency, we used the suggested pre-processing steps. Furthermore, as seen in Figure 4, enhanced GA shrinks the size of the chromosomes when compared to regular GA. The graph below illustrates the average chromosomal size during the experiment. The improved version of GA's smaller chromosome sizes increases the effectiveness of the GA by finding the optimal solution by utilising short chromosomes, thanks to the suggested pre-process that picks the appropriate CHs to be included in the GA.

Figure 3 depicts how much faster the improved GA runs, on average, than the standard GA. (Number of intermediate CHs) is less for each run in the improved GA than it is for each run in the standard GA (Fig. 4). In terms of running time and chromosomal size, the results show that the proposed GA's pre-processes are more efficient than the standard GA. Various scenarios were developed in order to assess the OMPFM's feasibility. The simulations were run a total of 20 times to provide a fair comparison. Each sensor node in the network has its own array data structure that is used to calculate the fitness value of the suggested strategy. To illustrate the array data structure, see Table 5.

TABLE IV. Parameters and Values used in the Simulation

Representation	Declaration	Value
A	Size of the network	100×100
BS(i,j)	Base station location	area center (50×50)
N	The total no. of nodes	100
Etx	Transmission energy	51 nJ/bit
Eo	Initial energy	0.5 Joule, 1 Joule
Eelec	Consumption of electronic resources	51 nJ/bit
Erx	Energy for reception	51 nJ/bit
Eamp	amplified signal transmission	12 pJ/bit/m2
Eda	energy used for data collection and analysis	6 nJ/bit
Rmax	Number of rounds allowed as a maximum	5000
Pack/CtrPack	Packet size for data and control	528 bytes/50 bytes
Indiv	No. of Individuals	50
Iter	No. of iterations	120
Cr	Ratio of changeover	0.9
Mr	Change rate	0.05

Fig. 3. Time Spent Running in the First Ten Rounds.

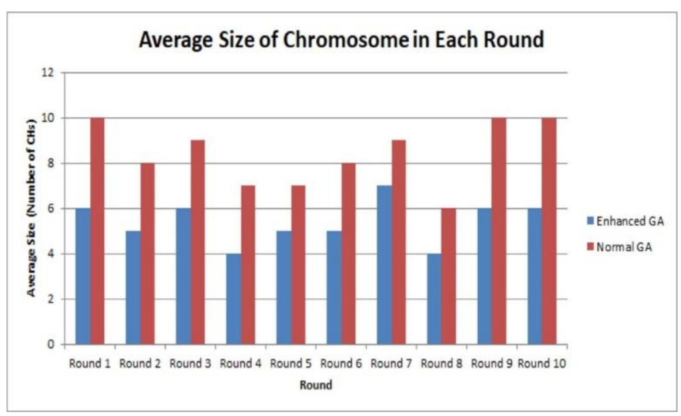

Fig. 4. The Average Chromosomal Size in the First Ten Rounds.

TABLE V. ARRAY DATA STRUCTURE

Fields	xd	yd	G	Status	No. of Parameters	Members	ToBs	Types	E
1	99.83	63.79	0	1	26	0	140.35	'C'	-0.0059
2	59.61	51.53	0	1	16	0	143.78	'C'	-0.0037
3	66.36	39.48	0	1	36	0	156.37	'C'	-0.0031
4	56.56	69.30	0	1	29	0	125.86	'N'	-9.81e-05
5	9.62	90.97	0	1	31	0	111.58	'N'	-5.33e-04
6	51.71	19.61	0	1	29	0	175.38	'N'	-1.80e-04
7	61.13	15.54	0	1	32	0	179.79	'N'	-1.62e-04
8	73.02	72.88	0	1	0	0	124.26	'A'	-0.007
9	75.32	33.67	0	1	29	0	163.30	'N'	-4.177e-04
10	85.66	75.07	0	1	46	0	125.11	'N'	-5.14e-05
11	80.81	5.71	0	1	31	0	191.78	'N'	-2.87e-04
12	44.25	6.17	0	1	28	0	188.91	'N'	-2.26e-05
13	32.27	3.22	0	0	0	0	192.60	'A'	-0.0030

Table 6 and Fig. 5 show the outcomes of using the proposed technique in comparison to the comparable methods [5,14,16,22,36]. When compared to techniques based on the number of dead nodes, the recommended strategy leads in longer network lifetimes, as shown by the findings above. The recommended approach outperforms the LEACH protocol by 28%, the GCA by 25%, the EAERP by 18%, and the GAECH by 11% in dead node percentages of 10% compared to the LEACH protocol. As compared to the standard LEACH protocol, this one outperforms it by 35%, as well as the GCA (34%), EAERP (26%), and GAECH (19% when including HND, or 50% of dead nodes). The new approach beat the previous ones by a factor of 101 percent when compared to LEACH and a factor of 99 percent when compared to GCA and EAERP. Longevity gains are seen when employing the recommended technique, and these gains can be ascribed to using energy-efficient intermediate CHs in the selection process for the fitness function.

To simulate the second case, the starting energy of each node was reduced to 0.5 Joule from 1 Joule as per [11]. Table 7 shows the FND and LND of the proposed OMPFM. Table 7 shows the average values of the FND and LND parameters over tens of thousands of runs, which are 1695 and 3946, respectively. Figure 5 depicts the [11]'s FND and LND. Table 6 and Table. 7 [11] reveal that our OMPFM has superior FND and LND values than previous techniques. A FND of 1695 characterises the suggested OMPFM, while a FND of 800 characterises the techniques outlined in [11]. The LND in the OMPFM is 3946, but in the approaches in [11], it's roughly 2000. In terms of running time, the recommended OMPFM performs better thanks to better parameter selection in the fitness function and better utilisation of the pre-processing.

TABLE VI. PERCENTAGE OF DEAD NODES AND NUMBER OF ROUNDS

Dead nodes%	No. of Rounds				
	LEACH	CGA	EAERP	GAECH	OMPFM
10%	1898	2163	2244	2440	2646
20%	2013	2146	21782	2331	2713
40%	2057	22602	2334	2366	2644
60%	2201	2277	2356	2478	2994
80%	2225	2274	2366	2522	3244
100%	2255	2354	2409	2490	4418

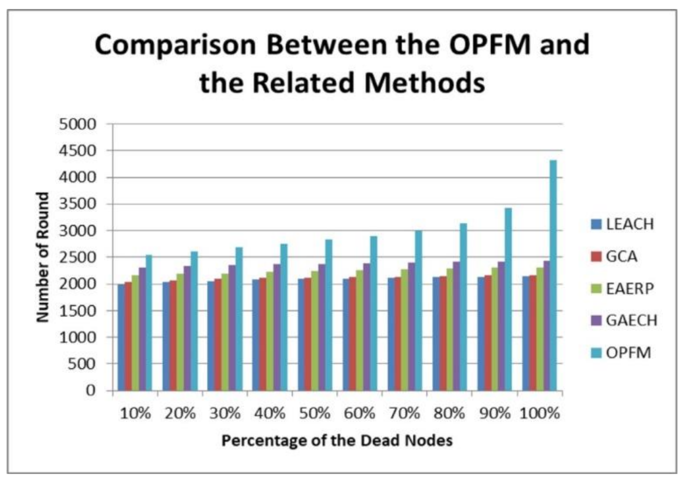

Fig. 5. Results of the Suggested Method's Simulation Compared to Similar Techniques.

TABLE VII. PROPOSED MODEL OMPFM FOR LND AND FND

FND	LND
1633	4155
1778	4422
1781	3754
1752	3889
1614	4167
1622	3923
1689	3855
1798	4109
1789	3755
1699	3666

V. CONCLUSION AND FUTURE SCOPE

Data transmission in WSNs has a significant impact on a network's lifetime performance. It's difficult to use direct transmission in WSNs because of the increased energy usage. This is especially true when the source CH is far from the BS. Furthermore, choosing the right CHs is a problem that has a big impact on the network's lifespan. These issues have been the subject of a slew of investigations. A novel approach to the direct transmission problem, based on a modified GA, is given in this work. The settings of the boundary variables for the cluster head selection function can be altered to improve results based on the specific application. A change is recommended to the CHs selection threshold. Since the suggested technique is half as good as the LEACH protocol and other comparable methods presently in use in terms of network lifetimes and power consumption, this would lead to longer run times. Eventually, a new evolutionary algorithm will be implemented to speed up the processing time. Additionally, future mobile WSNs will consider a multi-hop routing method.

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