IJE TRANSACTIONS C: Aspects Vol. 37 No. 09, (September 2024) 1800-1811

International Journal of Engineering

Journal Homepage: www.ije.ir

Improvement of Low Energy Adaptive Clustering Hierarchical Protocol Based on Genetic Algorithm to Increase Network Lifetime of Wireless Sensor Network

S. Haghzad Klidbary*[a], M. Javadian[b]

[a] *Faculty of Engineering, Department of Electrical and Computer Engineering, University of Zanjan, Zanjan, Iran*
[b] *Department of Electrical Engineering, Technical and Vocational University (TVU), Tehran, Iran*

P A P E R I N F O

Paper history:
Received 14 January 2024
Received in revised form.09 March 2024
Accepted 02 April 2024

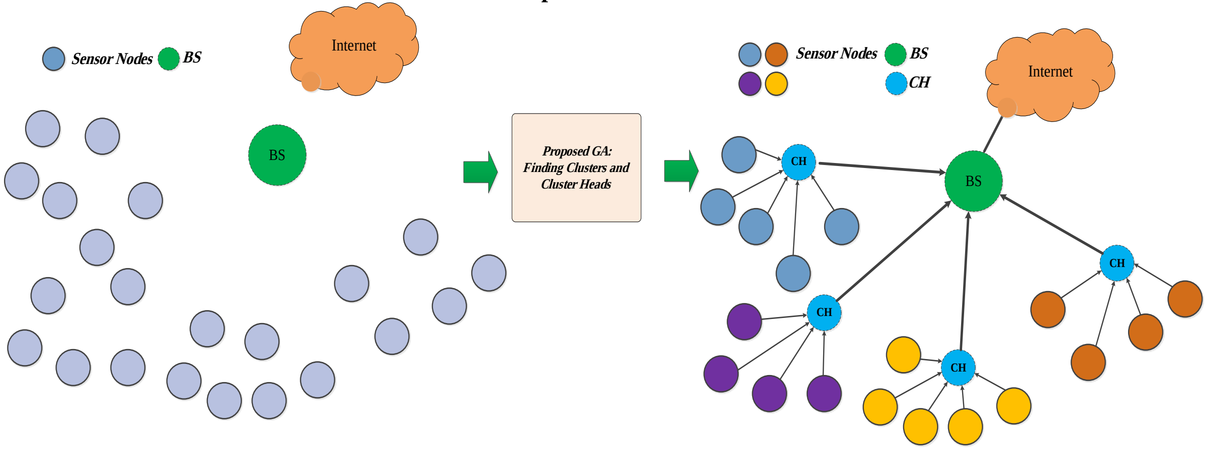
Keywords:
Wireless Sensor Network
Optimization
Cluster Head
Genetic Algorithm
Low Energy Adaptive Clustering Hierarchical Protocol
Clustering

A B S T R A C T

Wireless sensor networks contain of many sensors that can serve as powerful tools for data collection in environments. A key challenge in these networks is the limited lifetime of sensor batteries. Ideally, all nodes would exhaust their energy simultaneously or through regular scheduling, maximizing the lifetime. Consequently, the primary concern is achieving optimal energy utilization to extend the network's lifetime over a logical duration. Depleting the batteries of the sensors means stopping the operation of the network, because it is practically impossible to replace the batteries of thousands of nodes. To address this issue, the low energy adaptive clustering hierarchical (LEACH) protocol has been widely recognized as one of the prominent solutions for clustering WSNs. However, the random selection of cluster heads in each round under the LEACH protocol fails to guarantee proper convergence. To overcome this limitation, this paper proposes a refined approach by utilizing a genetic algorithm and a novel objective function that incorporates various factors, including energy level and distance. The algorithm employs chromosomes to represent CHs and facilitates the selection of cluster nodes. Notably, the proposed algorithm dynamically performs clustering, meaning that clustering is conducted iteratively, considering identifying dead nodes. By leveraging this approach, the algorithm significantly enhances the clustering quality, ultimately leading to an increased network lifetime. To validate its effectiveness, it is compared with LEACH, LEACH_E and LEACH_EX algorithms, demonstrating its superior capabilities. On average, the proposed algorithm has more alive nodes in the network, and the remaining energy is at least 11% higher than the best other algorithms.

doi: *10.5829/ije.2024.37.09c.10*

Graphical Abstract



* Corresponding Author Email: s.haghzad@znu.ac.ir (S. H. Klidbary)

Please cite this article as: Haghzad Klidbary S, Javadian M. Improvement of Low Energy Adaptive Clustering Hierarchical Protocol Based on Genetic Algorithm to Increase Network Lifetime of Wireless Sensor Network. International Journal of Engineering, Transactions C: Aspects. 2024;37(06):1800-11.

1. INTRODUCTION

The demand for observing unfamiliar environments and their surrounding conditions has necessitated using robust wireless communication tools. To meet this need, microsensors have been developed, giving rise to the concept of WSNs (1-3). These networks encompass a multitude of sensors capable of efficient data collection across diverse environments. Each sensor is equipped with a sensor module, processing module, communication module, and battery, all working together to gather valuable information. The collected data is wirelessly transmitted to a central station for presentation to end-users. The primary, and main objective of WSNs is to monitor and control environmental conditions within a specific range. In Figure 1, a visual representation of a hypothetical environment and its key components is depicted.

Energy consumption poses a significant challenge in WSNs and should be minimized. To achieve this, restrictions can be imposed on node access to the base station (BS), resulting in substantial energy savings. Hence, a select number of nodes, known as CHs, are granted access to the central station. Other nodes within a subnetwork send their information to the CH, which accumulates and forwards the received information to the BS. Consequently, selecting a proper clustering algorithm and also CHs becomes a critical concern in WSNs (4, 5).

The LEACH algorithm (6) is one of the protocols that adopts a probabilistic model for selecting CHs in network. In this protocol, all nodes are periodically chosen as CHs. Each round encompasses two phases: the first phase focuses on forming clusters, while the second phase involves transmitting data to the BS.

The CH selection procedure in the LEACH algorithm is based on a probabilistic model, which means there is a possibility of clustering neighboring CHs. Unfortunately, this could result in inefficient selection and suboptimal energy consumption. The LEACH algorithm has two key phases: CH selection and information transmission. The fundamental concept behind the LEACH algorithm is that all nodes are chosen as CHs during periodic rounds. The main relationship of this algorithm can be expressed as follows:

$$T(n) = \begin{cases} \frac{P}{1-P\left(r \bmod \left(\frac{1}{P}\right)\right)} & if, n \in G \\ 0 & O.W, \end{cases} \tag{1}$$

In the LEACH algorithm, the value of P represents the probability of becoming a CH. The variable r presents the current round number, while G represents the nodes that have not served as CHs in the past $1/P$ rounds. Each CH creates a scheduling table to determine when data transmission should occur for each member. Once the clusters are made, each CH sends a TDMA scheduling program to the nodes within its cluster. This program specifies the time intervals each node can transmit its information to the CH. A radio model is employed as the basis for LEACH algorithm.

To ensure balanced energy consumption, and extend the network lifetime in WSNs, the energy consumption model should be carefully designed. The energy consumed through information transmission operations includes the usage of electronic circuits and transmission amplifiers. In contrast, the energy consumed during data reception operations only considers the energy used by electronic circuits. Hence, data transmission operations generally consume more energy than data reception operations. It is also worth noting that wireless data exchange consumes more energy compared to sensory or memory operations within the sensor itself. In our model, we specifically focus on the energy consumed by the sensor nodes during data exchange, and exclude the energy consumption of other operations. The radio model is visualized in Figure 2.

Therefore, we can establish the following relationships:

$$E_{TX}(k,d) = (E_{elec} * k) + (E_{amp} * k * d^2) \tag{2}$$

$$E_{RX} = E_{elec} * k \tag{3}$$

In the equations, E_{RX} represents the energy loss of the receiving node, and E_{TX} represents the energy loss of the transmitting node. E_{elec} represents the energy used for

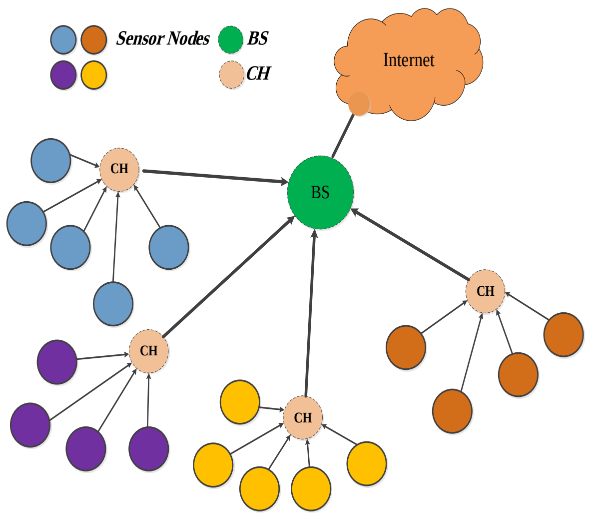


Figure 1. Communication architecture of WSNs

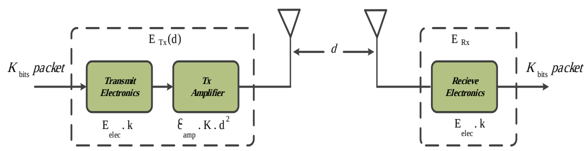


Figure 2. The energy consumption model is considered in this paper (Model of wireless communication energy consumption)

sending and receiving one bit of information, independent of distance. E_{amp} represents the energy required to amplify the transmitted signal over the desired distance. The variable k denotes the length of the message (bits), and d indicates the distance to the receiving node.

Several methods have been proposed to increase the performance of LEACH algorithm. The relevant algorithms are listed in Tables 1 and 2. All the efforts taken so far have been directed towards improving the efficiency of the LEACH algorithm. Similar to other applications, the genetic algorithm (GA) has been utilized in the LEACH protocol to enhance its performance. Researchers have also conducted studies on enhancing the LEACH CH selection algorithm to improve further the routing protocol's efficiency and network lifetime of WSN (7), A genetic algorithm is proposed that randomly selects nodes in a network to serve as cluster heads (8). It then determines the number of predefined independent clusters to reduce and minimize communication distance. They claimed to have obtained good results. Bari et al. (9) introduced an energy-saving method based on a GA for arrangement information gathering among relay nodes. This approach considerably prolongs the lifetime of a relay node network. It focuses on determining an appropriate routing policy for upper-tier relay node networks. The GA-based technique always finds the best solution (or convergence towards the optimal solution) for smaller networks in WSNs.

Liu and Ravishankar (10) introduced LEACH-GA, a variant incorporating a GA in the preparation phase. This algorithm determines the optimal probability to find CH. The set-up and steady-state phases follow this selection process. Rahmanian et al. (11) presented the results of applying two new objective functions (to four different types of sensor networks), and compared with the results obtained by the SA method. These objective functions were designed to select nodes in clusters that minimize energy consumption and maximize lifetime for each node. Peiravi and Javadi (12) proposed an optimal solution for clustering WSNs using a multi-objective two-nested GA, referred to as M2NGA. This proposed algorithm is executed by the Base Station (BS) node to optimize both network lifetime and minimize delay in WSN (wireless sensor network).

TABLE 1. Types of protocols derived from the base LEACH algorithm (Single-hop, Dis: Distributed, Hyb: Hybrid, Cen: Centralized)

Single-hop LEACH						
	LEACH successor	**Year**	**Clustering**	**Overhead**	**Scalability**	**Energy efficiency**
1	LEACH	May 2000	Dis.	High	Low	Moderate
2	LEACH-C	Oct 2002	Cen.	Low	Low	High
3	LEACH-DCHS	Sep 2002	Dis.	High	Low	High
4	Solar-LEACH	June 2004	Hyb.	High	Moderate	Very high
5	SLEACH	April 2005	Dis.	High	Moderate	Low
6	LEACH-Mobile	June 2006	Dis.	Very High	Low	Low
7	Sec-LEACH	July 2006	Dis.	Very High	High	Low
8	A-sLEACH	April 2007	Dis.	High	Moderate	High
9	Q-LEACH	May 2007	Dis.	High	High	High
10	ME-LEACH	July 2008	Dis.	Low	Low	Moderate
11	Armor-LEACH	Aug 2008	Dis.	Very High	Low	Low
12	A-LEACH	Dec 2008	Dis.	High	Moderate	High
13	T-LEACH	June 2009	Dis.	Moderate	High	High
14	LEACH-H	Nov 2009	Hyb.	High	Moderate	High
15	U-LEACH	March 2010	Dis.	Low	Low	High
16	LEACH-B	Aug 2010	Dis.	High	Low	High
17	LEACH-GA	April 2011	Dis.	High	Low	High
18	FL-LEACH	April-2012	Dis.	Low	High	Low
19	LEACH-SWDN	May 2012	Dis.	Moderate	High	Low
20	EP-LEACH	April 2013	Dis.	High	Low	Very high

21	I-LEACH	May 2013	Dis.	Moderate	High	High
22	LEACH-G	Oct 2013	Hyb.	Low	High	High
23	FT-LEACH	March 2014	Dis.	High	Low	Moderate
24	IB-LEACH	Aug 2014	Dis.	High	Low	High
25	V-LEACH	June 2015	Dis.	High	Low	Very high
26	EMOD-LEACH	Sept 2015	Dis.	High	Low	High
27	EHA-LEACH	Feb 2016	Dis.	High	High	Very high
28	LEACH-MAC	July 2016	Dis.	High	Moderate	High

TABLE 2. Types of protocols derived from the base LEACH algorithm (Multi-hop, Dis: Distributed, Hyb: Hybrid, Cen: Centralized)

Multi-hop LEACH

	LEACH successor	**Year**	**Clustering**	**Overhead**	**Scalability**	**Energy efficiency**
1	LEACH-B	April 2003	Dis.	High	Low	High
2	LEACH-B+	May 2005	Dis.	High	Low	Very high
3	Multi-hop LEACH	May 2005	Dis.	Moderate	High	High
4	TL-LEACH	Sept 2005	Dis.	Low	Low	High
5	LEACH-M	Dec 2007	Dis.	High	High	Low
6	ME-LEACH-L	Oct 2008	Dis.	High	Very high	Moderate
7	LEACH-DCHS-CM	June 2008	Dis.	High	High	High
8	LEACH-L	Nov 2008	Dis.	High	High	High
9	MS-LEACH	May 2009	Dis.	High	Very high	Very high
10	WST-LEACH	May 2010	Dis.	High	High	Very high
11	MR-LEACH	July 2010	Dis.	High	High	High
12	Coop-LEACH	Aug 2010	Dis.	High	Low	High
13	LEACH-D	Sept 2010	Dis.	High	Very high	Very high
14	UWSN-LEACH	Jan 2011	Dis.	Very high	Low	Moderate
15	FZ-LEACH	May 2011	Dis.	High	High	High
16	Cell-LEACH	Feb 2012	Dis.	Very high	Very high	Moderate
17	Wise-LEACH	Nov 2012	Dis.	High	High	Very high
18	Enhanced LEACH	May 2012	Dis.	High	Very high	High
19	DAO-LEACH	July 2013	Dis.	High	Moderate	High
20	LEACH-SAGA	March 2014	Cen.	Moderate	High	High
21	P-LEACH	March 2014	Dis.	Very high	High	Very high
22	EEM-LEACH	July 2014	Dis.	High	Moderate	Very high
23	LEACH-IR	March 2015	Dis.	Low	Low	High
24	O-LEACH	April 2016	Dis.	High	High	High
25	CL-LEACH	March 2016	Dis.	High	Moderate	High
26	DL-LEACH	July 2016	Dis.	Moderate	High	High

In the M2NGA, the top-level GA focuses on maximizing network lifecycle by considering energy consumption for data transfer to the CH and delay in terms of hop count as objective functions. Meanwhile, the lower-level GA is employed within the cluster to enhance communication from nodes to the CH. The GAEEP clustering protocol is introduced by Abo-Zahhad et al. (13), which is effectively improved the period. GAEEP utilizes a GA to determine the optimal number and positions of CHs, reducing energy loss and extending the stability phase while minimizing the instability period. This enhances the reliability of the clustering process. Zhang et al. (14) analyzed the pros and cons of the LEACH protocol and proposed a clustering routing protocol aiming for energy balance in WSNs. The protocol, clusters randomly organized sensor nodes using a combination of Simulated Annealing (SA) and GA. It calculates the cluster center for each cluster and selects the candidate CH based on the node's energy compared to the average energy of the cluster. Finally, the candidate CH is chosen based on the distance from the cluster center. Miao et al. (15) presents an improved version of the LEACH method called LEACH-H, which incorporates a GA. The GA is used to calculate weights based on three parameters: distance between nodes, residual energy, and the number of neighbors. The results demonstrate that LEACH-H significantly increases the network lifetime. Hatamian et al. (16)introduced the CGC protocol based on an onion approach. The CGC algorithm selects suitable nodes as CHs by evaluating three criteria to prolong the network lifetime. They explored the utilization of a GA as a dynamic technique for finding optimal CHs according to specified parameters. Additionally, the concept of the onion approach is introduced for upper-level routing, dividing the network into multiple layers to reduce communication overhead. Bhatia et al. (17) proposed a GADA-LEACH scheme, which enhances CH selection in the LEACH protocol using a GA. This paper introduces a relay node between the sink node and the CH node to enable distance-aware routing. The objective function considers (three terms) energy parameters, the distance of the CH from associated nodes, and the distance of the BS from the CH.

Annushakumar and Padmathilagam (18) introduced a revised hybrid fusion routing algorithm that combines Q-LEACH, and QDIR to maximize the network's lifetime. The network is divided into four quadrants, and the selection of CHs in each division is based on a threshold value. Information transmission from sensor nodes to CHs in different regions is optimized using a GA. The GA employs FND, and HND to calculate weight values in the objective function. A GA is applied to LEACH to establish the shortest rout from the source to the destination, aiming to achieve optimal path establishment (19). Previous studies have shown that the use of GAs in the LEACH protocol effectively optimizes energy consumption in WSNs and extends the network's lifetime. Al Rasyid and Abdulrokhim (20) presented additional scenarios, particularly focusing on the placement of the BS. By experimenting with various scenarios, LEACH-GA outperforms regular LEACH in terms of network longevity, energy efficiency, and data collection at the BS. Khunteta and Bajpai (19) proposed a method for selecting CHs in the LEACH protocol using a GA. This method improved WSN lifetime by dividing the network into specific classes. The GA is utilized to determine the best path between the CH, the BS, and its performance is compared to that of the standard LEACH protocol. Energy efficiency and prolonging sensor node lifetime are crucial challenges in WSNs. Bhola and Cheema (21) presented an energy-effective routing protocol that incorporates the optimization algorithm GA. LEACH operates in a hierarchical manner, with specific nodes acting as CHs to gather and compress data before transmitting it to the target node. The GA assists in finding the optimal routing path by leveraging its fitness function. Extending the lifetime of a WSN while efficiently managing energy resources is a significant challenge. The LEACH protocol faces limitations such as uneven cluster energy distribution, and random CH selection. To address these issues Kumari and Gurjinder (22) proposed an improved method for CH selection, and reducing CH energy degradation. The proposed LEACH-CHGA, enhances CH selection compared to the existing protocol and simultaneously reducing network energy consumption. A wireless sensor network consists of numerous microsensor nodes that collect and transmit data to a BS based on predefined instructions. The LEACH protocol is commonly used to optimize CH selection, and improve system performance. Harun et al. (23) utilized a GA for optimal CH selection in the LEACH protocol. The proposed GA-based technique is compared with the traditional LEACH, and I-LEACH algorithms in terms of lifetime, throughput, and energy. The results demonstrate that the GA-based LEACH method outperforms the conventional approaches in all measured aspects.

Correct selecting of an objective function in the GA is a crucial challenge. This paper introduces an innovative approach using the GA to select optimal CHs. The proposed objective function incorporates various optimization coefficients, considering node energy, node-to-node distance, and node-to-cluster head distance.

The paper is structured as follows: the second section presents the proposed GA, the third section provides an analysis and simulations, and the final section includes conclusions, summaries, and future works.

2. PROPOSED GA AlGORITHM

Optimal selection and design are vital role in achieving the best possible outcome in many scientific, and technical problems, considering specific conditions. However, when dealing with a vast search space and finding a suitable solution that meets user requirements, employing precise algorithms to evaluate all possible solutions becomes exceedingly challenging. Optimization algorithms are broadly categorized as classical and modern approaches.

The GA, proposed by Sohail (24) is a modern optimization algorithm that draws inspiration from the principles of natural evolution (Darwin's theory). It has found applications in various domains. The GA operates by iteratively randomly exploring the problem space, to uncover improved solutions at each step compared to previous ones. Figure 3 illustrates the overall structure of the proposed GA. Let us consider a BS, and a set of sensor nodes (SNs), described as follows:

$$S = [S_1, S_2, S_3, \ldots, S_n]. \tag{4}$$

In Equation 4, n indicates the number of nodes distributed across a area. Our objective is to choose a set of CHs that cover the whole area. Each sensor node is denoted by S_i, where $1 \leq i \leq n$. Additionally, we describe the set of CHs as follows:

$$C = [C_1, C_2, C_3, \ldots, C_m]. \tag{5}$$

In Equation 5, m indicates the number of clusters, with $n \geq m$, presenting that the number of sensor nodes is always more significant than the number of CHs. As depicted in Figure 3, the initial and crucial step involves selecting an appropriate coding scheme (chromosome definition). The defined chromosome is shown in Figure 4. The genes within each chromosome represent a randomized selection of nodes from each cluster.

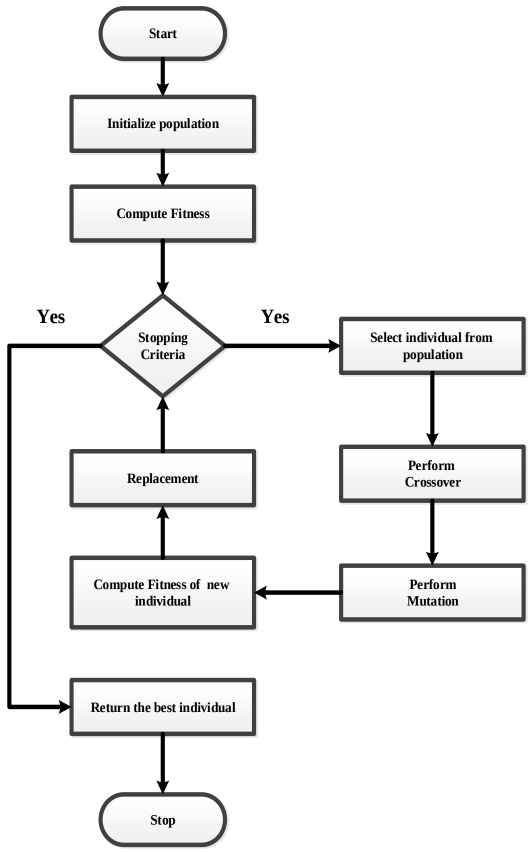


Figure 3. The general structure of the proposed GA algorithm (Proposed LEACH)

The type of coding used in this algorithm varies depending on the number of chromosomes, the number of genes, and ultimately the length of the chromosome. Initially, many nodes are randomly chosen as CHs. Through the objective function, the population is then progressed to the subsequent generation. Once the chromosome is defined, it is essential to select an appropriate initial population. In the proposed algorithm, the initial population is derived from the network nodes. A small population may hinder the exploration of the entire search space, while a large initial population can slow down the algorithm. Therefore, it is important to choose a suitable population size. The proposed genetic algorithm comprises three operators: Selection, Crossover, and Mutation. Further elaboration on these operators will be provided in the following.

2. 1. Selection Operator In this section, we will discuss the selection process for generating a new population from the previous generations. There are various methods for selection operator, including roulette wheels, random selection, tournaments, and more. In the proposed algorithm, the roulette wheel selection method is used. This method involves assigning a portion of the roulette wheel to each chromosome in proportion to its fitness function value (Other methods can also be used). Chromosomes with higher fitness have a greater likelihood of being chosen for the next generation's production. The selecting probability a particular chromosome, denoted as p_i, is determined using the following equation:

$$p_i = \frac{F_i}{\sum_{j=1}^{m} F_j} \tag{6}$$

The reason for employing different selection methods is to prevent the algorithm from becoming trapped in a local minimum instead of finding the global optimum. When two different chromosomes are combined, it can sometimes lead to such undesired scenarios.

2. 2. Crossover Operator This operator plays a crucial role in GAs as it drives the reproduction process. This operation involves sharing genes between two chromosomes. There are various types of crossover methods used to combine these chromosomes, including One-point Crossover, Two-point Crossover, and Uniform Crossover. In the proposed GA, after selecting

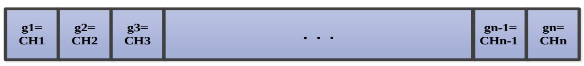


Figure 4. Chromosome defined in the proposed GA algorithm

two chromosomes using the selection methods discussed earlier, the one-point crossover method is employed. This method is depicted in Figure 5.

2. 3. Mutation Operator The mutation operator is a crucial component within the GA. Mutation is an operator used to maintain gen diversity of the chromosomes of a previus population. It involves randomly altering one or more genes within the parent chromosomes, leading to a random change in their values. Maintaining the integrity of proper chromosome representations for each cluster is vital. Hence, this operator incorporates a constraint to prevent nodes from exiting the internal nodes of the clusters.

2. 4. Fitness Function (Evaluation) The fitness function determines and evaluates the fitness value of each chromosome. The goal is to minimize energy consumption, which consists of three components ($f_1, f_2, and\ f_3$). These components are combined with different coefficients to form the overall sum (f).

$$f_1 = \sum_{i=1}^{n} e_i \Big/ E_{T_{CHs}},\ E_{T_{CHs}} = \sum_{i=1}^{m} e_i\ ,E_{T_{Nodes}} = \sum_{i=1}^{n} e_i \tag{7}$$

$$f_2 = \sum_{j=1}^{n}\sum_{i=1}^{m} z_i \Big/ \sum_{j=1}^{n}\sum_{i=1}^{m} g_i,\ z_i = \sqrt{(CH_i - s_j)^2},\ g_i = \sqrt{(s_i - s_j)^2} \tag{8}$$

$$f_3 = \sum_{i=1}^{m} d_i \Big/ \sum_{i=1}^{n} p_i,\ d_i = \sqrt{(xy_{CH_i} - xy_{BS})^2},\ p_i = \sqrt{(xy_{s_i} - xy_{BS})^2} \tag{9}$$

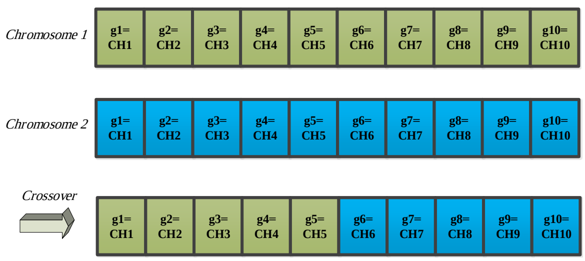


Figure 5. Applying crossover operator on two separate parent chromosomes

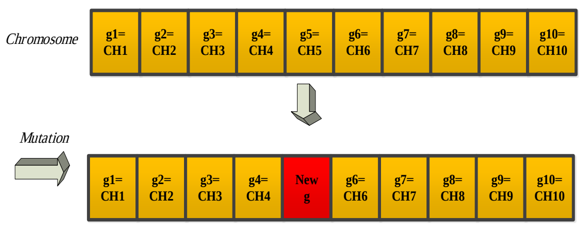


Figure 6. Illustrates the operational mode of the mutation operator

$$f = \alpha \times f_1 + \beta \times f_2 + \gamma \times f_3 \tag{10}$$

In the above equations, e_i is energy of each node, xy is location of each node, f_1 represents the sum of energy of all nodes divided by the energy of all cluster CHs ($E_{T_{CHs}}$). This function to select the nodes with more energy as the cluster head. Function f_2 calculates the Euclidean distance (ED) between a node, and its neighboring nodes, divided by the distanec of whole number of nodes within the cluster (sigma). The second function is to reduce the transmission distance between nodes in the cluster and ultimately reduce transmission energy consumption. Function f_3 calculates the Euclidean distance (ED) between the BS and all CHs, divided by the distance of whole number of CHs to BS. The third function is to reduce the transmission distance between clusters and bs and finally reduce transmission energy consumption. The coefficients α, β, and γ are optimization coefficients. It is worth mentioning that additional criteria can be incorporated into the algorithm and used as parameters to achieve the optimal CHs in network.

2. 5. Next Generation After applying all the operators in the previous sections (selection, crossover, and mutation), the next generation chromosomes must be selected from the existing ones. The policy of elitism is employed in this stage. To consistently enhance the value of the objective function across successive generations, a certain percentage of the top-performing chromosomes from each generation are chosen to be transferred to the next iterarion. This approach ensures continuous improvement of the objective function, and strives towards the optimal chromosome. Replacement strategies involve methods where offspring generated from GA operators replace their parents. In Figure 7, initially, 25% of the best parents from each generation are chosen. These chosen parents are directly passed on to the next iteration without undergoing any GA operator. Subsequently, crossover, and mutation are applied to the entire population. The desired process is illustrated in the accompanying Figure 7. As seen in the figure, to add diversity, 20% of the next generation is randomly generated.

3. SIMULATION RESULTS

In this section, we carried out several simulations to assess the effectiveness of the proposed algorithm. All simulations were executed using MATLAB 2017a on a personal computer equipped with a Core i5 processor, running at 2.4 GHz, and with 4GB of RAM.

To measure the efficiency of the proposed algorithm and compare it with other algorithms, two different scenarios were examined. In the first scenario, 120 sensors were randomly distributed, while in the second

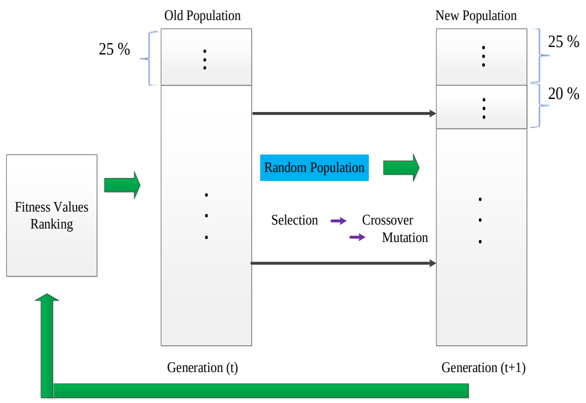


Figure 7. Step-by-step diagram of the proposed GA operators used to generate new offsprings (25% of the best parents from each generation are chosen)

scenario, 160 sensors (Nodes) were randomly distributed. The simulation environment size was set to 100 by 100 units. Figure 8 illustrates the hypothetical location of the BS for both scenarios. The capability of the proposed algorithm, as well as existing algorithms (LEACH (9), LEACH_E (25), and LEACH_EX (1)), was investigated and evaluated in these environments. These algorithms have the following characteristics: random distribution of nodes, stationary sink node, static position of nodes, and sensor death due to battery depletion. Three criteria were considered for comparison: energy consumption of the network, number of packets sent, and number of dead nodes. For the two proposed scenarios, all parameters related to the algorithm simulations can be found in Table 3 (In the proposed GA-based LEACH algorithm, like other existing algorithms, the trial-and-error method has been used).

Lastly, the pseudo-code for the proposed GA algorithm is presented below. The code comprises five main components: population selection, crossover, mutation, evaluation, and next generation.

```
Algorithm: Pseudo-code of proposed GA-Based LEACH
Begin
Initialization ( population);
   Evaluate each chromosome;
    While (Stop Condition)
      Do
         1: Select parents;
         2: Crossover;
         3: Mutation;
         4: Evaluation;
         5: Select a chromosome for the next generation;
      End
End
```

3. 1. First Scenario

In the first scenario, the test environment contains 120 nodes. Figure 9 shows the clusters found, total network energy, number of sent packets, and number of dead nodes. For a detailed quantitative presentation, refer to Table 4. As can be seen

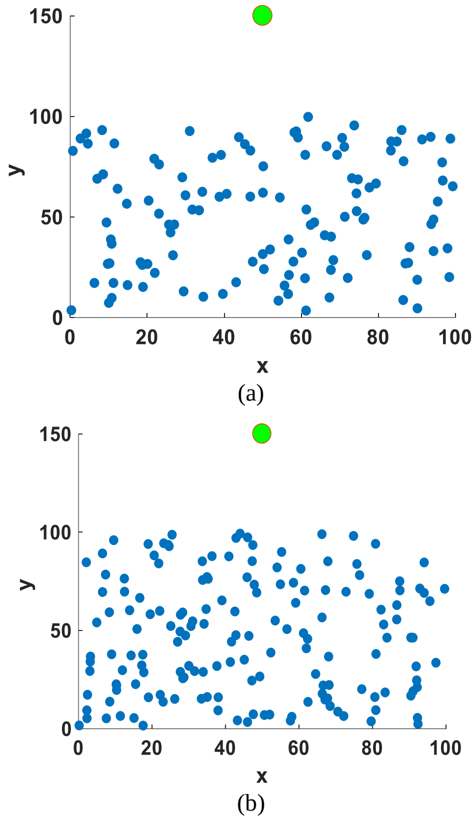


Figure 8. Hypothetical environment with 120 nodes, and b) Hypothetical environment with 160 nodes and fixed location of BS in both environments

TABLE 3. Simulation parameters were used in two proposed scenarios (Proposed GA-based LEACH algorithm parameters)

#	Parameters	Scenario 1	Scenario 2
1	Number of nodes	120	160
2	Location of node	Random	Random
3	Chromosome length	10	10
4	Size of the initial population	100	140
5	Number of Iteration	200	400
6	Crossover Possibility (p_c)	0.4	0.48
7	Mutation Possibility (p_m)	0.2	0.25
8	α, β and γ	$0.3, 0.35,$ and 0.35	
9	Selection operator	Roulette wheel	
10	Size of area	$100 \times 100\ m^2$	
11	BS location	(50,150)	
12	Initial energy	0.3 J	
13	Maximum round	1000	
14	Data packet size	500 *Bytes*	
15	E_{TX} and E_{RX}	$50\ nJ/bit$	
16	Cluster head probability, p	0.05	

from the Figure 9 and Table 4, the proposed Genetic algorithm has obtained a suitable position for the CHs by using suitable fitness functions. It has performed better in the comparison criteria (three parameters: total energy, sent packets, and dead nodes) than other algorithms.

3. 2. Second Scenario In this scenario, there are 160 nodes distributed in the environment. Figure 10 showcases the clusters found, the total network energy, the number of sent packets, and dead nodes. Additionally, for more details on the obtained results, these results are quantitatively presented in Table 5.

The simulation results (Figures and Tables) demonstrate that the proposed GA surpasses other algorithms in terms of energy stability, and exhibiting a higher level of performance (indicating a delayed overall energy decrease). Additionally, the proposed GA-Based LEACH algorithm outperforms in various criteria. The energy consumption calculation considers factors such as the number of packets, clusters, and the distance between nodes. Through its effective measures, the proposed algorithm significantly reduces node mortality rate and enhances the network's lifetime, while achieving a balanced energy consumption. In addition, it can be said that different results can be obtained by changing the coefficients in the fitness function. One of the disadvantages of the proposed algorithm is that due to the use of a genetic algorithm, it requires more processing time than other algorithms.

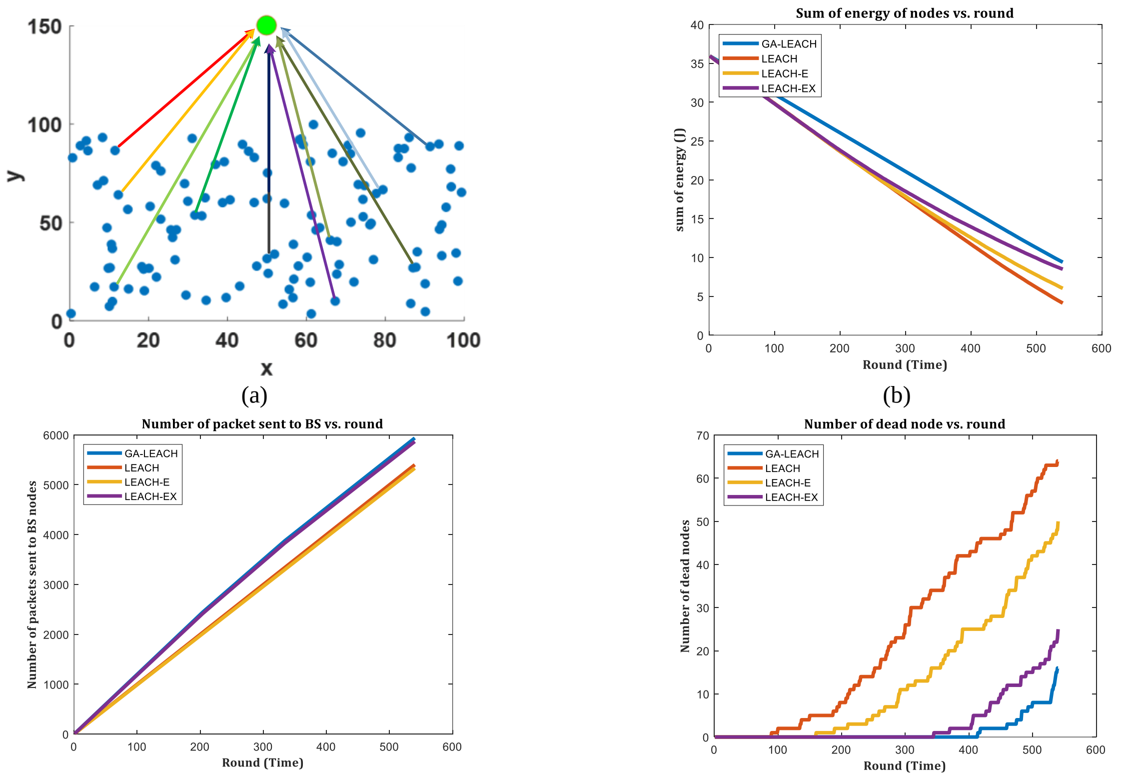


Figure 9. Showcases the following: a) CHs found by GA_LEACH, b) Total network energy vs. rounds in all algorithms, c) Number of sent packets vs. rounds in all algorithms, d) Number of dead nodes vs. rounds in all algorithms

TABLE 4. The results of the first scenario (regarding the number of rounds) – 120 Nodes

Algorithm	FND Round	HND Round	LND Round	Energy Consumption (EC) $Joul - (Round = 540)$
GA-LEACH	411	649	1307	9.437
LEACH	89	507	1011	4.171
LEACH_E	160	577	1182	6.031
LEACH_EX	344	602	1243	8.494

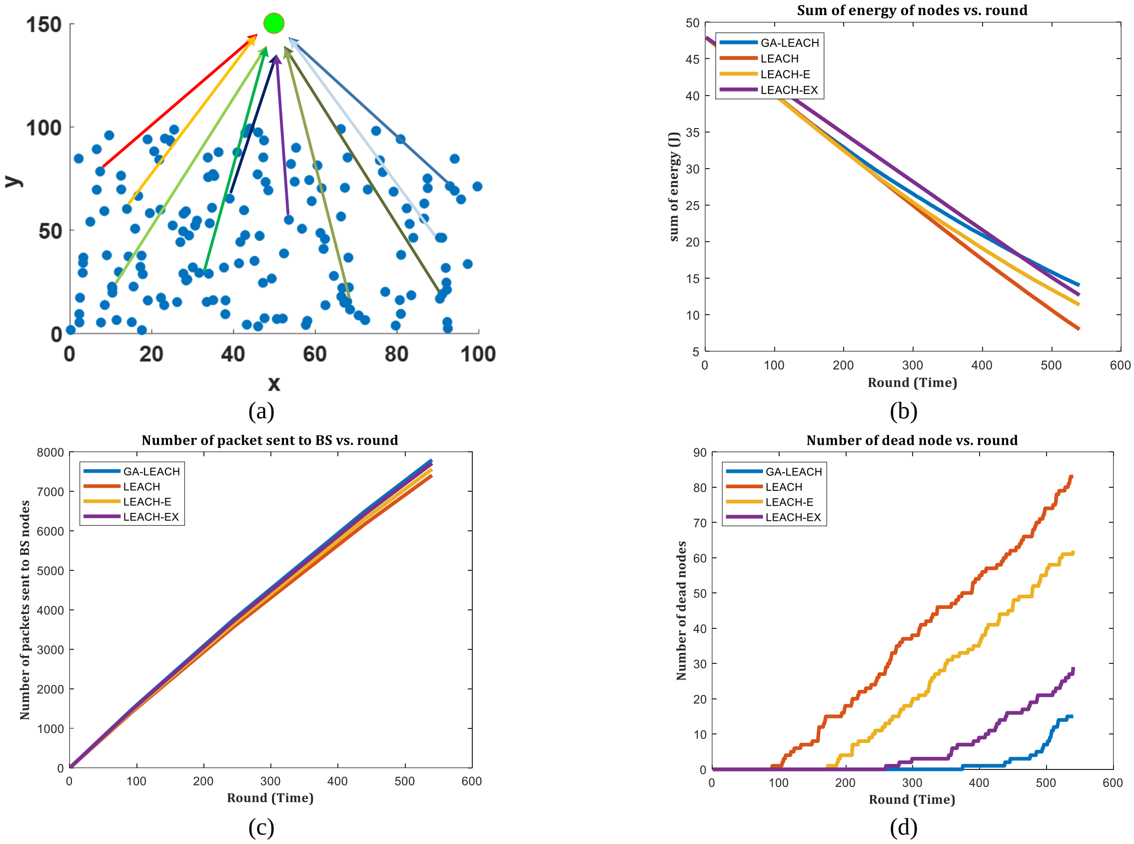


Figure 10. Showcases the following: a) CHs found by GA_LEACH, b) Total network energy vs. rounds in all algorithms, c) Number of sent packets vs. rounds in all algorithms, d) Number of dead nodes vs. rounds in all algorithms

TABLE 5. The results of the second scenario (regarding the number of rounds) – 160 Nodes.

Algorithm	**FND Round**	**HND Round**	**LND Round**	**Energy Consumption (EC)** $Joul-(Round = 540)$
GA-LEACH	374	709	1488	14.014
LEACH	91	431	1203	7.991
LEACH_E	174	520	1299	11.348
LEACH_EX	259	670	1405	12.672

4. CONCLUSION

The progress in industry and technology has resulted in the growth of wireless communications, specifically using sensors in WSNs. Sensor network technology is a crucial advancement and can be regarded as one of the most vital technologies of the 21^{st} century. Time, and energy management pose significant challenges in these networks. Clustering, an unsupervised method, is crucial in addressing these challenges. In the proposed genetic algorithm, CHs form the chromosomes, and the selection of cluster centers occurs. The proposed algorithm dynamically performs clustering, meaning it is executed repeatedly to identify of dead nodes. This algorithm enhances clustering quality, ultimately leading to an extended network lifetime. A quantitative and qualitative comparison with widely used algorithms like LEACH, LEACH_E, and LEACH_EX showcases the exceptional capabilities of the proposed algorithm. One of the disadvantages of the proposed algorithm is its time-consuming nature compaer to LEACH, LEACH_E, and LEACH_EX. Future work may involve exploring other evolutionary algorithms.

5. REFERENCES

1. Akyildiz IF, Su W, Sankarasubramaniam Y, Cayirci E. A survey on sensor networks. IEEE Communications magazine. 2002;40(8):102-14. 10.1109/MCOM.2002.1024422

2. Mohammed FAB, Mekky N, Suleiman HH, Hikal NA. Sectored LEACH (S-LEACH): An enhanced LEACH for wireless sensor network. IET Wireless Sensor Systems. 2022;12(2):56-66. 10.1049/wss2.12036

3. Yadav A, Kohli N. Prolong Stability Period in Node Pairing Protocol for Wireless Sensor Networks. International Journal of Engineering, Transactions C: Aspects. 2021;34(12):2679-87. 10.5829/IJE.2021.34.12C.14

4. Singh SK, Singh M, Singh DK. Energy-efficient homogeneous clustering algorithm for wireless sensor network. International Journal of Wireless & Mobile Networks (IJWMN). 2010;2(3):49-61.

5. Shende MSS. A review on wireless sensor network: Its applications and challenges. International Journal of Computational Research in Engineering and Science. 2023;1(01):18-25.

6. Hoang DB, Kamyabpour N, editors. Energy-constrained paths for optimization of energy consumption in Wireless Sensor Networks. 2013 Fourth International Conference on Networking and Distributed Computing; 2013: IEEE. 10.1109/ICNDC.2013.17

7. Dhouib S. Hierarchical Coverage Repair Policies Optimization by Dhouib-Matrix-4 Metaheuristic for Wireless Sensor Networks using Mobile Robot. International Journal of Engineering, Transactions C: Aspects. 2023;36(12):2153-60. 10.5829/IJE.2023.36.12C.03

8. Yaro AS, Malý F, Malý K. A Two-Nearest Wireless Access Point-Based Fingerprint Clustering Algorithm for Improved Indoor Wireless Localization. Emerging Science Journal. 2023;7(5):1762-70.

9. Heinzelman WR, Chandrakasan A, Balakrishnan H, editors. Energy-efficient communication protocol for wireless microsensor networks. Proceedings of the 33rd annual Hawaii international conference on system sciences; 2000: IEEE. 10.1109/HICSS.2000.926982

10. Liu J-L, Ravishankar CV. LEACH-GA: Genetic algorithm-based energy-efficient adaptive clustering protocol for wireless sensor networks. International Journal of Machine Learning and Computing. 2011;1(1):79.

11. Rahmanian A, Omranpour H, Akbari M, Raahemifar K, editors. A novel genetic algorithm in LEACH-C routing protocol for sensor networks. 2011 24th Canadian Conference on Electrical and Computer Engineering (CCECE); 2011: IEEE. 0.1109/CCECE.2011.6030631

12. Peiravi A, Mashhadi HR, Hamed Javadi S. An optimal energy-efficient clustering method in wireless sensor networks using multi-objective genetic algorithm. International Journal of Communication Systems. 2013;26(1):114-26. 10.1002/dac.1336

13. Abo-Zahhad M, Ahmed SM, Sabor N, Sasaki S. A new energy-efficient adaptive clustering protocol based on genetic algorithm for improving the lifetime and the stable period of wireless sensor networks. International Journal of Energy, Information and Communications. 2014;5(3):47-72. 10.14257/ijeic.2014.5.3.05

14. Zhang H, Zhang S, Bu W. A clustering routing protocol for energy balance of wireless sensor network based on simulated annealing and genetic algorithm. International Journal of Hybrid Information Technology. 2014;7(2):71-82. 10.14257/ijhit.2014.7.2.08

15. Miao H, Xiao X, Qi B, Wang K, editors. Improvement and application of LEACH protocol based on genetic algorithm for WSN. 2015 IEEE 20th International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD); 2015: IEEE. 10.1109/CAMAD.2015.7390517

16. Hatamian M, Barati H, Movaghar A, Naghizadeh A. CGC: centralized genetic-based clustering protocol for wireless sensor networks using onion approach. Telecommunication systems. 2016;62:657-74. 10.1007/s11235-015-0102-x

17. Bhatia T, Kansal S, Goel S, Verma AK. A genetic algorithm based distance-aware routing protocol for wireless sensor networks. Computers & Electrical Engineering. 2016;56:441-55. 10.1016/j.compeleceng.2016.09.016

18. Annushakumar G, Padmathilagam V. Analysis and Implementation of Q-Leach Protocol Based on Genetic Algorithm for WSN. International Journal of Scientific Research in Science, Engineering and Technology. 2018;5(3):1-12.

19. Khunteta A, Bajpai A. Genetic algorithm with leach protocol for cluster head selection in wireless sensor networks. ICTACT J Commun Technol. 2020;11(2):2182-6. 10.21917/ijct.2019.0322

20. Al Rasyid MUH, Mubtadai NR, Abdulrokhim J, editors. Performance Analysis LEACH Based Genetic Algoritm In Wireless Sensor Network. 2019 International Seminar on Application for Technology of Information and Communication (iSemantic); 2019: IEEE. 10.1109/ISEMANTIC.2019.8884332

21. Bhola J, Soni S, Cheema GK. Genetic algorithm based optimized leach protocol for energy efficient wireless sensor networks. Journal of Ambient Intelligence and Humanized Computing. 2020;11:1281-8. 10.1007/s12652-019-01382-3

22. Kumari M, Kaur G. A genetic algorithm based leach protocol for cluster head selection to enhance the network lifetime of wireless sensor network. ICTACT J Commun Technol. 2020;11:2182-6. 10.21917/ijct.2021.0371

23. Harun HB, Islam MS, Hanif M, editors. Genetic algorithm for efficient cluster head selection in LEACH protocol of wireless sensor network. 2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE); 2022: IEEE. 10.1109/ICAEEE54957.2022.9836352

24. Sohail A. Genetic algorithms in the fields of artificial intelligence and data sciences. Annals of Data Science. 2023;10(4):1007-18. 10.1007/s40745-021-00354-9

25. Singh SK, Singh M, Singh D. A survey of energy-efficient hierarchical cluster-based routing in wireless sensor networks. International Journal of Advanced Networking and Application (IJANA). 2010;2(02):570-80.

Persian Abstract

چکیده

شبکه‌های حسگر بی سیم متشکل از تعداد زیادی از سنسورهای کوچک است که می‌توانند یک ابزار قوی برای جمع‌آوری داده در محیط‌ها باشند. یک چالش کلیدی، طول عمر شبکه حسگر است. در حالت ایده‌آل، همه گره‌ها انرژی خود را به طور هم‌زمان یا از طریق برنامه‌ریزی منظم تخلیه می‌کنند و طول عمر شبکه را به حداکثر می‌رسانند. با این حال، با در نظر گرفتن محدودیت‌های عملی مانند شرایط محیطی، جایگزینی باتری‌های گره غیر عملی می‌شود. در نتیجه، نگرانی اصلی دستیابی به استفاده بهینه از انرژی برای افزایش طول عمر شبکه در یک مدت زمان منطقی است. ضمنا دشارژ شدن باتری حسگرها به معنای توقف عملکرد شبکه است، زیرا عملاً جایگزینی باتری هزاران گره غیرممکن است. برای رفع این مشکل، پروتکل LEACH به طور گسترده به عنوان یکی از راه‌حل‌های برجسته برای خوشه‌بندی شبکه های حسگر بی سیم شناخته شده است. با این حال، انتخاب تصادفی سرخوشه‌ها (CHs) در هر دور تحت پروتکل LEACH نمی‌تواند همگرایی مناسب را تضمین کند. برای غلبه بر این محدودیت، این مقاله با استفاده از یک الگوریتم ژنتیک و یک تابع هدف جدید که شامل عوامل مختلفی از جمله سطح انرژی و فاصله است، یک رویکرد مناسب را پیشنهاد می‌دهد. این الگوریتم از ژن‌های کروموزوم برای نشان دادن سر خوشه ها استفاده می‌کند و انتخاب سر خوشه‌ها را تسهیل می‌کند. قابل ذکر است، الگوریتم پیشنهادی به صورت پویا خوشه‌بندی را انجام می‌دهد، به این معنی که خوشه‌بندی به صورت تکراری و با در نظر گرفتن شناسایی گره‌های مرده انجام می‌شود. با استفاده از این رویکرد، الگوریتم به طور قابل توجهی کیفیت خوشه‌بندی را افزایش می‌دهد و در نهایت منجر به افزایش طول عمر شبکه می‌شود. برای تایید عملکرد، الگوریتم پیشنهادی از نظر کمی و کیفی با الگوریتم‌های رایج مانند LEACH، LEACH_E و LEACH_EX مقایسه شده است. به طور میانگین، الگوریتم پیشنهادی دارای گره‌های زنده بیشتری در شبکه است و انرژی باقی‌مانده در آن حداقل یازده درصد بیشتر از بهترین مقدار انرژی الگوریتم‌های دیگر است.