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Asymmetric Clustering Approaches for Enhanced Energy Efficiency in Wireless Sensor Networks

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Abstract

This paper focuses on clustering and selecting an appropriate cluster head in wireless sensor networks. In symmetric clustering methods, the network is divided into several equal regions, and each region will have a cluster head regardless of the number of nodes within it. However, in our method, which employs asymmetric clustering, the centrality of nodes is calculated using the Fourier operator for the genetic algorithm. Additionally, using two other criteria—energy and dispersion—the number of cluster heads in the network is dynamically and variably selected in each round. As mentioned, in most existing methods, the cluster head was either selected in a distributed manner, leading to high energy consumption, or in a centralized manner, where one node makes decisions for the entire network, resulting in high traffic on that node. If this node encounters issues, the entire network suffers as a consequence. The proposed method, utilizing a genetic algorithm, achieved up to a 54% improvement in network energy consumption compared to the LEACH algorithm.

Introduction

Wireless sensor networks (WSNs) are generally data-driven, thus the communication structure among sensor nodes must be designed to align with the nature of these networks. Since most applications of sensor networks occur in scenarios where connecting nodes directly is impractical or cost-prohibitive, wireless communication is typically employed in these networks.

Some protocols in WSNs utilize clustering to meet the requirements of sensor networks. In this approach, sensors are divided into areas, each having a cluster head. After an event occurs, the sensors in each area send their information to the cluster head, which then forwards this information directly to the sink. Key characteristics of wireless sensor networks include self-organization in the environment, short-range communication, and multi-hop routing. Additionally, due to failures, energy limitations, memory constraints, and communication capabilities, these networks have variable topologies [1].

In wireless sensor networks, clustering methods are well-known for their specific advantages in scalability and efficient communications. In this context, the entire network is divided into clusters, each of which selects a cluster head, typically based on the maximum remaining energy. However, there are other parameters to consider for selecting a cluster head regarding longevity, which must be addressed. Wireless sensor networks have significant potential to enhance our ability to observe and control the physical environment; however, energy consumption has become a critical parameter affecting their reliability. Since many applications of wireless sensor networks require assurance of certain end-to-end quality parameters, supporting quality of service in these networks is of paramount importance. One of the critical issues in wireless sensor networks is the longevity of each

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network, which is directly related to the energy consumption balance of the network's sensors. Increasing the network's longevity is the most challenging requirement in these types of networks. Utilizing a genetic algorithm, the impacts of various parameters on the selection of an appropriate cluster head in wireless sensor networks can be evaluated, allowing for the best cluster head to be selected [2].

Literature Review and Background

In wireless sensor networks, clustering nodes is performed to optimize energy consumption, enhance efficiency, and improve data management. Below are four main categories of clustering methods in these networks:

1- Location-based methods. These methods use the geographical location information of nodes to form clusters, selecting nodes that are close to each other as members of a cluster. This approach is highly effective due to reduced data transmission distance and optimized energy consumption. Algorithms like LEACH (Low-Energy Adaptive Clustering Hierarchy) fall into this category [3-6].

2- Energy-based methods. In these methods, nodes are selected for clustering based on their available energy levels. Nodes with higher energy are chosen as cluster heads to collect data and send it to the network center. This approach helps to preserve network longevity and prevents rapid depletion of nodes [7-10].

3- Data-type-based methods. In this category, nodes are clustered based on the types of data they collect and their specific applications. For example, sensor nodes that collect similar data are grouped together. This method improves data processing efficiency and reduces interference in information transmission [11-14].

4- Hybrid methods. Hybrid methods utilize two or more different approaches for clustering. For instance, a combination of location and energy may be used to select cluster heads. This approach aids in further optimization and can enhance network performance under various conditions [15-18].

Table 1 compares the clustering methods in wireless sensor networks according to the aforementioned four categories.

Table 1. Comparison of Clustering Methods in Wireless Sensor Networks

Category	**Main Idea**	**Advantages**	**Disadvantages**	**Accuracy**	**Execution Time**	**Energy**
Center-based clustering	Determining the cluster center and assigning sensors to the nearest center	- Simple implementation - High efficiency	- Sensitive to initial center selection - Management of heterogeneous clusters	Average	Fast	Average
Hierarchical clustering	Organizing sensors in a hierarchical manner and forming clusters at different levels	- High scalability - Efficiency in large networks	- Complexity in implementation - Requires more management	High	Moderate	Low
Data-based clustering	Clustering based on data characteristics	- High accuracy - Ability to manage diverse data	- Requires more computations - Time-consuming	Very high	Long	High
Energy-based clustering	Optimizing energy consumption based on network needs	- Increased network longevity - Energy consumption optimization	- Complexity in implementation - May reduce data quality	Average	Moderate	Very low

The LEACH (Low-Energy Adaptive Clustering Hierarchy) algorithm is one of the popular methods in wireless sensor networks (WSNs) designed for energy optimization and increasing network longevity. This algorithm automatically divides sensors into different clusters and selects a cluster head for each cluster, responsible for collecting data from other sensors and sending it to the control center. The selection of the cluster head is done randomly based on the remaining energy of the sensors, ensuring a uniform distribution of load across the network.

The advantages of the LEACH algorithm include reduced energy consumption due to the intelligent selection of cluster heads, increased network lifespan, and improved efficiency in data transmission. Additionally, due to its hierarchical structure, this algorithm can easily adapt to changes in the network, such as adding or removing sensors. LEACH also prevents data collisions and congestion, as data is collected locally and then sent to the control center. These features make LEACH a suitable option for wireless sensor networks, especially in applications requiring optimized energy consumption and extended network longevity. Various versions of the LEACH algorithm have been proposed, each with specific advantages and disadvantages. Generally, these different versions can be categorized into three groups:

1- Base versions: The base versions of the LEACH algorithm include the original LEACH algorithm designed for optimizing energy consumption in wireless sensor networks. These versions divide sensors into different clusters, randomly selecting a cluster head for each cluster. Cluster heads are responsible for collecting data from other sensors and sending it to the control center. The simplicity of implementation and reduced energy consumption are notable features of this category; however, sensitivity to the initial selection of the cluster head may lead to imbalanced energy consumption.

2- Optimized versions: Optimized versions, such as LEACH-C (LEACH Centralized), assist in better management of cluster heads and reduce data collisions. In these versions, a central control mechanism is employed for selecting cluster heads, allowing for better selection through the analysis of sensor data. This results in increased accuracy and improved energy management in the network. However, the need for a central infrastructure can be a disadvantage of this category, as performance may decline in situations where central infrastructure is unavailable.

3- Advanced versions: Advanced versions of the LEACH algorithm, such as LEACH-D (LEACH Distributed) and LEACH-M (LEACH-Mobile), provide improvements in energy load distribution and adaptability to mobile sensors. In LEACH-D, the selection of cluster heads is done in a distributed manner, leading to increased network longevity and uniform load distribution. Meanwhile, LEACH-M responds to mobile sensors and can adapt to changes in sensor positions. Due to increased complexity in implementation, these versions may present challenges; however, they offer significant benefits in optimizing energy consumption and enhancing network efficiency.

Table 3 presents a comparison of the various versions of the LEACH (Low-Energy Adaptive Clustering Hierarchy) algorithm. These versions are divided into three main categories:

Table 2: Comparison of Various Versions of the LEACH Algorithm

Category	**Algorithm Name**	**Description**	**Advantages**	**Disadvantages**
Base versions	LEACH	The original algorithm that divides sensors into clusters and selects cluster heads.	- Simple implementation - Reduced energy consumption	- Sensitive to initial cluster head selection
Optimized versions	LEACH-C (LEACH Centralized)	A version with central control for selecting cluster heads.	- Higher accuracy - Better management	- Requires central infrastructure
Advanced versions	LEACH-D (LEACH Distributed)	A version with better energy load distribution and improved cluster head selection.	- Increased network longevity - Uniform load distribution	- Greater complexity in implementation
	LEACH-F (LEACH-Fixed)	Cluster heads are selected for a fixed duration.	- Greater stability in clusters	- May lead to suboptimal energy consumption
	LEACH-M (LEACH-Mobile)	A version for mobile sensor networks that responds to changes in sensor positions.	- Compatibility with mobile sensors	- Complexity in managing clusters

In the article [19], an optimized protocol named Modified LEACH is introduced, which significantly increases network longevity based on the results obtained. The modified LEACH protocol enhances longevity based on the number of live nodes present in the network. In the modified LEACH, the cluster head is selected based on the maximum remaining energy and the minimum distance to nodes. If the energy of certain nodes is at a minimal level, those nodes are removed from the network, and the network's lifespan ends.

In the article [1], a method for correcting and enhancing the LEACH clustering algorithm is presented. This method preserves hierarchical features while reducing energy consumption and considering the current energy levels of nodes in the clustering process, which is initially performed randomly using the first phase of the LEACH algorithm.

In most routing protocols, fault tolerance is not considered, especially in LEACH. The article [2] also aims to improve the LEACH algorithm. The cluster architecture includes two cluster heads in each cluster. The goal is to produce clusters whose members are related to cluster heads and parameters of nodes with higher remaining energy selected from their neighbors. Each cluster member generates a hello message that includes additional fields such as weight and the initial cluster head, broadcasting it among its neighbors for them to overhear the hello message.

In the article [20], a method for selecting secure cluster heads is presented to enhance the security of wireless sensor networks. They first examine the cluster nodes and remove any node with a high vulnerability probability from the pool of potential candidates for becoming a cluster head. Their goal in presenting this method is to

increase trust in wireless sensor networks.
In [21], a time-based algorithm for improving the LEACH protocol is proposed. Their algorithm is named TB-LEACH. In their method, a random variable is used to select cluster heads without any specific information about the nodes being available. Thus, at random times, the cluster heads change. Their experimental results indicated that this method achieved a 20 to 30 percent improvement over the LEACH method.
In the article [22], an algorithm was presented for selecting cluster heads and subsequently reducing energy consumption in wireless sensor networks. In this algorithm, three parameters—energy, movement, and the distance of a node to the cluster center—are considered. The work is done centrally, and the node that makes the final decision regarding the selection of the cluster head is the central station. They achieved a 5% optimization in energy consumption.
In most existing methods, the cluster head was either selected in a distributed manner, which led to high energy consumption, or in a centralized manner, where one node makes decisions for the entire network, resulting in high traffic on that node. If this node encounters issues, the entire network suffers as a consequence. In this paper, a method for selecting an appropriate cluster head in wireless sensor networks using a genetic algorithm is proposed. Key features of this method include the following:
In the proposed method, the cluster head is selected in a decentralized manner based on the objective function of the genetic algorithm. There are many parameters that can be used in selecting the cluster head; however, it should be noted that as the number of parameters increases, the time of the algorithm also increases, leading to increased computations and, consequently, increased time and energy consumption.

Proposed Method

In each cycle, each node calculates its chance parameter using the genetic algorithm based on three main descriptors: energy, dispersion, and centrality relative to neighbors. Subsequently, all nodes participate in selecting the cluster head, comparing their status with that of neighboring nodes. If a node's conditions are better than its neighbors, it identifies itself as the cluster head. The deployment of wireless sensor networks in a geographical area implies that the primary goal of the nodes is to sense and collect data. In this paper, it is assumed that the nodes are stationary, and each node is equipped with a GPS device to determine its geographical location, which it sends to neighboring nodes during the setup phase. Cluster head n collects K-bit messages from the nodes belonging to its cluster and then performs compression, creating a cnk-bit message (c: compression factor, c ≥ 1). The cluster head selection process in this paper occurs in two stages, similar to the LEACH algorithm: in the setup phase, the cluster head is selected, and in the stability phase, data compression, conversion to a single signal, and sending to the central station occur.The radio model used is:

$$E_{elec} = 50nJ/bi \qquad (1)$$

The energy consumed by the radio for sending or receiving is calculated from the following relationship:

$$\varepsilon_{amp} = \frac{\frac{100pJ}{bit}}{m^2} \qquad (2)$$

The energy consumed by each node to send and receive a k-bit message over a distance d is represented in the following relations [7]:

$$E_{\mathrm{TX}}(\mathrm{K,d}) = \mathrm{E_{elec}} * \mathrm{K} + \varepsilon_{\mathrm{amp}} * d^{\lambda} * K \text{ , } \lambda\text{: } path\ loss\ exponent \text{ , } \lambda >= 2 \qquad (3)$$

$$E_{\mathrm{RX}}(\mathrm{k}) = \mathrm{E_{elec}} * \mathrm{k} \qquad (4)$$

In the proposed genetic algorithm system, there are four main components. Each system operates based on a number of input and output variables that form the basis of decision-making. In this paper, the chromosomes of the genetic algorithm include factors such as node energy, location within the cluster, proximity to the sink, etc. The key components of the proposed system are introduced as follows: chromosomes, which are the deterministic inputs to the genetic algorithm values; the objective function, which contains the rules and functions; the combination, which specifies the system's convergence mechanism; and mutation, which prevents the algorithm from getting stuck in local minima.
The overall process is illustrated in Fig.1.

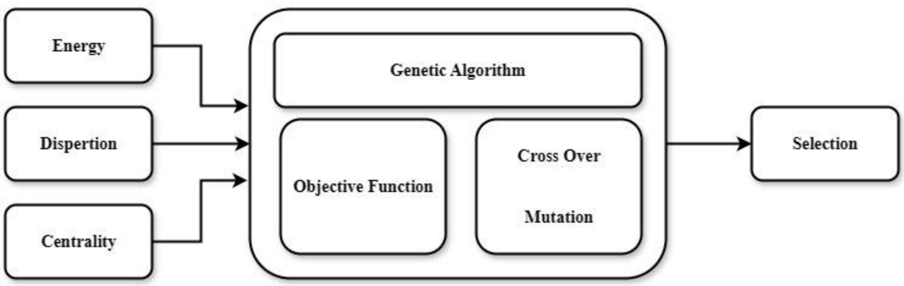


Fig.1: Overall Model for Cluster Head Selection in the Genetic Algorithm

Problem assumptions

Energy: Each node has a certain amount of energy, which it will lose during the simulation run. Therefore, the energy variable maintains the energy level of a node.

Dispersion: Each node has a number of neighbors, and the dispersion variable keeps track of the number of neighbors of a node.

Centrality: This variable indicates the degree of centrality of a node within a group. The closer a node is to the center, the better the access for other members, resulting in higher efficiency. The centrality variable specifies how centrally located a node is within a cluster.

To find the centrality value, each node calculates its distance to its neighbors. Since energy consumption for sending a message is directly proportional to the square of the distance between two nodes, represented as d^2 according to relation (3), the sum of these squares is computed. The lower the calculated value, the higher the chance for a node to become a cluster head.

Simulation Results

In this paper, a clustered wireless sensor network was simulated in an area measuring 100×100 meters, with one hundred sensors randomly distributed uniformly within it. In this simulation, the sink is located at the center, and the maximum distance from the sensors to the sink is 70 meters. The initial energy of the sensors is configured such that the total energy for 100 nodes equals 40 Joules. (This energy configuration is due to the use of heterogeneous sensors and does not affect the behavior of the protocol; other standard protocols like SEP and LEACH also follow this rule.)

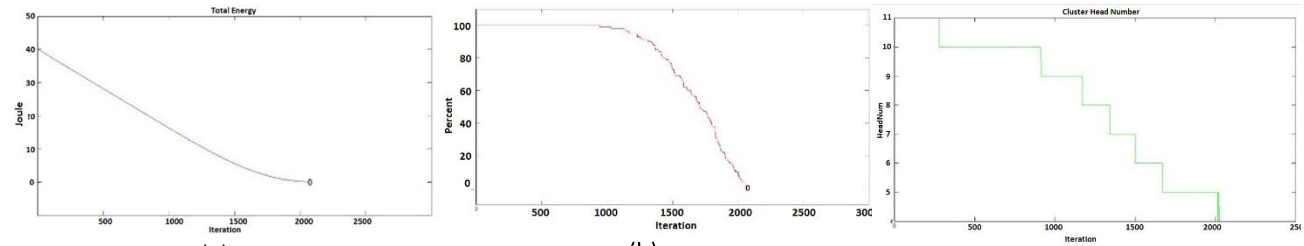
Wireless sensor networks have significant potential to enhance our ability to observe and control the physical environment; however, energy consumption has become a critical parameter affecting their reliability. Since many applications of wireless sensor networks require assurance of certain end-to-end quality parameters, supporting quality of service in these networks is of great importance. One of the critical issues in wireless sensor networks is the longevity of each network, which is directly related to the energy consumption balance of the network's sensors. Increasing the network's longevity is the most challenging requirement in these types of networks.

Data aggregation typically involves linking data obtained from multiple sensors in intermediate nodes and transferring the collected information to the main station. Data aggregation can eliminate redundant parts and minimize the number of transmissions, ultimately conserving energy [23].

To achieve this, we first divide the sensor network area into 16 segments. We then calculate the total energy of the nodes in each segment and create a 16-element matrix. Next, we apply the Fourier transform to the energy matrix and calculate the energy density for each segment relative to others. In this case, a segment with a Fourier value exceeding a threshold becomes a candidate for cluster head. This threshold is dynamic and changes with each iteration. The average energy in segment x and its preceding and succeeding segments is calculated; if the energy in segment x is greater than K times the averages, then segment x is a candidate for cluster head. Here, we set kk to 0.9. The following relationships were used to calculate energy in the i'th segment:

$$E(i^{th}\ segment) = \begin{cases} \sum_{s=1}^{3}\sum_{j=1}^{n} e(n_j) & if\ s=1 \\ \sum_{s=i-1}^{i+1}\sum_{j=1}^{n} e(n_j) & if\ 1<s<m \\ \sum_{s=n-2}^{s}\sum_{j=1}^{n} e(n_j) & if\ s=m \end{cases} \tag{5}$$

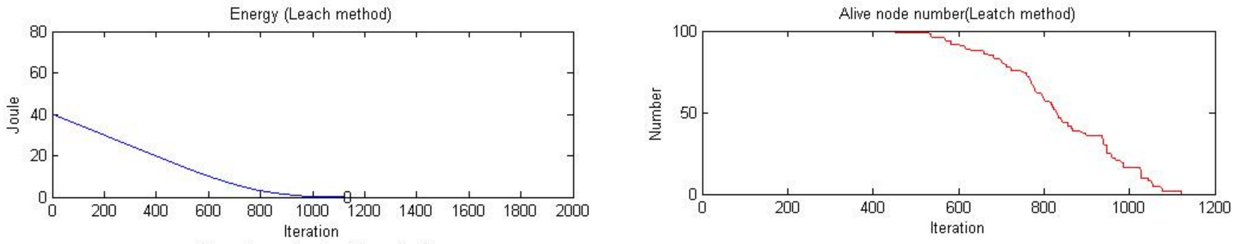
In the above equations, ss denotes the segment number, n represents the number of nodes within a segment, and m is the last segment number in the row.



(a) (b)

Fig. 2.a) Total Energy Consumption of the Network, b) Node Death Rate in the Network, c) Number of Segments with Cluster Heads

In Fig. 2(b), the graph of node death rates in the network is shown. The first node dies at iteration 948, the mid-life of the network occurs at iteration 1711, and the end of the network's life (the iteration at which the last node dies) is at iteration 2056. Fig. 2(c) illustrates the number of segments with cluster heads. As can be seen, initially, there were 11 segments with cluster heads, followed by 10 segments, and finally 5 and 4 segments with cluster heads.



(a) (b)

Fig. 3. a) Energy of Nodes in the LEACH Network, b) Node Death Rate in the LEACH-Based Network

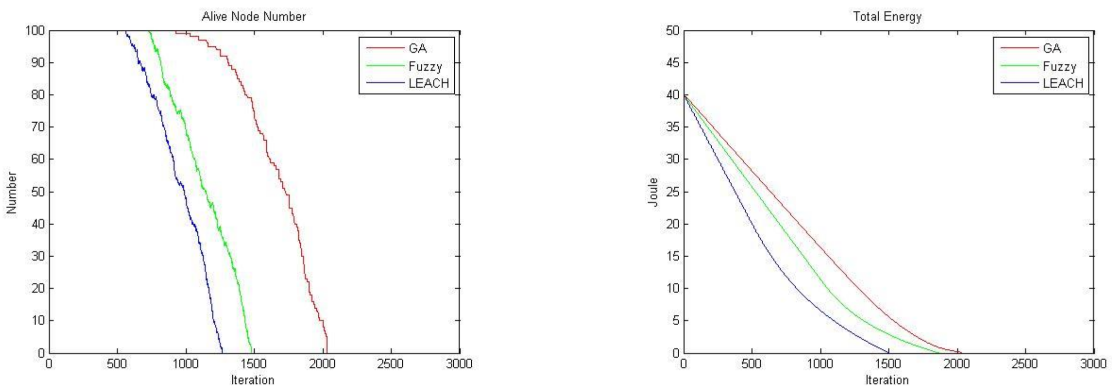
To demonstrate the superiority of the proposed method, it has been compared with the LEACH method. As previously mentioned, LEACH is one of the most well-known energy-efficient clustering algorithms in wireless sensor networks, forming cluster heads based on received signal strength and using these local cluster heads as the main station, as transferring information to the main station consumes a significant amount of energy. All sensor nodes are organized into a cluster by rotating the cluster head, which balances the energy consumption of all nodes and thus increases the network's lifespan. In Fig. 3(a), the energy levels of nodes in the LEACH-based network are visible. As shown in this figure, the total energy of the nodes initially equals 40 Joules, and by the last iteration, it drops to zero. The last iteration is iteration 1123. In Fig. 3(b), the node death rate graph for the LEACH-based network is displayed. As indicated, the first node dies at iteration 451, the mid-life of the network occurs at iteration 830, and the end of the network's life (the iteration at which the last node dies) is at iteration 1123.

Table 3 presents the experimental results for the proposed method and the LEACH method. As shown in the table, the proposed method and LEACH have been compared for scenarios with 100, 200, 300, and 400 nodes in the network.

Table 3: Experimental Results for the Proposed Method and LEACH Method

Number of Nodes	Method	First Death	Mid-Life	Total Network Death
100	LEACH	451	830	1123
	Proposed Method	948	1711	2056
200	LEACH	1569	1607	1980
	Proposed Method	1073	2388	2740
300	LEACH	1918	2002	2411
	Proposed Method	1348	2701	3125
400	LEACH	2314	2283	2604
	Proposed Method	1653	2916	3511

To evaluate the performance of the proposed method, we compare this algorithm with a fuzzy system. Fig. 5 shows four fuzzy graphs, with three graphs corresponding to inputs and one graph representing the fuzzy output.



(a) (b)

Fig. 4. a) Alive Nodes in Two Methods Compared with the Proposed Genetic Algorithm, b) Energy Comparison Between Two Methods with the Proposed Genetic Algorithm

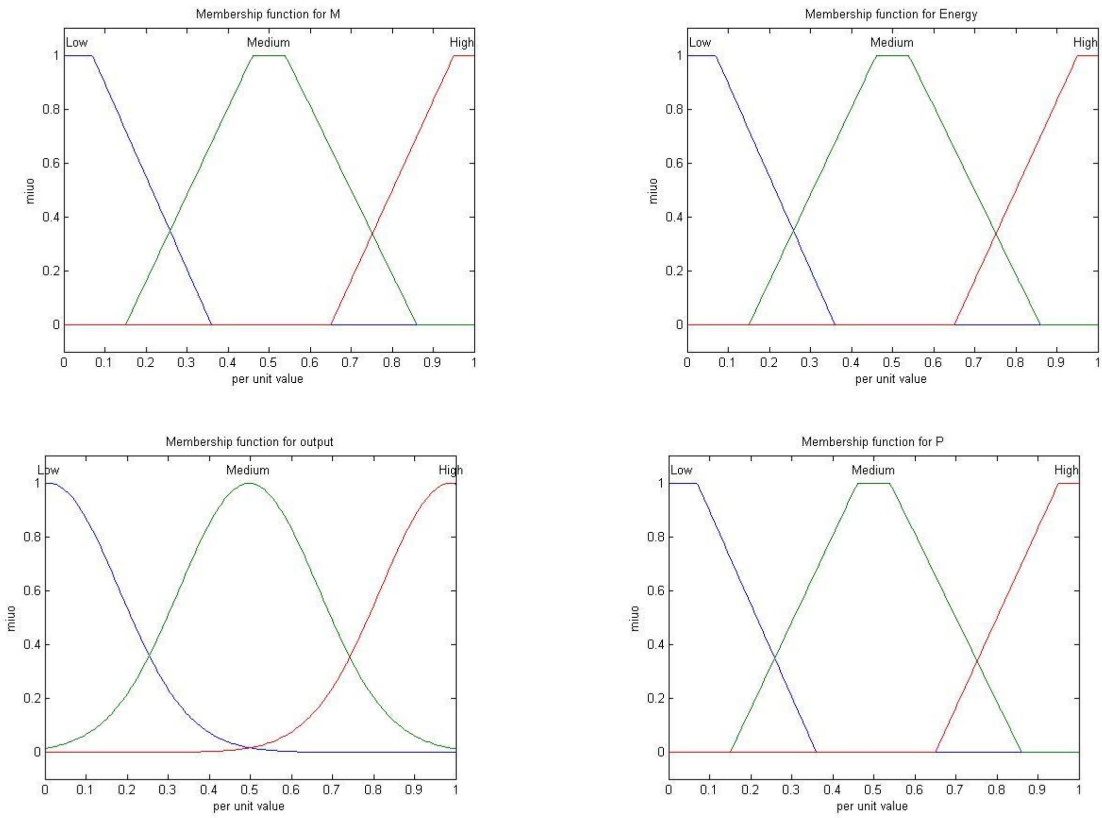
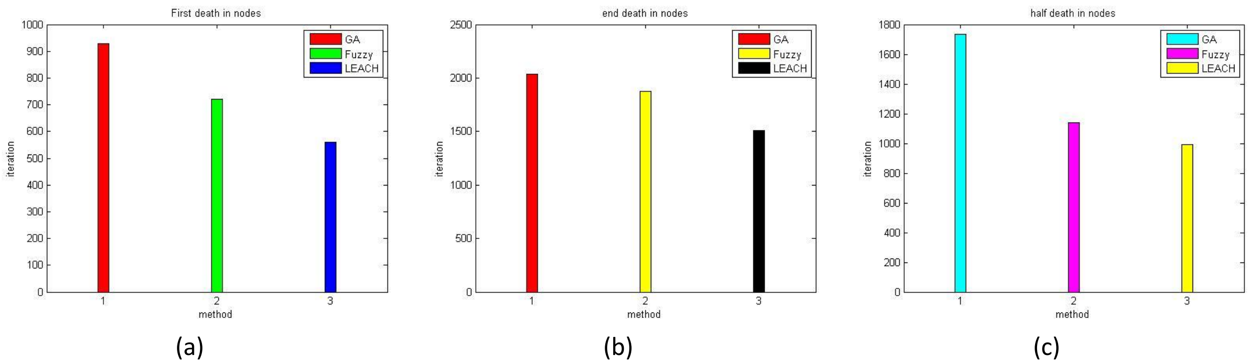


Fig. 5. Fuzzy Graph

After the simulation, the alive nodes graph is shown in Fig. 4(a). We observe that our proposed method, based on the genetic algorithm, outperformed the fuzzy method in all three aspects: first node death, mid-node death, and network lifespan. Additionally, the energy consumption graph in the proposed method is compared with the LEACH and fuzzy algorithms, as shown in Fig. 4(b).

The comparison between the proposed method and the two algorithms (LEACH and fuzzy) for the first node death in the network is illustrated as a bar graph in Fig. 6(a). The left graph, corresponding to our proposed method, is taller, indicating better performance improvement.



(a) (b) (c)

Fig. 6. a) First Node Death Comparison in Two Methods with the Proposed Genetic Algorithm, b) Mid-Node Death Comparison in Two Methods with the Proposed Genetic Algorithm, c) Last Node Death Comparison in Two Methods with the Proposed Genetic Algorithm

The comparison between the proposed method and the two algorithms (LEACH and fuzzy) for the last node death in the network is illustrated as a bar graph in Fig. 6(b). The left graph, corresponding to our proposed method, is taller, indicating better performance improvement.

The comparison between the proposed method and the two algorithms (LEACH and fuzzy) for mid-node death in the network is illustrated as a bar graph in Fig. 6(c). The left graph, corresponding to our proposed method, is taller, indicating better performance improvement.

Conclusion

In this paper, a method for clustering and selecting an appropriate cluster head in wireless sensor networks was presented. In symmetric clustering methods, for example, the network is divided into a total of 16 segments, and each segment will have a cluster head regardless of the number of nodes within it. However, in our method, which utilizes asymmetric clustering, the centrality of nodes is calculated using the Fourier operator for the genetic algorithm, and using two other criteria—energy and dispersion—the number of cluster heads in the network is dynamically and variably selected in each round. As stated, in most existing methods, the cluster head was either selected in a distributed manner, leading to high energy consumption, or in a centralized manner, where one node makes decisions for the entire network, resulting in high traffic on that node. If this node encounters issues, the entire network suffers as a consequence. Key features of this method include the following:

- A minimum energy threshold is set for becoming a cluster head, ensuring that any node with energy below this threshold is not considered for cluster head selection.
- A node that is in a blind spot or has very few neighbors is not considered a candidate for cluster head, even if it has high energy.
- Each node calculates its own chance parameter, which indicates how likely it is to become a cluster head compared to other nodes. To increase network longevity, if two nodes have the same chance and are neighbors, one of them will turn off in that round to help extend the network's lifespan.
  In each round, eligible nodes execute this algorithm, and a chance value is determined for each node. In the proposed algorithm, each node knows its chance and also the chances of the neighboring nodes. Then, each node compares its chance with others. If it is the highest, it declares itself the cluster head; otherwise, it attempts to join the cluster head that is closest to it. A node that determines it is the cluster head after comparison announces this to the others. Consequently, the remaining nodes try to join the cluster that is nearest to that cluster head. As the experimental results indicate, the proposed method improves upon the LEACH method in 100 nodes with values of 46.52%, 49.51%, and 37.45% in terms of first death, mid-life, and total network death, respectively.

Data Availability

Data underlying the results presented in this paper are available from the corresponding author upon reasonable request.

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Conflicts of interest

The authors declare no conflict of interest.

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