Fuzzy based energy efficient cluster head selection with balanced clusters formation in wireless sensor networks

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ABSTRACT

The importance of energy conservation presents a considerable challenge in wireless sensor networks (WSNs), where the sensor nodes (SNs) that constitute the network depend on battery power. Recharging the batteries of SNs in the field is challenging. The clustering technique is a commonly employed method for attaining energy efficiency. In this article, we are proposing a fuzzy-based energy efficient cluster head (CH) selection with the balanced cluster formation (FEECH-BCF) technique. It is a hybrid of the k-means algorithm, low energy adaptive clustering hierarchy- uniform size cluster (LEACH-USC) technique, and fuzzy logic technique. To create the clusters, the k-means approach is employed. The idea of LEACH-USC is used for load balancing to produce clusters with uniform size by assigning member nodes (MNs) from larger clusters to smaller clusters. Optimized CHs are selected using fuzzy based CH selection technique. The k-means algorithm is simple and quick to set up, assigning the membership of SNs to the next best cluster based on centroid locations of clusters reduces intra-cluster distance among clusters, and with the help of fuzzy logic, optimized CHs will be selected. The proposed algorithm performs exceptionally well in attaining uniform energy consumption amongst clusters and extends the network's lifetime to a greater extent.

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1. INTRODUCTION

A wireless sensor network (WSN) consists of sensor nodes (SNs) that are compact, cost-effective, simple, and can be deployed quickly [1], [2]. SNs interact with each other and perceive their environment, encompassing factors such as light, temperature, vibration, sound, motion, and numerous additional parameters. Each node frequently links to other nodes in order to exchange information regarding potential events that may take place in a specific environment. The clustering technique is widely utilized for energy-efficient communication between the SNs and the base station (BS). The BS can either be mobile or fixed. A clustered WSN comprises multiple clusters, with each cluster containing a cluster head (CH) and its associated member nodes (MNs). SNs gather information and record values before sending them to the BS [3], [4]. The function of CH is to gather data from its MNs and transmit it to the BS through either single-hop or multi-hop data transmission [5]. The clustering technique enhances network longevity by reducing energy usage and communication overhead [6], [7]. A typical clustered WSN model is shown in Figure 1.

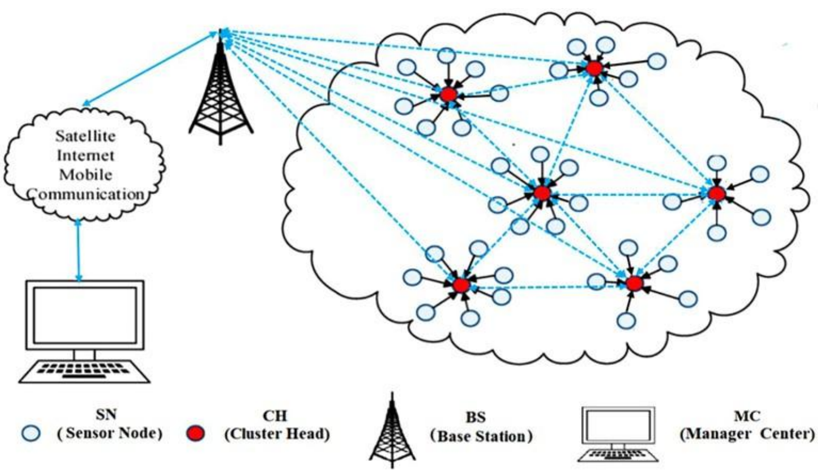


Figure 1. Typical clustered WSN model

One of the prominent protocols in the clustering technique, low energy adaptive clustering hierarchy (LEACH) [8], considers SNs to be homogeneous and distributed in the deployment area randomly. This protocol has three phases per round: the advertisement phase, the setup phase, and the steady state phase. Every round, SNs will compete to become CH using the threshold formula.

$$Tr(n) = \begin{cases} \frac{K}{1-K\left(r \bmod \frac{1}{K}\right)}, & if\ n \in S \\ 0, & otherwise \end{cases} \tag{1}$$

Where,
K Preferred percentage of CHs,
r Current round,
S Set of nodes that were not CHs in rounds 1/K,
Tr(n) Threshold value of nth node.

Using (1), each SN evaluates random numbers they generate (ranging from 0 to 1) against the established threshold value. Should the produced random number fall below the threshold value, the designated node assumes the role of CH for that round, subsequently announcing itself as CH. The remaining SNs connect to the chosen CH according to the signal strength of the advertising CH they receive. During the setup phase, MNs inform their membership status to the CH using carrier sense multiple access/collision avoidance (CSMA/CA). A time division multiple access (TDMA) schedule is implemented, featuring a variable number of time slots that correspond to the number of MNs involved. During the steady state phase, MNs will sleep until their scheduled time and transmit during their time slot. CH gathers information from MNs, aggregates all the data from its MNs, and transmits it to the BS. Clusters created by LEACH are unbalanced as the number of nodes per cluster is unequal, leading to small-sized clusters having more timeslots in the data transmission phase and consuming more energy compared to large-sized clusters as those MNs transmit their data more often compared to larger clusters.

The balanced cluster size formation (BCF) approach was introduced by Pal *et al.* [9] to create clusters having balanced size. The cluster generation procedure in BCF is divided into two steps. The rescue phase follows the initial cluster formation. Nodes will join up with the nearest CH during the initial phase, referred to as initial cluster formation, determined by the signal intensity of the advertisements received from the CHs., and each cluster can have maximum $Th_{cluster}$ MNs, which is given by the (2):

$$Th_{cluster} = \frac{N}{X} \tag{2}$$

N denotes the total count of SNs, while X signifies the number of CHs. The $Th_{cluster}$ constraint may result in a limited number of nodes remaining unclustered. During the rescue phase, unclustered nodes will connect to the CH that is within a distance equal to or less than $Th_{distance}$ and has a number of MNs fewer than $Th_{cluster}$. However, clusters formed by this method will overlap in nature and quickly deplete energy.

To solve this issue Singh *et al.* [10] introduced the low energy adaptive clustering hierarchy uniform size cluster (LEACH-USC) approach. This approach also employs the cluster formation and refurbishment phase. By using the LEACH technique clusters are formed in the cluster formation phase. In the refurbishing phase, clusters are arranged in decreasing order by considering each cluster's total number of MNs. The biggest cluster is found first. The excess nodes, $k = MNs - Th_{cluster}$, are assigned to the next best cluster based on the distance from SNs to other CHs provided $k < 0$ for the next best CH. Uniform-sized clusters decrease intra-cluster distance while enabling effective data flow on the network.

Creating uniform clusters based on CH location after each round increases the computation complexity and reclustering the network increases energy consumption. In our proposed approach, we have used the k-means algorithm to create initial clusters. The largest cluster is identified among all. Based on $Th_{cluster}$, the excess numbers of MNs from that cluster are assigned to the next best cluster. The centroid of the cluster is used instead of CH for assigning membership to the next best cluster. The created cluster will be untouched further. Among the rest of the clusters, the largest cluster is identified again and the same process continues until all the clusters have an equal number of MNs. Once the uniform-sized clusters are created, no further reclustering is required. Among MNs in each cluster, CH will be chosen using fuzzy logic. Network longevity is increased by an effective CH selection method [11]. The attributes used for this purpose are the node's remaining energy and node centrality. The proposed approach demonstrates improved uniform-sized clusters, which leads to a reduction in intra-cluster communication distance and an extended network lifetime when compared to LEACH, BCF, and LEACH-USC. The subsequent sections of the article are structured as follows: section 2 presents the problem statement, section 3 reviews related works, section 4 outlines the proposed approach, and section 5 addresses results and discussion. In section 6 provides the conclusion of this article.

2. PROBLEM STATEMENT

Energy efficiency is crucial while designing the WSN. The clustering technique can increase the energy efficiency. However, creating efficient clusters and selecting optimal CHs are the key concerns. The issue associated with the overlapping of clusters as in BCF is addressed in LEACH-USC. The clusters are formed based on the CH. However, cluster formation is ineffective, as CHs are selected based on the probability value as used in the LEACH protocol. Further, based on the initial cluster size, if $k<=0$ for the particular cluster, the MNs already assigned to that corresponding CH will be untouched. However, the distance between the MNs and CH is not considered. Keeping those MNs untouched and only the required number of MNs (i.e., $m = Th_{cluster}$ - MNs) to that cluster will be given membership from other clusters. It will lead to increased intra-cluster distance. The conventional LEACH technique selects CH in each round, which will not guarantee higher energy efficiency. The frequency with which the same nodes become CH again might affect the network's longevity as CHs are picked randomly. Also, reclustering is done after each round and consumes significant energy. To resolve these issues, fuzzy-based energy efficient CH selection with the balanced cluster formation FEECH-BCF, which achieves balanced clusters, reduced intra-cluster communication distance, and efficient CH selection, is proposed in this work.

3. RELATED WORK

Each node gathers data from the environment and transmits it to its CH in the LEACH protocol. Data is compressed before being sent to the sink. Reduced communication packets are sent, and the lifespan of WSNs is extended [12]. Nevertheless, it presents several limitations, such as the arbitrary selection of CHs and the necessity of forming clusters in each iteration.

Wibowo *et al.* [13] explores how the machine learning (ML) methods employed in WSNs affect energy efficiency by comparing them to the LEACH protocol and proposing cluster-based routing algorithms that take advantage of the k-means and the optimal value for clustering. This solution reduces energy usage, resulting in a balance between the energy consumption of the CHs.

Puri and Bhushan [14] included the k-means clustering approach in their method used in unsupervised ML under clustering since it is beneficial in prolonging the network's life. In this procedure, K points or means are initially assigned at random, and then each item is classified using the mean that is closest to it. The averages of the elements formerly designated as the mean are updated after the mean's placements have been modified. The process is continued until no new modifications to the procedures are found. This approach is called iterative refining.

A novel concept for WSNs that integrates ant colony optimization with k-means clustering for energy-efficient routing is shown in [15]. The findings indicate that the method (AOC + k-means) surpasses the most prevalent power-aware protocols. Fuzzy logic is frequently employed in clustering algorithms because to its relatively lower computational expense, reduced processing demands, efficient implementation, and extended network longevity [16]–[18]. The overhead linked to selecting CH is diminished by the application of fuzzy logic-based clustering techniques. Examples of fuzzy logic-based algorithms include the fuzzy logic-based clustering protocol for uniform size cluster formation (FUSA) [19], CH election with fuzzy logic (CHEF) [20], FLECH [21], energy aware unequal clustering with fuzzy logic (EAUCF) [22], and energy efficient algorithm-fuzzy C-means (EEA-FCM) [23]. Notably, these fuzzy logic-based clustering methods extend the longevity of networks.

4. PROPOSED WORK

The proposed FEECH-BCF approach has the following objectives:

- Generate clusters of uniform size.
- Reduce intra-cluster distance.
- Employ an efficient CH selection method.
- Increase network lifetime.

Euclidian distance is used in the k-means algorithm to form the clusters. Centroids are initially selected randomly within the network. Node ID, its remaining energy, and location are collected [24]. The centroid closest to the node should be chosen after calculating the Euclidian distance between each node and each centroid and updating the location of the centroid till the optimal location is found. However, the clusters created will be of non-uniform sizes initially.

We are inspired by LEACH-USC to assign excess MNs from a larger cluster to a smaller cluster by considering the distance between the next best centroids and excess SNs of the larger cluster. To determine the $Th_{cluster}$, we calculated the total number of SNs within the deployment area and divided it by the required clusters. Two cases exist. In the first scenario, when the remainder is zero, it indicates that each cluster will contain an identical number of MNs. In case 2, when the remainder is non-zero, it can be observed that all but one cluster will contain an equal number of MNs. For example, if the total number of SNs is 50 and the required clusters are 3, then two clusters will have 17 MNs, and one cluster have 16 MNs. The remainder was rounded off by considering the digit in the tenths place; if it is less than 5, both the tenths place and the subsequent place are set to 0. When the digit in the tenths place is 5 or higher, the digit in the ones place is incremented by 1, and all subsequent digits after the decimal point are set to 0. MNs of smaller clusters will also be considered to be assigned to the next best cluster while creating balanced clusters. Balanced clusters created by this method remain the same until the end of the network lifetime, i.e., there will be no reclustering. After making the uniform-sized clusters, CHs will be chosen using the fuzzy logic approach using residual energy and centrality parameters.

4.1. Network configuration

Consider a WSN including 'N' SNs placed within a M×M m^2 area. These SNs detect the environmental physical factors. The network model and its assumptions are outlined as follows: Nodes are uniform, static, and oblivious to their position. Every SN possesses a sleep mode. Nodes can modify their signal power based on free space or multipath propagation conditions.

4.2. Energy model

The first-order radio model calculates the necessary energy for executing various operations. This model posits that the energy expended in data transmission consists of two components: energy lost in operating electronic circuitry and energy utilized in signal amplification. Figure 2 shows an energy model. The energy expended in transmitting a l-bit message across a distance d is represented by (3).

$$E_{Tx} = \begin{cases} l.E_{elect} + l.\epsilon_{fs}.d^2 & d < d_{co} \\ l.E_{elect} + l.\epsilon_{mp}.d^4 & d \geq d_{co} \end{cases} \quad (3)$$

The electronic energy E_{elect} represents the energy dissipation per bit of the transmitter or receiver circuitry, while ε_{fs} and ε_{mp} denote the amplifier models. Here, d signifies the distance between the transmitter and receiver, and d_{co} is the reference distance value. If d is less than d_{co}, the free-space model is employed. If $d \geq d_{co}$, a multipath propagation model is employed. In free space, energy diminishes inversely with the square of the distance. In the ε_{mp} model, energy diminishes inversely to the d^4.

To receive the data, the energy required is (4).

$$E_{Rx}(l) = l.E_{elec} \quad (4)$$

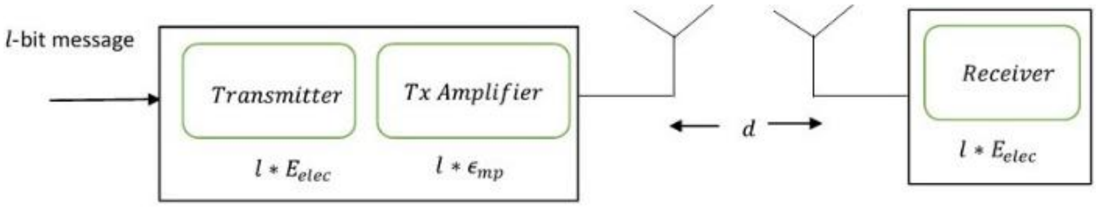


Figure 2. Energy model of WSN

4.3. K-means clustering

The FEECH-BCF approach generates clusters via the k-means algorithm [25] as outlined below.

a. To create ‘k’ clusters, initially position ‘k’ centroids at arbitrary places.
b. The centroid nearest to the node should be selected after computing the Euclidean distance between each node and each centroid. Initial clusters are generated by this ‘k.’ Assume that ‘n’ nodes are provided, each of which belongs to R_d. The challenge of determining the minimum variance clustering of these nodes into ‘k’ clusters involves identifying the ‘k’ centroids $m_j^k = 1$ in R_d such that,

$$\frac{1}{n}\sum\left(mind^2(X_i, m_j)\right) \; for\ i = 1\ to\ n \tag{5}$$

where $d^2(X_i, m_j)$ denotes the Euclidean distance between X_i and m_j. The points $j^k i = 1$ are known as cluster centroids or as cluster means.

c. Recompute the location of each cluster’s centroids and identify any positional alterations from the prior iteration.
d. Proceed to STEP 2 if any centroid positions change; otherwise, the clusters are finalized, and the clustering procedure is completed.

4.4. Load balancing

The proposed algorithm is inspired by the LEACH-USC load-balancing technique. K-means clustering outputs MNs and centroids of each cluster. The proposed FEECH-BCF incorporates a modified refurbishment phase as specified in the following steps, contingent upon the total number of SNs being wholly divisible by the entire number of centroids.

a. Based on the MNs in the cluster, the clusters are sorted in descending order.
b. The largest cluster, which has the highest number of MNs is identified.
c. Excess nodes in the largest cluster k= MNs-$Th_{cluster}$ is calculated.
d. The distance between excess nodes and other centroids is calculated.
e. Cluster centroid, nearest to the largest cluster’s excess MNs, is identified.
f. Assign excess nodes to the nearest centroid cluster.
g. Nodes from which nodes are assigned to the next best clusters whose ‘k’ is now zero will be excluded for further load balancing.
h. Go to step 2 until all clusters have an equal number of MNs.

The concept is explained by considering 100 SNs that are deployed in the deployment area of 100×100 m^2, and 10 clusters are formed. Figure 3 shows how the geographically distributed SNs are assigned as MNs to clusters. Figures 3(a) and 3(b) show the geographical distribution of SNs and the probability distribution of MNs in each cluster after k-means clustering. Figure 3(c) shows that clusters are arranged in descending order. Figure 4 shows how MNs are equally assigned to each cluster. MNs of larger clusters take membership in the next best clusters based on the distance between the MNs and the centroid. Hence formed clusters are well-balanced and have crisp boundaries, as shown in Figures 4(a) and 4(b).

4.5. Fuzzy logic-based cluster head selection

Key components of a fuzzy logic system are the fuzzifier, inference engine, rule base, and defuzzifier. The fuzzyifier is used to converts discrete data into fuzzy sets. The fuzzy rule base is used to generate outputs by Mamdani’s fuzzy inference engine. Figure 5 shows the fuzzy logic system’s block diagram.

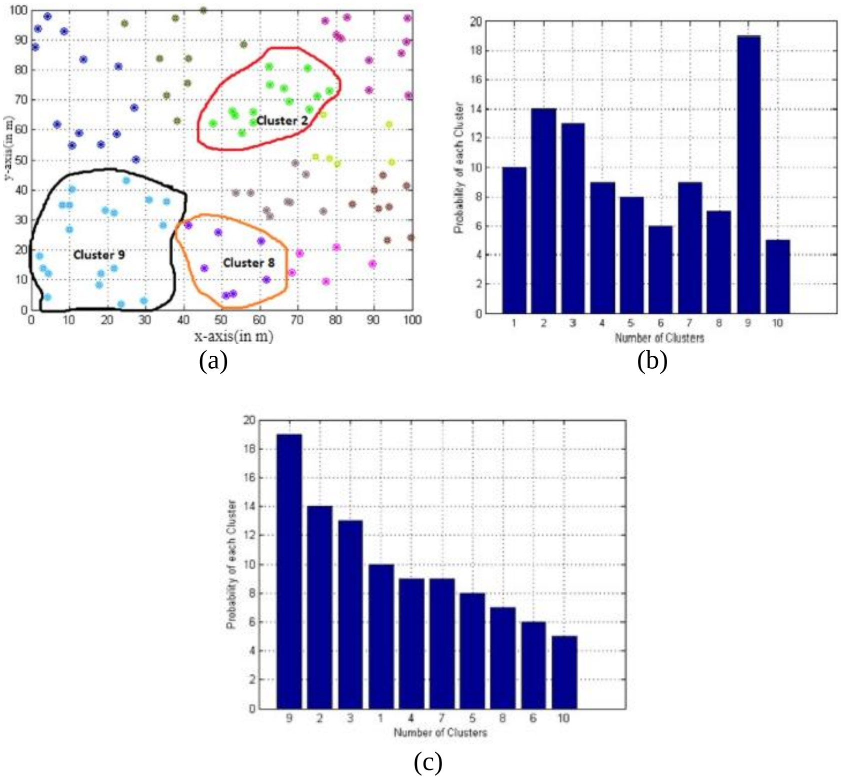


Figure 3. Shows the approach to create clusters of equal size: (a) geographical distribution of SNs, (b) shows the probability distribution of MNs in each cluster, and (c) shows that MNs are sorted in descending order

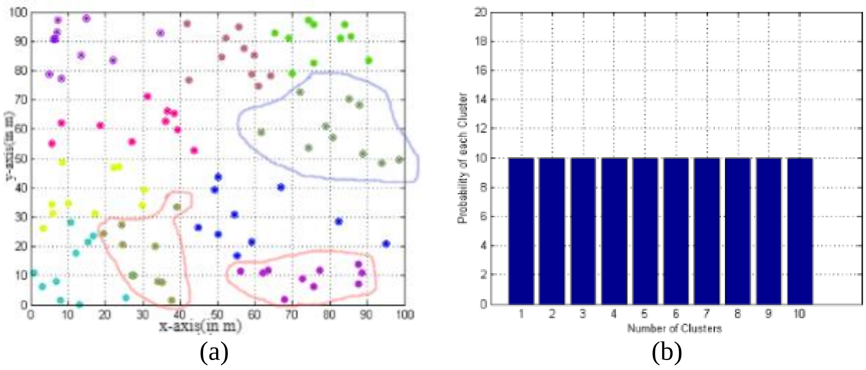


Figure 4. Shows the proposed method (a) of crisp boundary clusters and (b) distribution of MNs equally in every cluster

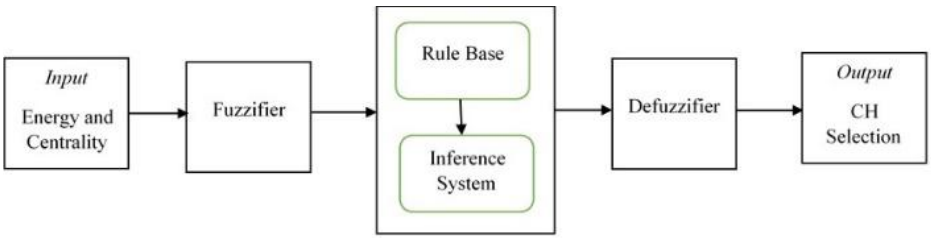


Figure. 5 Shows the typical fuzzy logic system

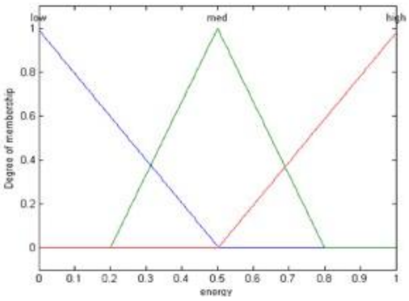
1) Fuzzification: the following fuzzy descriptors are fed into the fuzzifier in the proposed FEECH-BCF.
Residual energy: the energy of a node is crucial in the choosing of the CH. A CH node must possess higher energy levels to accommodate aggregation and transmission demands.
Node centrality: how central a node is among its neighbors in a cluster is known as node centrality [26]. Node centrality nc_i is mathematically defined as (6).

$$nc_i = \frac{\sqrt{\frac{\sum_{j \in n_{nbr}(i)} d^2(i,j)}{|n_{nbr}(i)|}}}{size\ of\ the\ network} \tag{6}$$

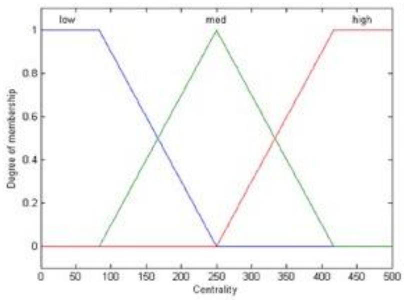
where the size of the network is the length of the edge of the network area M×M m^2. $n_{nbr}(i)$ denotes the number of neighboring nodes associated with node i, while $d^2(i,j)$ signifies the distance between node i and node j. A smaller node centrality value is advantageous since it results in diminished energy consumption.
2) Fuzzy rule base: the fuzzy descriptors in the fuzzy rule base for IF-then rules are node energy and node centrality. We utilize fuzzy AND and OR operators to generate fuzzy rules. The fuzzy inference engine employs a rule base to determine the final probability of each node becoming CH. Very small, small, rather small, mid small, mid, mid large, rather large, large, and very large are the terms used to describe local qualification. Table 1 illustrates a fuzzy rule base.
3) Defuzzification: the defuzzifier transforms the final output into a value referred to as local qualification. Here, the local qualification of the node with "very large" will be the more suitable candidate to become CH, and the least, which has a "very small" local qualification. The plot of the membership functions is presented in Figure 6. The plots of the membership functions for energy, centrality, and local qualification are presented in Figures 6(a)-6(c) respectively.

Table 1. Fuzzy rules for CH selection

Rule	Residual energy	Centrality	Local qualification
1	Low	High	Very small
2	Low	Mid	Small
3	Low	Low	Rather small
4	Mid	High	Mid small
5	Mid	Mid	Mid
6	Mid	Low	Mid large
7	High	High	Rather large
8	High	Mid	Large
9	High	Low	Very large



(a)



(b)

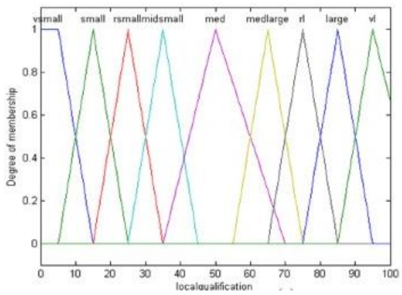


Figure 6. Shows the membership function plot: (a) for energy, (b) for centrality, and (c) for local qualification

The workflow algorithm is provided below:

Algorithm 1. Workflow of FEECH-BCF

```
Input: Number of centroids (X), Each cluster's node count (CLUSTER[]), Thcluster
Important variables: K, largest, MN, Centroid[], SecondBestCentroid[], k
Result: CH, Uniform Size Clusters

k-means Algorithm
1: Indicate the requisite number of clusters.
2: Initialise K centroids in a random fashion.
3: repeat
4: Assign SNs to their nearest Centroids[]
5: Calculate the updated mean for each CLUSTER[]
6: until The locations of the centroids remain unchanged.

Load Balancing Technique
7: Sort CLUSTER[] in Descending order
8: for i = 1; i ≤ X; i++ do
9:      largest = i
10.     MN = CLUSTER[largest]
11.     for j = 1; j ≤ MN; j++ do
12.            SecondBestCentroid[] = Distance to second best centroid
13.     end for
14.     Sort SecondBestCentroid[] in Ascending order
15.     k = MN - Thcluster
16.     if k > 0 then
17.     Sort SecondBestCentroid[] and assign first k nodes.
18.     UPDATE CLUSTER[]
19      end if
20.     The formed cluster of k = 0 is removed from further load balancing consideration
21.     Sort CLUSTER[] in Descending order
22. end for
23. until Uniform Size Clusters

Cluster Head Selection Technique
24. for each CLUSTER[] do
25. MNs calculates localqualification   //refer Table 1
26. Qualified MN becomes new CH
27. Steady state phase
28. Go back to step 24 until network lifetime
29. end for
```

5. RESULTS AND DISCUSSION

WSN will be operational until the energy is present in the network. It is practically not feasible to charge the battery of SNs when the energy gets low. Hence energy conservation is most important to consider while configure ring the network. In our proposed work we considered the hybrid technique along with the core novelty concept. The simulation is conducted using MATLAB. Table 2 describes the primary simulation parameters.

Table 2. Network parameters

Parameter	Network size	Total number of SNs	Initial energy of each nodes	Size of data packet	Sink position (x, y) coordinate	Free space model energy parameter (ε_{fs})	Multipath model energy parameter (ε_{mp})	Data aggregation energy	Required energy to run circuitry (E_{elec})	CH percentage
Value	50×50 m^2	50	2 J	4,000 bits	(25, 48)	10 pJ/bit/m2	0.0013 pJ/bit/m4	5 nJ/bit/signal	50 nJ/bit	5

Initial clusters are formed based on k-means clustering as shown in Figure 7. But the created clusters are of non-uniform size. Here the clusters with fewer number of members will die early due to more often transmission than the cluster with larger number of members. To resolve this scenario, LEACH-USC algorithm can be used to assign the SN membership in such a way that all clusters are of equal size. But, LEACH-USC is complex and time-consuming to recluster after every round and membership is to be assigned each time based on CH location.

In our approach, the clusters are formed based on centroids using k-means algorithm. Members are assigned based on LEACH-USC protocol. We do not perform recluster once clusters are formed and membership of SNs is also fixed as shown in Figure 8. It saves time and energy required for reclustering and selecting CH. Potential CHs are identified by fuzzy logic, considering residual energy and node centrality, as indicated in Table 1, and it is not obligatory to alter the CH after each round.

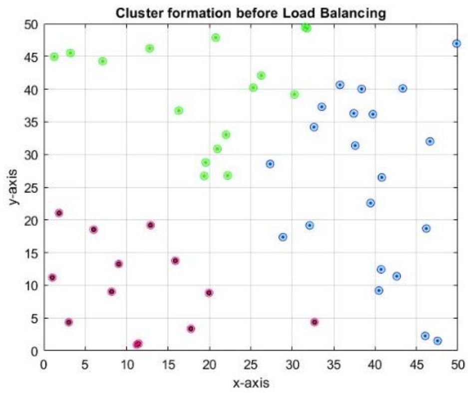


Figure 7. Shows the cluster structure using k-means algorithm

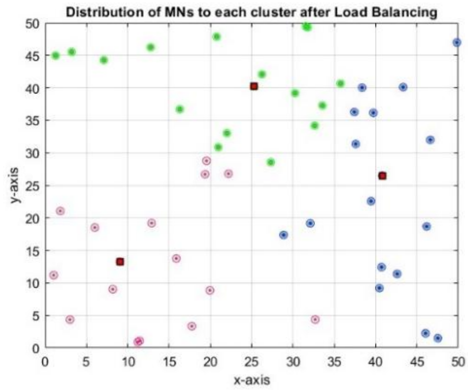


Figure 8. Shows the cluster structure using FEECH-BCF

We made the assumption that every node in the region of interest is identical and distributed at random. The number of rounds, energy usage, and active node count were used to assess the efficiency of the suggested FEECH-BCF system. The network performance evaluation's results have been averaged over 50 iterations. The resulting cluster structures and their quality are compared among LEACH, BCF, LEACH-USC, and FEECH-BCF. Subsequently, the network performance is evaluated in comparison to one another.

5.1. Comparison based on cluster structures

An analysis of the clusters created by LEACH, BCF, LEACH-USC, and FEECH-BCF in a round is presented in this section. SNs will join the nearest CH in case of LEACH protocol, so there is no guarantee of equal-size clusters. BCF forms the clusters in a well-balanced manner in terms of cluster size, but there will be clusters overlapping. LEACH-USC forms clusters of equal size and have crisp boundaries but it is more complex and time-consuming. In contrast, the proposed FEECH-BCF creates well-balanced clusters as shown in Figures 8 and 9.

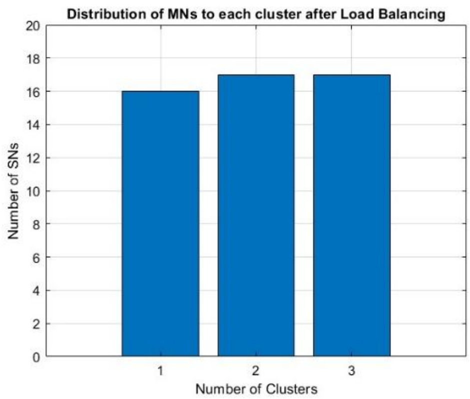


Figure 9. Shows the distribution of MNs to each cluster in FEECH-BCF

5.2. Comparison based on intra-cluster distance

The suggested approach is evaluated against the LEACH, BCF, and LEACH-USC techniques to determine intra-cluster distance. Table 3 presents a compilation of the total intra-cluster distance during different iterations.

Table 3. Comparison of cluster size and total intra-cluster communication distance

Approach	LEACH			BCF			LEACH-USC			FEECH-BCF		
Iteration	1	2	3	1	2	3	1	2	3	1	2	3
Size of cluster 1	20	16	17	18	17	17	17	17	17	17	17	17
Size of cluster 2	9	13	24	15	17	23	16	16	16	17	16	17
Size of cluster 3	21	21	9	17	16	13	17	17	17	16	17	16
Total intra-cluster distance	695	694	791	892	870	995	758	735	889	608	661	502

The intra-cluster distance of BCF is highest due to the predetermined cluster size. During the rescue phase, unclustered nodes will join the clusters based on threshold distance and the maximum permissible MNs per cluster. This method results in a balanced cluster; however, it also leads to an increase in intra-cluster distance. LEACH-USC demonstrates a reduced intra-cluster distance compared with BCF, as the MNs in the largest clusters select membership with the next optimal cluster based on the second-best CH parameter. LEACH results in a reduced intra-cluster distance, as SNs select the nearest cluster membership; however, the clusters exhibit uneven sizes. The proposed FEECH-BCF protocol achieves the minimum intra-cluster distance by allowing excess SNs from the largest cluster to join the next best cluster, determined by proximity to the nearest centroid distance to the SNs. The distribution of members to clusters, determined by centroid location, minimizes intra-cluster distance.

5.3. Network performance

The metrics taken into account for network analysis include the count of active nodes over the rounds, first node death (FND), half node death (HND), and last node death (LND). Figure 10 illustrates the number of nodes that remained operational during the network's lifespan. The results are presented in Table 4.

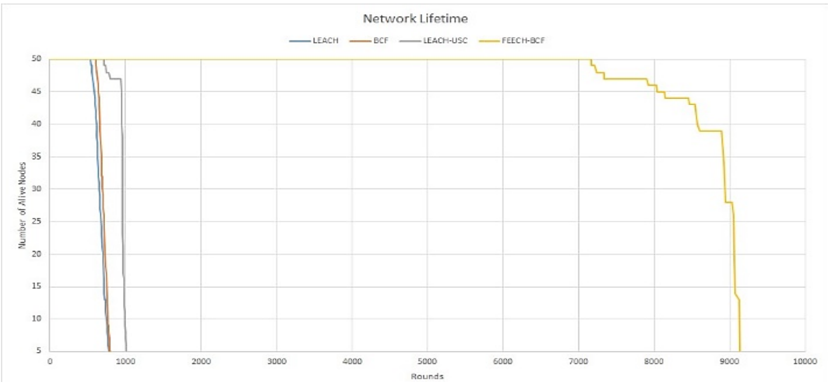


Figure 10. Shows the network lifetime

Table 4. Network lifetime

Approach	Network lifetime		
	FND	HND	LND
LEACH	540	674	800
BCF	612	721	852
LEACH-USC	718	962	1015
FEECH-BCF	7163	9054	9130

Compared with LEACH, FEECH-BCF achieves 1226%, 1243%, and 1041% increase in lifetime for FND, HND, and LND, respectively. While for BCF, FEECH-BCF achieves 1070%, 1156%, and 972% increase in lifetime for FND, HND, and LND respectively. While for LEACH-USC, FEECH-BCF achieves 898%, 841%, and 798% increase in a lifetime for FND, HND, and LND respectively.

During more than 78% of the total network lifespan, all nodes remain operational. The region under monitoring is consistently monitored during the network's lifespan. In comparison to the LEACH-USC, BCF, and LEACH methodologies, the proposed FEECH-BCF demonstrates a markedly lower incidence of node deaths over the network's duration. The suggested approach outperforms previous techniques due to well-balanced clusters, the avoidance of reclustering, reduced intra-cluster communication distance, and effective selection of CHs, significantly enhancing network longevity.

6. CONCLUSION

The FEECH-BCF technique employs a k-means algorithm to establish the initial clusters. The centroids of each initial cluster are used to attain load balancing and fuzzy logic for the selection of optimal CHs. The simulation results indicate that the proposed approach surpasses LEACH, BCF, and LEACH-USC in network longevity and establishes well-balanced clusters, with reduced intra-cluster distance and an efficient CH selection technique.

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