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Optimizing Cluster Head Selection for Enhanced Energy Efficiency in WSNs through AHP and TOPSIS Techniques

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Abstract: Wireless sensor networks (WSNs) describe an infinite number of low-power wireless nodes that are used to monitor and record environmental events and activities, like temperature, humidity readings and fire detection. These days, WSN lifespan and energy consumption are thought to be difficult problems. Numerous routing protocols have been put forth to increase network lifetime and promote energy-efficient wireless communication. When it comes to these protocols, network design is key to enhancing network performance. Net-work design parameters determine how the sensor nodes communicate with one another. In this study, we present an Optimizing Cluster Head Selection through Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution Preference Ranking Organization (TOPSIS) Techniques (OCHSAT) to lengthen the network's lifespan and use less energy. Cluster heads (CHs) are spread, and cluster creation is centralized in the clustering phase. A centralized K-means approach is utilized to create the stationary clustering, and the resulting clusters stay static during the operation. AHP and TOPSIS are used to rank and choose the CHs in the best possible way. TOPSIS is a model for Multi-Attribute Decision Making (MADM) that chooses the optimal option by weighing several competing criteria. Rather than altering CHs with dynamic clustering at every interval, increasing the sensor network's lifespan is our goal by postulating CH dynamicity based on present energy levels using an energy threshold. A customized simulator built on Python was used, the suggested OCHSAT greatly lengthens the network's lifetime and successfully tackles the issue of energy usage.

Keywords: AHP, Clustering, Energy consumption, Improve energy efficiency, K-Means, TOPSIS, WSN

1 Introduction and Overview

The Recent decades have seen the fast development comprising microcontroller units, integrated sensors, and low-power wireless transceivers, which have allowed for the availability of inexpensive, multifunctional, compact sensing platforms. Wireless sensor networks (WSNs) are critical to many application domains, including environmental and healthcare monitoring, transportation management, smart cities and security guarding. Typically, the aggressive, unmonitored environment is where the battery powered sensor nodes are situated. Thus, in WSNs, clustering is a helpful strategy in order to decrease the sensor nodes' energy loss [1], [2]. Cluster Head (CH) is found inside each cluster formed by sensor nodes during the clustering process. The information is subsequently gathered and distributed by this CH to the base station (BS) by data transfer, either one-hop or multiple-hop [3]. Energy usage in WSN is significantly influenced by the CH choice. In addition to enhancing network performance metrics like latency, energy economy, and network longevity, this also helps to balance power usage. In the WSN, CHs are increasingly significant for transmissions both inside and between clusters. Generally speaking, these broadcasts use more energy than non-CH sensor nodes. Every network includes of BS and CH, which serve as gateways to additional sensor nodes [4]. There are several benefits to using clustering algorithms in data collecting networks. The goal of the sensor clustering is to reduce the number of long-distance transfers, which will save energy [5]. Furthermore, by lowering the number of delivered packets, clustering enhances data aggregation at the CH and lowers sensor node energy consumption. Two phases of communication occur during clustering: intra-cluster communication happens within clusters, while communication between clusters happens across clusters and the base station [6] as shown in Figure 1.

In the current study, the BS is in charge of network clustering. Using this centralized method, the network is divided into clusters by the BS. when the protocol first starts, the node is given the function of CH with the highest

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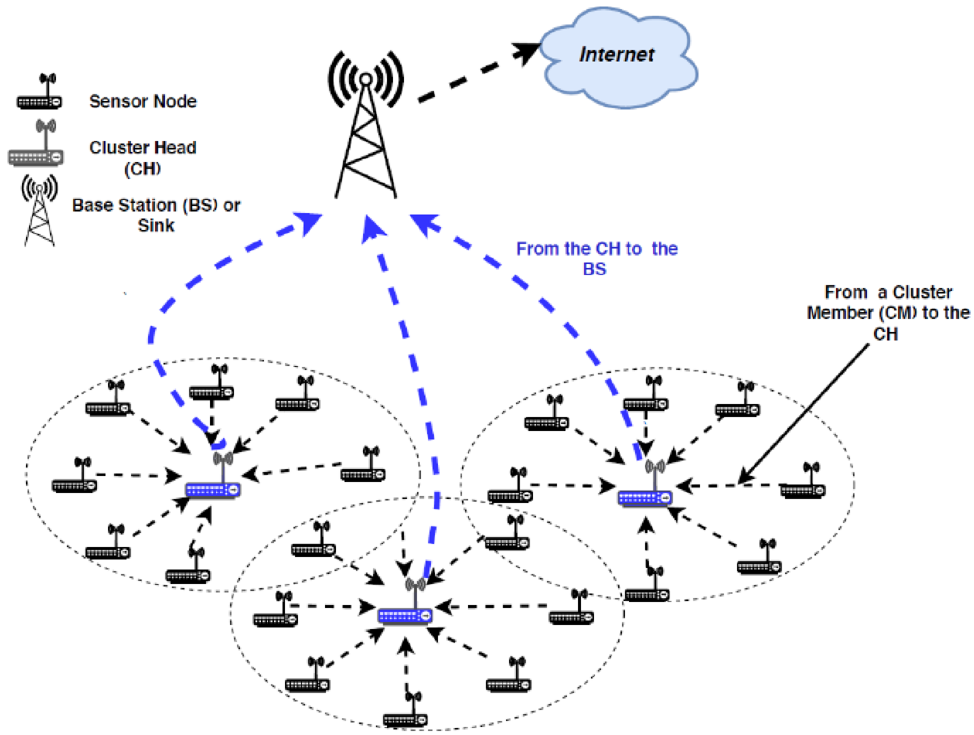

Figure 1. An illustration of a WSN with many clusters.

energy level in each cluster. It then selects and switches the CHs around in such groups based on the different levels of energy in the nodes in order to save energy usage before the data transmission stage to the BS. A centralized K-means method is applied to identify the stationary clustering inside the network, and the clusters that are established stay static throughout the procedure. The CH selection strategy relies on AHP and TOPSIS algorithms. Noteworthy is the fact that different network deployment characteristics influence the proportion of CHs in the system; the most important ones are the network's topology and, in the case of the K-means algorithm, the number of k that meet the needs of the application utilizing this WSN.

The sections of the document that remain are explained below. The related works are included in Section 2. The concept of the network and the model of energy consumption are introduced in brief in Section 3. An extensive synopsis of the recommended protocol is provided in Section 4. The simulation's outcomes and discussions are shown in Section 5. The conclusion of the article is described in Section 6.

2 Related Work

In order for a WSN to function for an extended period of time, one of the primary difficulties in the current study is finding an energy-efficient solution. As a result, optimizing is essential to the operational process of data gathering. WSN lifespan is limited be-cause direct data transfer while data collection, more energy is used traveling from the sensor node to the BS or Sink. Recent years have seen a rise in interest in the study of clustering in ad hoc networks and WSNs.

Many strategies are put out to route data from sensors to BSs. The idea of clustering in WSN was initially introduced by the Low Energy Adaptive Clustering Hierarchy (LEACH). Initially, a random selection of nodes is made as CH in LEACH. LEACH distributes the energy across the nodes using the CH rotation pol-icy. A node that has been designated since CH in LEACH cannot be labeled as CH once more until all other nodes have likewise attained the CH status [7]. LEACH has various downsides. When choosing the CH, it doesn't take into account any parameters like remaining energy (RE), away from the base station, or away from neighboring nodes. Thus, by taking these characteristics into account, other models are suggested as an enhancement over LEACH.

In order to increase network longevity and connectedness, the research presents a modified Adaptive clustering hierarchy with low energy version protocol (LEACH) method [8]. Election criteria are flexible since the procedure for selecting CHs is adjusted according to the network's energy status at any given time. The improved LEACH algorithm's performance is evaluated in relation to packet transfer and network life according to the simulation findings. The findings demonstrate that having more nodes in a WSN does not always translate into increased dependability. There is a connection between the life of the network and the quantity of nodes. Network connection is enhanced with the improved LEACH algorithm, which offers a better packet transfer rate.

Fuzzy C-means (FCM) clustering was presented by the authors in [9] as a technique for choosing the best CH in a WSN. Several parameters are considered in the process of selecting the CH, such as the node degree, node history, energy's leftover ratio, and distance to the BS. The weights allocated to these characteristics are varied using a brute-force method to find the most effective weights that can increase the WSN's lifespan. To guarantee the selection of the optimal CH, experimental simulations are run to assess the efficiency of different combinations of parameters and weights. The efficacy of the suggested technique is juxtaposed with established methodologies like LEACH and FCM. The outcomes of the simulations indicate that the inclusion of the specified parameters enhances network stability by 140.10% and 45.09%, respectively.

An improved method for choosing CHs for Industrial WSNs (IWSNs) is provided in [10] by use of the Multi-Objective Cluster Head Selection Optimization Model (MOCHSOM). Maximize the network node alive time, balance the usage of energy of each network cluster, and decrease the overall network's usage energy are the objectives of the model. The study uses an Evolutionary Algorithm with Reference-point Based Non-dominated Sorting Approach (NSGA-III) in order to enhance the MOCHSOM model. The experimental findings show that, in comparison to traditional clustering techniques, the suggested approach greatly extends the network lifespan.

In [11] an energy-efficient method for choosing the CH and forming clusters (EEA-CFCHS) is a revolutionary technique for heterogeneous WSN that was proposed in the study. The threshold value for energy degeneracy for different types of nodes in a WSN is taken into account by the suggested technique. Each cycle in the procedure finishes with a computation of the remaining energy of CH, and if the energy remaining is less than the threshold value, a new cluster is constructed and a new CH is elected. Network longevity is increased by 62% and stability period by 42%, respectively, with the EEA-CFCHS contributing to a 73.16% increase in network lifetime.

In [12] the study presented the lifespan of WSNs can be extended by using the IMDCH algorithm, which is a CH selection technique based on IMD. The CH and Assistant CH are chosen by the algorithm based on dynamic decision factors such neighborhood degree, residual energy, and distance. By lowering energy usage and routing overhead, adaptive selection seeks to extend network lifetime. In order to evaluate the recommended IMDCH algorithm's effectiveness, two methods currently in use—LEACH and V-LEACH—are contrast-ed. To illustrate the increase in network longevity attained by the recommended approach, the comparisons are provided and analyzed.

In [13] for WSNs, a hierarchical CH selection technique called a selection of K-Weighted CHs (K-WCH) is intended. Through a decrease in dead nodes, the K-WCH technique lowers computing costs and lengthens network lifespan. It makes use of a weight factor to do this. The approach divides sensor nodes into groups, or clusters, and selects CHs for each cluster. Utilizing simulation data, the energy usage is assessed and number of dead nodes of the K-WCH algorithm with various techniques like the LEACH procedure and K-means analysis.

A new method for choosing CHs in WSNs called GWO-CH is described in [14]. It makes use of the grey wolf optimization algorithm (GWO) to pick CHs in a way that uses less energy. To choose the best CHs, the GWO-CH algorithm takes into account variables such sink distance, intra-cluster distance, and residual energy. To ensure effective CH selection and cluster formation, the authors additionally develop an objective function and weight factors. The number of sensor nodes and CHs is changed to test the suggested technique in various WSN settings. The observed findings show that when it comes to achieving improved network performance, the GWO-CH algorithm works better than other methods.

The study in [15] recommended clustering nodes using the k-means algorithm and representing each cluster with one sensor node. To address the non-convex optimization issue of determining the ideal placement for the single CH, particle swarm optimization (PSO) is utilized. enhanced data transmission and network longevity at the BS are achieved by the proposed method.

A weighted K-means based LEACH-C (WLEACH-CK) method was presented by the authors in [16] for the purpose of clustering sensor nodes in a WSN in an energy-efficient manner for effective routing. The Low Energy Adaptive Clustering Hierarchy (LEACH) and its centralized variant, LEACH-C, serve as the foundation for the method. Using the K-means clustering method, the BS decides the ideal number of CHs. The CH is chosen according to the lowest weighted communication distance; the weight is determined by dividing the original energy by the remaining energy. When the system is in a steady state, data is sent from non-CH nodes to their CH. The data is subsequently sent to the BS by the CH following data fusion. According on simulation findings, com-pared to LEACH and LEACH-CK, the suggested WLEACH-CK algorithm achieves well-balanced usage of energy, extending the lifetime of the WSNs.

In [17] a network clustering approach that is independent of dispersion and energy efficient is introduced. By calculating the number of non-uniform and uniform network distributions, the researchers tackled the hole or energy-hotspot problem. The method being discussed is called the Multi-Objective Fuzzy Clustering method (MOFCA). The findings demonstrated the supremacy of MOFCA over alternative established methods in terms of First Node Dies (FND), Half of the Nodes Alive (HNA), and Total Remaining Energy (TRE). An improved multi-criteria zone head selecting method for grid-based WSN was created by the authors in [18], hence introducing the grid-based hybrid network deployment (IGHND) technique. The GHND algorithm was created with the IGHND version, which optimizes zone head selection by taking into account five characteristics as opposed to three. When compared to current approaches, the recommended method's efficacy was demonstrated.

In [4] an Energy-Saving Clustering Algorithm (ES-CA) with distributed CHs and centralized cluster creation was presented for WSNs. The generated clusters stay unchanged during the clustering phase, which is based on a centralized Kmeans algorithm for cluster identification. The ESCA method demonstrates a sizable quantity of residual energy, which increases network longevity and enables nodes to transmit data for longer intervals of time.

A comparison of CH selection algorithms in WSNs shown in Table I.

3 Preliminaries

The models for energy consumption and networks are provided in this section.

A. Network Model

There are N sensor nodes in the network with comparable properties, randomly placed in a $X \times Y$ monitoring region. The suggested approach takes into account the following presumptions:

- The locations of SNs are known, and the network architecture is set.
- Every SN is the same.
- Each SN is energy-constrained and has an initial budget.
- Energy, processing, or network coverage shouldn't be limitations for the BS.
- No consideration is given to radio interference, obstructions, or signal attenuation resulting from the presence of tangible items.
- There is a strong link among the data gathered in each cluster.
- Since the function of aggregation employed by the CHs is the average of the data, all CHs aggregate packet sizes of a similar size.

B. Energy Consumption Model

The usage of energy of nodes is determined utilizing the radio model, sometimes referred to as the first-order radio model [19], [20]. Depending on how close the transmitting and receiving nodes are to one another, Free-space channels and multipath fading are used in this paradigm. The multipath (mp) idea is used if the closeness is greater than a threshold (d_0); if not, the idea of free space (fs) is applied. The calculation of the energy needed to transfer $k-bit$ data bits across a network over a $k-distance$ is explained by Equation (1).

$$E_{TX}(m,d) = \begin{cases} m \times E_{elec} + m \times \epsilon_{fs} \times d^2 & \text{if } d < d_0 \\ m \times E_{elec} + m \times \epsilon_{mp} \times d^4 & \text{if } d \geq d_0 \end{cases}$$

The amount of energy used by the electrical circuit is represented by E_{elec}, whereas the amount of energy used for multipath fading and free-space channels is represented by ϵ_{mp} and ϵ_{fs}, respectively. The following equation shows the energy required Receiving m-bits of data via radio.

$$E_{RX}(m) = m \times E_{elec} \tag{1}$$

Utilizing the formula below, one can determine the total energy used by the CH when collecting data from every member of the cluster:

$$E_{Total} = E_{intra-cluster} + E_{inter-cluster} \tag{2}$$

where

$$E_{intra-cluster} = E_{RX} + E_{DA} + E_{non-CH} \tag{3}$$

The energy used when receiving data is represented by E_{RX}. The term "energy" refers to the energy consumed in aggregation. The energy used by the non-CH nodes in a given cluster is represented by the symbol E_{non-CH}.

$$E_{non-CH} = \sum_{j=1}^{K} \sum_{i=1}^{|C_j|} E_{TX}\left(x_i, CH_j\right) \tag{4}$$

Where $E_{TX}\left(x_i, CH_j\right)$ shows the used energy quantity when sending data starting from node x_i and ending at its CH in the j^{th} cluster, $|C_j|$ specifies the number of nodes in the cluster C_j's, and $j \in [1, 2, \ldots, K]$ represents the number of clusters

$$E_{DA} = m \times |C_j| \times E_{sdb} \tag{5}$$

where E_{sdb} is the aggregate energy of a solitary data bit, where m represents the bit count.

$$E_{inter-cluster} = \sum_{i=1}^{K} E_{TX}\left(CH_i, BS\right) \tag{6}$$

TABLE I. Comparison of Cluster Head Selection Algorithms in WSNs.

Algorithm	Description	Advantages	Disadvantages	Selection Criteria	Network Structure	Centralized/ Distributed	Ref.
LEACH	Random selection of CHs	Simple to implement, distributes energy load	Doesn't consider factors like remaining energy or distance	-	Homogeneous	Centralized	[7]
Improved LEACH	Adaptive CH selection based on current network energy	Improves network lifetime and connectivity	Details on selection criteria not provided	Residual Energy	Homogeneous	Centralized	[8]
Fuzzy c-means (FCM)	Uses fuzzy logic to consider multiple factors for CH selection	Improves network stability	High computational cost	Remaining Energy, Distance to BS, Node Degree	Homogeneous	Centralized	[9]
Optimizing the Multi-Objective Cluster Head Selection Model (MOCHSOM)	Uses evolutionary algorithm to optimize CH selection for IWSNs	Improves network lifetime, balances energy consumption	Complex implementation	Not specified	Industrial WSNs (May/may not be homogeneous)	Centralized	[10]
Energy-Efficient Approach for CH Selection and Cluster Formation (EEA-CFCHS)	Considers energy threshold for heterogeneous WSNs	Significantly increases network lifetime	Relies on predefined threshold	Remaining Energy	Heterogeneous	Distributed	[11]
IMD-based CH selection (IMDCH)	Uses dynamic decision factors for CH selection	Lowers energy consumption and routing overhead	Details on decision factors not provided	Not specified	Homogeneous	Distributed	[12]
K-Weighted Cluster Heads (K-WCH)	Uses weight factor to select CHs and minimize dead nodes	Reduces dead nodes and extends network lifetime	Might not be suitable for highly dynamic networks	Remaining Energy (Weighted)	Homogeneous	Distributed	[13]
GWO-CH	Uses Grey Wolf Optimization algorithm for CH selection	Considers residual energy, distance metrics, and weight parameter	Requires tuning of weight parameter	Residual Energy, Intra-cluster Distance, Distance to Sink	Homogeneous	Distributed	[14]
K-means and PSO for CH selection	Uses k-means for clustering and PSO for CH selection within clusters	Improves data delivery and network lifetime	Two-step approach might increase complexity	Not specified (learns from data)	Homogeneous	Centralized (K-means) & Distributed (PSO)	[15]
Weighted LEACH-C (WLEACH-CK)	Adaptive clustering based on K-means and weighted communication distance	Well-balanced energy consumption and extended network lifetime	Relies on centralized control by BS	Remaining Energy (Weighted)	Homogeneous	Centralized	[16]
Multi-Objective Fuzzy Clustering (MOFCA)	Dispersion-independent and energy-efficient clustering	Superior performance in terms of network lifetime metrics	Might have higher computational cost compared to simpler algorithms	Multiple factors (details in cited work)	Homogeneous	Distributed	[17]
Grid-based Hybrid Network Deployment (IGHND)	Enhanced zone head selection in grid-based WSNs	Improves zone head selection compared to existing methods	Limited to grid-based deployments	Not specified	Grid-based WSNs	Distributed	[18]
Energy-Saving Clustering Algorithm (ESCA)	Distributed CH selection with centralized cluster creation	High residual energy and extended network lifetime	Static clusters might not be optimal for dynamic environments	Not specified	Homogeneous	Centralized for Cluster Creation, Distributed for CH Selection	[4]

Furthermore, if CH does not supply any data on its own; rather, it serves as a gateway node for its members, then

$$E_{CH} = (m \times E_{elec} + m \times E_{DA})\left(\frac{N}{K} - 1\right) + \left(m \times E_{elec} + m \times \epsilon_{mp} \times d^4\right) \quad (7)$$

N is the number of nodes. On the other hand, if the CH engages data generation sense.

$$E_{CH} = \left(m \times E_{elec}\left(\frac{N}{K} - 1\right)\right) + \left(m \times E_{DA}\left(\frac{N}{K}\right)\right) + \left(m \times E_{elec} + m \times \epsilon_{mp} \times d^4\right) \quad (8)$$

C. Types of Messages

The BS sends the subsequent messages to selected CHs and standard sensors:

1) CHs_Advertisement_MSG_Snode

Sink determines the CHs and the sensors in each cluster after performing calculations and computations based on the characteristics. Sink then notifies all sensors about the CH and related cluster. Sensor_ID, CH_ID, and the amount of CH power left will be included.

2) CHs_Advertisement_MSGI_Sink

In addition to transmitting information about the sensors that will be in that CH's area, the sink notifies the gateways about the chosen CH. This message will include the CH_ID and Sensor_IDs. As seen in Figure 2a, a node that is chosen to be a CH in the upcoming rounds creates an ADV message and broadcasts it to its CMs. As a result, as seen in Figure 2b, each CM immediately reacts to join that particular CH.

4 The Proposed OCHSAT Protocol

Within the current study, the researcher suggested a CH selection method according to the AHP and the TOPSIS techniques. It is intended to assist in confronting difficult decision-making situations including several criteria and goals. To choose the optimal CH, the TOPSIS algorithm considers a number of contradictory qualities. The characteristics include the distance to BS, centrality, and residual energy. When taken into account altogether, these characteristics may be used to choose the optimal CH and distribute the load over the network clustering, which is managed by the BS. These criteria are employed in the proposed protocol to give weight to the sensor nodes using the AHP. However, the allocated weights are insufficient to pick a CH as many CHs may have the same estimated weight. To rank the available CHs, a different technique termed TOPSIS is employed. There are three parts to executing the suggested protocol. The first phase is the clustering procedure, which involves two steps: the first utilizing the silhouette score approach or the silhouette coefficient (SC) to determine how many clusters to use. In the second stage, the centralized k-means clustering algorithm is applied, and the clusters that are produced stay unchanged during the procedure. The nodes' remaining energy, distance to the base station, and cluster location in relation to other nodes are all taken into account during the second step, which is known as CH selection. OCHSAT employs a unique measure whereby the sensor node in closest proximity to every other node is selected as the CH, as opposed to the sensor node closest to the centroid. Instead of replacing dynamic clustering with CHs at each period in this investigation, nodes in each cluster can broadcast at significantly lower power levels because the proximity constraint ensures that they remain close to their CH at all times. The researcher goal is to use the current energy levels to hypothesize the dynamicity of CH by applying an energy threshold. After data is transmitted between nodes and CHs in the clusters, The average function is ultimately used to combine the data sets that have been gathered in the CHs and send them to the BS. The suggested OCHSAT protocol flowchart is shown in Figure 3.

A. The Clustering Process

By grouping consistent data points according to a certain similarity metric, clustering — an unsupervised learning technique — increases inter-cluster similarity while decreasing intra-cluster similarity. In order for the network's CHs to be chosen in each round, each sensor node must transmit its location and energy data to the BS once it has been installed. The first stage in creating the OCHSAT protocol consists of two steps. The first step is determining how many clusters will work best. Using the K-means approach, WSN clustering is the second step.

1) The Optimal Number of Clusters

Finding the ideal quantity (k) of clusters is important since the amount of connectivity between clusters increases with k. Nevertheless, if k is reduced, there are a significant number of intracluster contacts. The silhouette score method or the silhouette coefficient (SC) [21], The optimal number of clusters will be ascertained as follows:

$$SC(n_i) = \frac{b(n_i) - a(n_i)}{max\{a(n_i), b(n_i)\}} \quad (9)$$

where $SC(n_i)$ is the sensor node's silhouette coefficient; $a(n_i)$ represents the mean intra-cluster distance, that is, the mean separation between sensor node n_i and every other sensor node in the cluster that n_i is a portion of sensor node n_i's minimal average inter-cluster distance to every cluster where n_i is not a part of is indicated by $b(n_i)$. The SC's value ranges from [-1,1]. When a sensor node receives a score of 1, it means that it is situated distant from neighboring clusters and is quite compact inside the cluster that it is a part of.

2) K-means Clustering

Since one effective technique is K-means clustering that performs well in networks with non-uniform distribution,

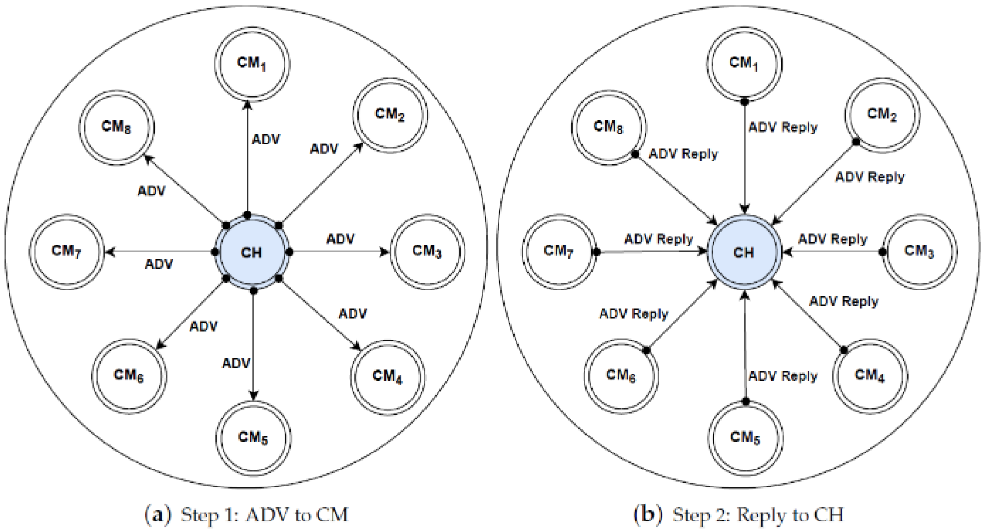

Figure 2. Choice of the energy-saving node to serve as the CH. (a) Step 1: ADV to CM; (b) Step 2: Reply to CH.

we employed it in this research. If the sensor nodes are distributed evenly, manually segmenting the network is simpler and there is no need to apply a method based on machine learning to group the nodes. The BS implements the K-means method to divide based on these locations, the network is divided into dense clusters. Additionally, it employs each node's energy level to identify every CH in the network. The clustering results are then sent directly to each and every node via the BS.

In actuality, because of the different types of nodes, the BS immediately sends the id of CH of the cluster i to which the SN belongs if it is a member node; if the node is a CH node, on the other hand, the CH receives the BS acknowledgment right away. The centralized process of network clustering is illustrated in Figure 4.

The first division of K clusters, $C = \{C_1, C_2, \ldots, C_K\}$, which the corresponding centroids indicate, $\mu = \{\mu_1, \mu_2, \ldots, \mu_K\}$, The K-means method randomly sets it. The next step involves using the unsupervised technique to shorten the time it takes for each sensor to get to the closest center.

$$J_{min} = \sum_{j=1}^{K} \sum_{x_i \in C_j} ||x_i - \mu_j||^2 \tag{10}$$

where x_i represents the C_j cluster's i^{th} node and $|C_j|$ specifies the number of nodes in the cluster C_j, $j \in [1, 2, \ldots, K]$, and μ_j denotes the sensor nodes' actual location (centroid) within the cluster C_j.:

$$\mu_j = \left(\frac{1}{|C_j|} \sum_{X_i \in C_j} X_i, \frac{1}{|C_j|} \sum_{Y_i \in C_j} Y_i \right) \tag{11}$$

The cluster sizes in this study are selected to ensure that there is only one hop required for communication between each node and the CH. This tactic makes sure that each cluster has a higher density and, as a result, that every member of the cluster is close to every other member. Because of this close proximity, reliable information may still be obtained in the cluster-monitored area even after several nodes in another zone's jurisdiction have failed.

B. The Cluster Head Selection

In this study, clustering is done before CH selection for the sake of reducing the amount of energy used amid the cluster construction procedure. Using techniques from Multi-Attribute Decision Making (MADM), the CH are chosen following the establishment of the cluster. The optimal set of CHs is chosen using MADM methods. In this section, we have applied AHP and TOPSIS to rank in the middle of the group. In our suggested study, we have chosen the CH based on three characteristics. The criteria include remaining energy, centrality, and distance to BS.

1) AHP Weight Calculation

When faced with several possibilities, decision-makers might utilize the Analytical Hierarchy Process (AHP) technique to make choices. Thomas Saaty, an American economist and mathematician, created AHP in the 1970s. The weights of the criteria are estimated using the AHP approach, and a pairwise comparison matrix (P) is created as in Equation (13). Weights are calculated according to the application and preferences. To obtain the decision matrix (E_{ij}), the first obtained matrix is normalized as in Equation (14). The scale of relative significance presented in Table II. AHP is used to evaluate difficult decisions. AHP Steps:

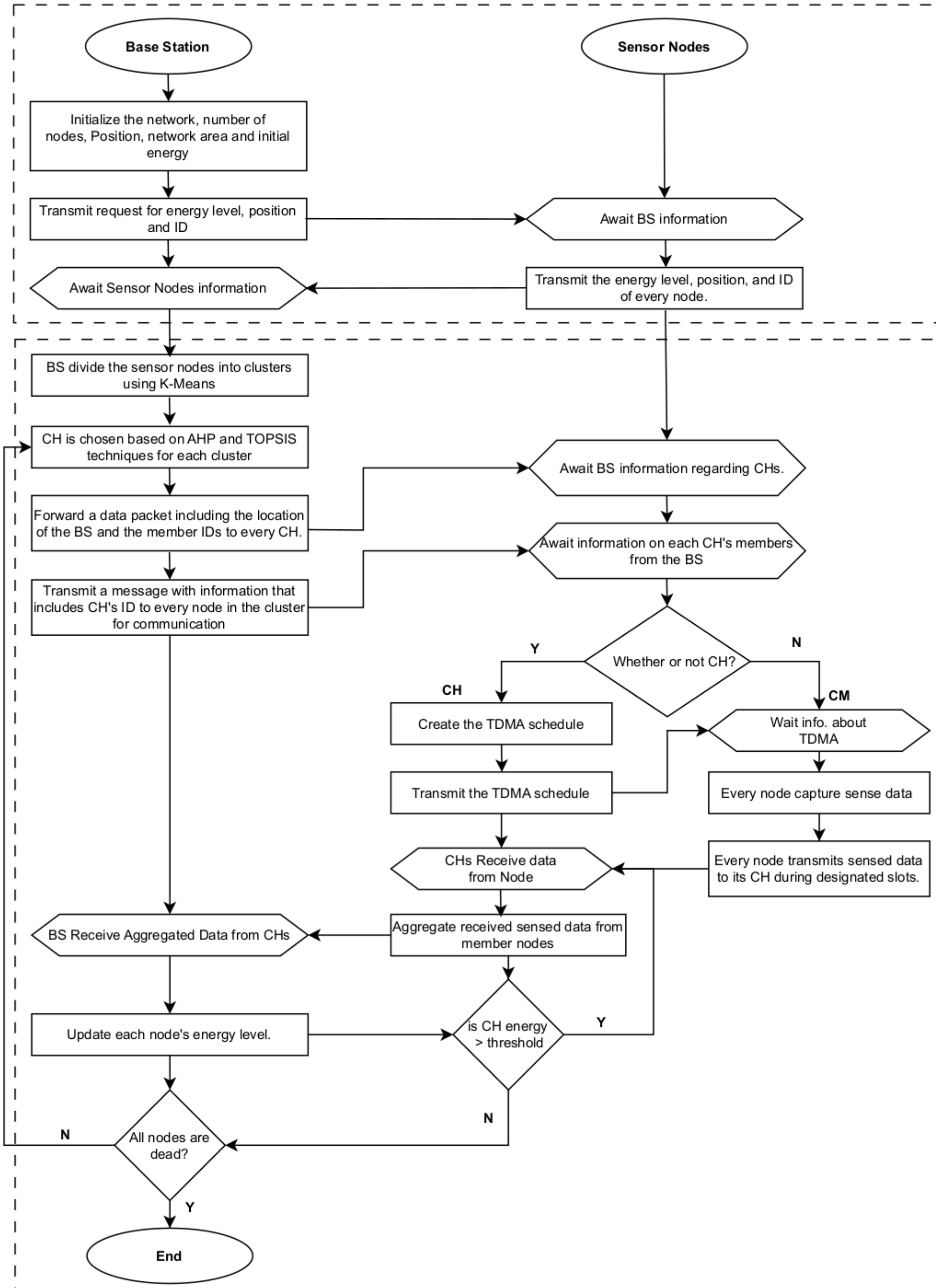

Figure 3. Flowchart for the proposed OCHSAT protocol.

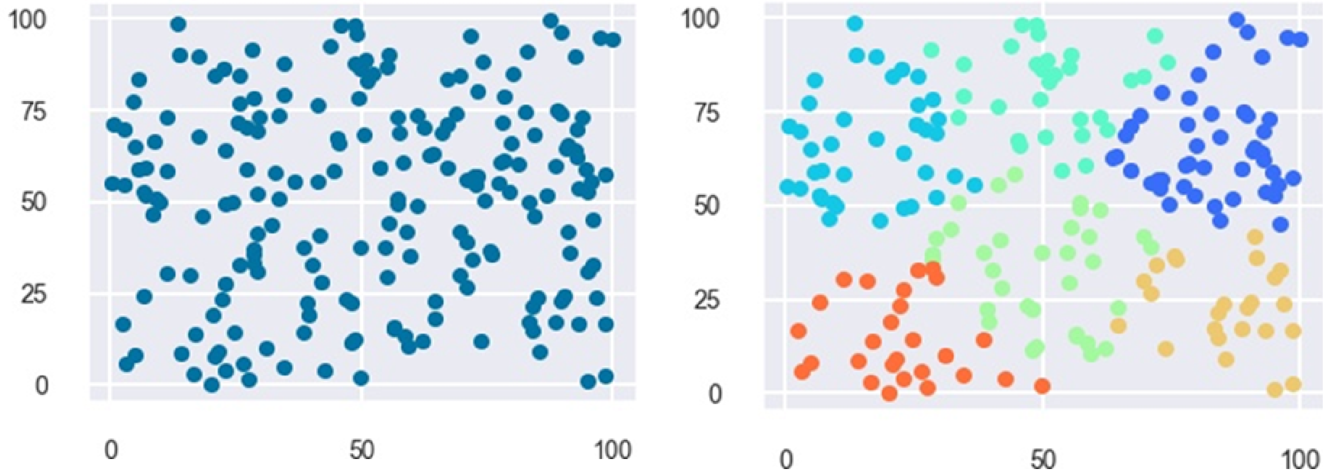

Figure 4. The centralized procedure of clustering network.

TABLE II. Relative importance scale.

Definition of intensity of importance	Definition
1	Equal significance
2	Weak
3	Moderate significance
4	Moderate plus
5	Strong significance
6	Strong plus
7	Very strong or Demonstrated significance
8	Very, very strong
9	Extreme significance

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{pmatrix}$$

$$\epsilon_{ij} = \frac{p_{ij}}{\sum_{i=1}^{n} p_{ij}} \tag{12}$$

Utilizing Equation (15), the normalized weighted decision matrix (W) on specific criterion n is calculated and generated.

$$W = \frac{\sum_{i=1}^{n} \epsilon_{ij}}{n} \tag{13}$$

and

$$\sum_{j=1}^{m} W_j = 1 \tag{14}$$

Pairwise Comparison Matrix Construction: Create a pairwise comparison matrix (W) for the criteria an sub-criteria. The relativity scale in Table II may be used to create the matrix W, which has components w_{ij} that indicate the relative relevance of criteria i in relation to criterion j. The significance ratio of i to j is represented by the positive real number w_{ij} for each element. Typically, specialists or decision-makers complete the matrix.

2) TOPSIS Calculation

The TOPSIS multi-criteria decision-making method is presented for the first time by [22]. It is regarded amongst the top models for multi-index decision making. To choose the best options, it considers a number of factors, each with a weight assigned to it. The TOPSIS approach is used to determine the ranking of CHs after the weight matrix was computed using AHP in the preceding section. Below is a description of the TOPSIS technique:

- Step 1: Create the decision matrix using the calculated criterion weights, as shown in Equation (13) Based on the determined weights of the criterion, as provided by Equation (16), create the decision matrix.

$$DM = \begin{pmatrix} d_{11} & d_{12} & \cdots & d_{1m} \\ d_{21} & d_{22} & \cdots & d_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nm} \end{pmatrix}$$

- Step 2: Using Equation (17), compute the normalized decision matrix (DM).

$$F_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij}^2}} \tag{15}$$

where $i = 1, 2, \ldots n$ and $j = 1, 2, \ldots m$.

- Step 3: Determine the normalized weighted decision matrix using Equation (18)

$$W2_{ij} = W_j \times F_{ij} \tag{16}$$

and

$$\sum_{j=1}^{m} W_j = 1 \tag{17}$$

- Step 4: The alternative is estimated and provided by Eqs. (19) and (20) for both positive and negative ideal solutions. Positive and negative impacts on the linked criterion are shown by the $u+$ and $u-$.

$$AIS^+ = [u_1^+, \ldots, u_m^+] = [(max_i W2_{ij} | i = 1, \ldots, n), j = 1, \ldots, m] \tag{18}$$

$$AIS^- = [u_1^-, \ldots, u_m^-] = [(max_i W2_{ij} | i = 1, \ldots, n), j = 1, \ldots, m] \tag{19}$$

- Step 5: Determine how far the options are from X^+ and X^-.

$$X_i^+ = \sqrt{\sum_{j=1}^{m} \left(W2_{ij} - u_j^+\right)^2} \quad , i = 1, \ldots, n \tag{20}$$

$$X_i^- = \sqrt{\sum_{j=1}^{m} \left(W2_{ij} - u_j^-\right)^2} \quad , i = 1, \ldots, n \tag{21}$$

- Step 6: Equation 23 can be used to determine the relative closeness G_i^* of the alternative from the negative ideal solution.

$$G_i^* = \frac{(X_i^-)}{(X_i^+ + X_i^-)} \quad , i = 1, \ldots, n \tag{22}$$

- Step 7: G_i^* will be used to rate each option, and the CH will be selected from among the nodes having the greatest G_i^* value.

C. Transmission of Data

The CHs are identified, and then the cluster members (CM) start sending data to respective CHs. The K-means algorithm clearly finds the lowest geographic distance to the CHs, which reduces the communication power of CM nodes. Data aggregation is carried out by the CHs, which lowers the amount of data and sends it to the BS. Every CM is assumed to have data to send at all times. The CH has to maintain its radio receiver turned on so that all data may be received from its CMs, regardless of the connectivity inside each cluster.

The distance separating the CH and its CMs is much less than separating between the BS and the CH, hence this transmission consumes more energy than other data transmission activities.

5 Simulation and Performance Evaluation

The recommended method is simulated using Python. Numerous scenarios are created for the simulations to show how successful the recommended method is. In a $100 \times 100M^2$ network, a selection of 100–200 sensor nodes is made. Initially, the BS is placed in the center of the network; later, it is moved to the corner. Consequently, four distinct scenarios are created, as seen in Table III. The settings utilized in the simulation are shown in Table IV. Performance comparisons are made between the suggested approach and popular clustering techniques such as MOFCA, IGHND, and ESCA.

TABLE III. Scenarios of assessment for the suggested technology.

Scenario	Network size	Nodes' count	BS location
SCEN#1	100×100	100	(50,50)
SCEN#2	100×100	200	(50,50)
SCEN#3	100×100	100	(100,100)
SCEN#4	100×100	200	(100,100)

TABLE IV. Parameters for simulation.

Parameters	Values
Network size (m2)	100×100
Nodes deployment	Randomly
BS location	Corner, Center
Nodes count	100 and 200
Initial energy	0.5 J
Data packet	4000 bits
Eelec	50 nJ/bit
Efs	10 pJ/bit/m2
Emp	0.0013 pJ/bit/m4
EDA	5nJ/bit/signal
d0	87 m

The network's lifespan is computed taking into account different circumstances. When calculating WSN efficacy, network longevity is a crucial factor to take into account. The number of rounds in which the initial node fails is represented by this measure. Table V displays The protocol-specific settings for the first node death (FND). The network lifetime for each of the four different node design scenarios is shown in Figures 5-8. The recommended approach shows 62–85%, 19–53%, and growth over the course of a lifetime compared to MOFCA, IGHND, and ESCA. In every one of the four scenarios, MOFCA, IGHND, and ESCA perform poorly, while the recommended approach works superbly.

Even when the node density increases, more rounds are generated by the OCHSAT protocol. The outcomes of cases 1 and 2 show that the network's lifespan may be increased by placing the BS close to the observation field's center.

TABLE V. Evaluation scenarios for the proposed technology.

Scenario	MOFCA	IGHND	ESCA	OCHSAT
SCEN#1	485	514	723	831
SCEN#2	419	491	787	905
SCEN#3	365	482	720	828
SCEN#4	284	440	773	888

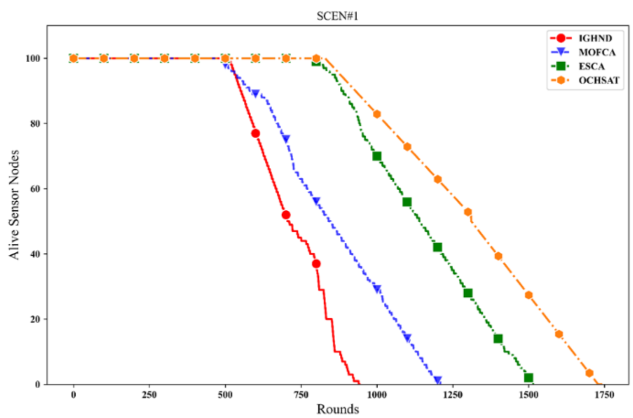

Figure 5. The Scenario 1 number of living sensor nodes compared to rounds.

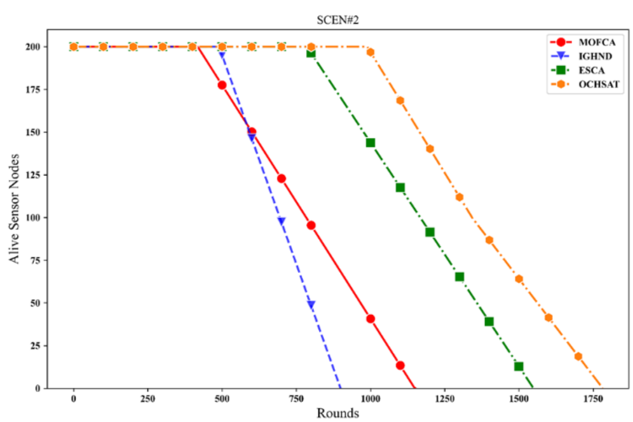

Figure 6. The Scenario 2 number of living sensor nodes compared to rounds.

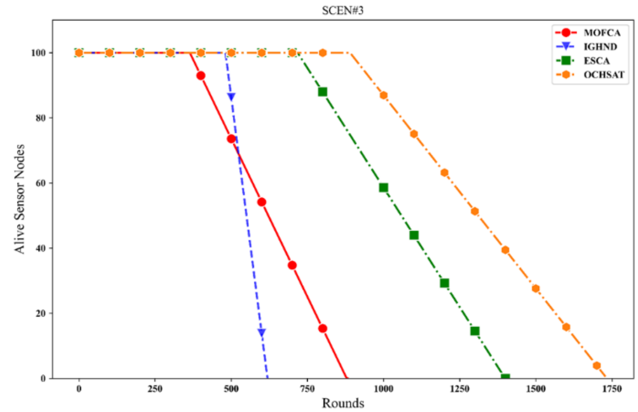

Figure 7. The Scenario 3 number of living sensor nodes compared to rounds.

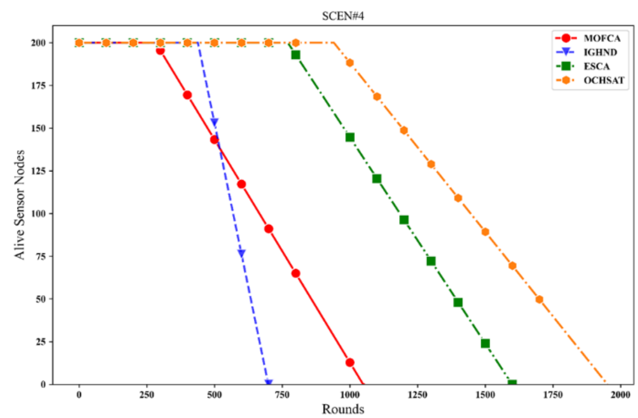

Figure 8. The Scenario 4 number of living sensor nodes compared to rounds.

Network residual energy is another metric to evaluate the proposed method. Table VI and Figure 9 give the mean remaining energy for each algorithm in every iteration for each situation. This energy computation considers all expenses throughout a round, such as data aggregation, both within and between clusters of information and cluster construction. When comparing the OCHSAT proposed approach with the MOFCA, IGHND, and ESCA procedures, there is a substantial quantity of energy left over. The network will last longer as a consequence of the energy savings, enabling nodes to deliver data for longer stretches of time.

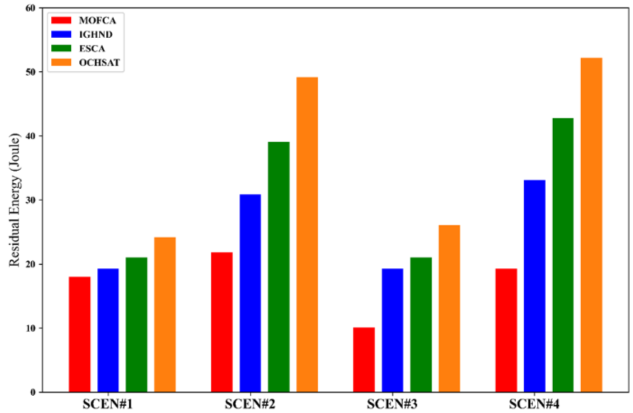

Figure 9. The residual energy.

TABLE VI. Assessment scenarios for the proposed technology.

Scenario	MOFCA	IGHND	ESCA	OCHSAT
SCEN#1	17.99	19.28	21.02	24.173
SCEN#2	21.84	30.88	39.07	44.9305
SCEN#3	10.11	19.30	21.06	24.219
SCEN#4	19.30	33.08	42.77	49.1855

6 Conclusions

This paper addresses the topic of decreasing energy waste in WSNs. When employing the K-means method for network clustering, the silhouette approach is used to determine the ideal number of clusters. For the sake of lowering network usage of energy and distribute the load across nodes, CHs are selected using TOPSIS and AHP. The suggested method is contrasted with well-known clustering techniques that are currently in use for diverse network scenarios. The network lifetime significantly increases in all of the cases. Compared to MOFCA, IGHND, and ESCA, the recommended approach displays within a lifetime, 62–85% and 19–53% expansion. Future evaluations of the proposed technique might consider node mobility and obstacles within the region of interest.

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