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Entropy Weighted TOPSIS Based Cluster Head Selection in Wireless Sensor Networks under Uncertainty

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Abstract: In recent decades, wireless sensor networks (WSNs) have become a popular ambient sensing and model-based solution for various applications. WSNs are now achievable due to the developments of micro electro mechanical and semiconductors logic circuits with rising computational power and wireless communication technology. The most difficult issues concerning WSNs are related to their energy consumption. Since communication typically requires a significant amount of energy, there are some techniques/ways to reduce energy consumption during the operation of the sensor's communication systems. The topology control technique is one such effective method for reducing WSNs' energy usage. A cluster head (CH) is usually selected using a topology control technique known as clustering to control the entire network. A single factor is inadequate for CH selection. Additionally, with the traditional clustering method, each round exhibits a new batch of head nodes. As a result, when using conventional techniques, nodes decay faster and require more energy. Furthermore, the inceptive energy of nodes, the range between sensor nodes and base stations, the size of data packets, voltage and transmission energy measurements, and other factors linked to sensor nodes are also completely unexpected due to irregular or hazardous natural circumstances. Here, unpredictability represented by Triangular Fuzzy Numbers (TFNs). The associated parameters of nodes were converted into crisp ones via the defuzzification of fuzzy numbers. The fuzzy number has been defuzzified using the well-known signed distance approach. Here, we have employed a multi-criteria decision-making (MCDM) approach to choosing the CHs depending on a bunch of characteristics of each node (i) residual energy, (ii) the number of neighbors, (iii) distance from the sink, (iv) average distance of cluster node, (v) distance ratio, and (vi) reliability. This study used the entropy-weighted Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) approach to select the CH in WSNs. For experiments, we have used the NSG2.1 simulator, and based on six characteristics comprising residual energy, number of neighbor nodes, distance from the sink or base station (BS), average distance of cluster nodes, distance ratio, and reliability, optimal CHs have been selected. Finally, experimental results have been presented and compared graphically with the existing literature. A statistical hypothesis test has also been conducted to verify the results that have been provided.

Keywords: wireless sensor networks; base station; TOPSIS; entropy; multi-criteria-decision-making; NSG2.1 simulator; NS2 simulator

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1. Introduction

WSNs have become popular as model-based ambient sensing solutions for various applications. Due to the advancements in microelectromechanical logic circuits, semiconductor logic circuits, growing computing power and communication capabilities, wireless sensor networks have recently become more popular. A WSN is mainly composed of sensor devices from different geographical locations. The sensor node may perform some functionalities, including accumulating sensed information and communicating with other interconnected sensors [1]. Various WSN development efforts aim to address sensor nodes' design, implementation, and deployment issues depending on a specific need for monitoring and sensing in real-time applications. A WSN type casting depends on the type of environment in which it is applied, like environment monitoring [2], industrial applications [3], surveillance [4], military applications, automation in transportation, and healthcare systems [5]. It has been observed that a WSN comprises of many detecting nodes and a base station (BS). The detecting nodes must transmit data to the base station through diverse areas. Source and sink are other names for the BS and the sensing node, respectively. The sink must gather and analyze the data from all source nodes in the network. The WSN may be used to connect to the base station, which may not have any energy restrictions.

On the other hand, the sensor nodes are completely dependent on their batteries, and they become inactive when they run out of power. Effective battery backup is critical for any WSN strategy based on the difference between WSN protocols and conventional wireless systems. By incorporating diverse clustering techniques, various techniques/methods have been proposed to effectively allocate nodes' energy in WSNs [6,7]. Non-stationary sensors gradually replace individual smart sensors, which sense, process, and transmit significant information. The merger of several sensors, processors, and other communication devices into a single sensor node component has allowed this to happen. Sensor nodes in large numbers are distributed to form a sensor network. WSNs are extensively used in several sectors viz. green agriculture, healthcare monitoring systems, environmental surveillance [8,9], smart homes [10], air purifiers [11], and disaster management systems [12,13], due to their easy integration, self-organization, and real-time tracking characteristics. Sensor nodes are usually deployed in vulnerable conditions, making battery replacement and node restoration difficult.

Moreover, enhancing the battery performance of nodes is very expensive. As a result, researchers have paid more attention to improving network lifetime and stability using existing network protocols [14]. In WSNs, one of the conventional relaying strategies is flat architecture or hierarchical architecture. Flat architectural techniques experience enormous amounts of information as a network's hubs grow, resulting in inefficient power generation and a lack of flexibility. Due to this, hierarchical routing algorithms have become more prevalent. Low-Energy Adaptive Clustering Hierarchy (LEACH) [15] is the hierarchical protocol for WSNs. LEACH tends to be the most prominent and commonly used protocol compared to the other protocols.

Moreover, it is a challenging task to obtain information from the interconnected network environment. While transmission will occur, receiving this data at the BS simultaneously is impossible. Using techniques like time division multiple access, node information synchronizes in LEACH-Fuzzy Clustering (LEACH-FC) [16] to acquire the remaining energy information across networks. Along with making a range of information accessible, LEACH-FC also increases the BS's computing capability compared to the nodes. Consequently, such a centralized process can be used to enhance clustering. Energy consumption depends on their connection while data is transmitted from a node to a BS. Nodes that are not CHs, which aggregate and distribute data from neighboring nodes, can transmit information farther due to clustering. As a result, good CH selection provides improved energy efficiency.

Clustering is the method used in WSNs for wireless communication. Each cluster's controller also called the "cluster head, " collects all the data from each sensor node in that cluster and transfers it to the intended location. The node that gets the message from the cluster head joins the cluster after every successive round. If the cluster contains many nodes, the CH will reduce the message's intensity so fewer nodes may receive it. On the other hand, if the cluster size is small, the CH will increase the message strength to enable many nodes to receive the message [17]. Sensor nodes are distributed relatively densely to meet coverage requirements, allowing some nodes to be idle and extending the network's life. The number of neighbors, the residual energy level, the distance between the cluster head (CHs) and the receiving station, the rate at which charge is diminished over data transmission, and the average distance between nodes of the same cluster are only a few of the variables that are taken into consideration when selecting a CH. Utilizing multiple attribute decision-making (MADM) techniques helps simplify the difficult and occasionally laborious process of choosing CHs [18–21]. Various MADM/MCDM techniques address different decision-making problems in engineering, science, and even social science. This strategy's guiding premise is to select options based on many qualities or criteria, which frequently causes problems in real-world applications because estimating the exact value of all the traits or features is difficult. Fuzzy-based techniques can also be used to lessen these kinds of challenges [22,23]. Cluster head selection is vital for efficient data aggregation, network scalability, load balancing, accurate decision-making, and ensuring security in wireless sensor networks. It determines energy distribution, reduces communication overhead, extends network lifetime, and enhances data fusion. Proper selection maximizes network performance and optimizes resource utilization. Several studies have been made to select CHs based on a single parameter. It has been observed that CHs selected by a single parameter may decrease the network lifetime. Therefore, we have included six characteristics/parameters used to determine the CHs in this research. These characteristics are mainly (i) residual energy (ii) the number of neighbors (iii) distance from the sink, (iv) average distance from cluster node, (v) distance ratio, and (vi) reliability. In this study, we have adopted the entropy weighted TOPSIS method [24–26] to select the cluster head in WSNs depending on each node's mentioned characteristics.

Here, we have applied these approaches to extend the network's lifetime. Generally, the CHs selection problem is solved, assuming that the initial energy and other related parameters are precisely determined. Also, due to the non-availability of the distribution function of the measurement system, all the parameters can be measured in terms of some special values. However, in reality, the irregular/dangerous natural conditions also cause completely unanticipated changes in the initial energy of nodes, the distance between sensor nodes and base stations, the size of data packets, voltage and transmission energy measurements, and other elements connected to sensor nodes [27,28]. Therefore, the possibility of adjusting the parameter is quite important. Therefore, erroneous parameter values result in uncertainty measures. As a fuzzy set is very helpful in representing uncertainty, Triangular Fuzzy Numbers (TFNs) were used in this work to convey uncertainty [29,30]. The associated parameters of nodes were then converted into crisp ones via the defuzzification of fuzzy numbers. The commonly accepted signed distance technique was used for defuzzification in this scenario. For experiments, we considered a hundred nodes of WSNs where all the nodes were randomly distributed within a 100×100 m^2 area and utilized the OPNET modeler to assess the MAC layer functionality of 802.15.4 slotted CSMA/CA. Here, we also considered uncertain parameters for the entire network setup. Overall, the work conducted for this study can be summed up as follows: (i) Cluster head selection in the WSN has been conducted using the entropy-weighted TOPSIS approach. (ii) TFNs were utilized to express all the metrics, including initial node energy, the distance between sensor nodes and base stations, data packet size, voltage and transmission energy measurements, and other aspects related to sensor nodes. (iii) We used uniform distribution to create all nodes in the network design. (iv) The NSG2.1 Simulator was employed for the simulation process. (v) For experiment purposes, the Ad hoc On-Demand Distance Vector (AODV) routing protocol [31] was employed. Finally, experimental results were presented and compared graphically.

The rest of the work is presented as follows. The fundamental mathematical underpinnings and approaches used to build the entire work and theoretical background are presented in Section 2. Section 3 gives certain assumptions and notations to help with the investigation. The mechanism for forming cluster heads for WSNs has been explained in Section 4. Numerical experiments and discussions have been made in Section 5. Section 6 of this study contains its concluding observations.

2. Theoretical Background and the Related Work

This section presents related work as well as some essential concepts that have been employed throughout the investigation.

2.1. Background and Related Work

MCDM and TOPSIS [32] are highly useful in WSN applications. MCDM [33] enables informed decision-making by assessing multiple criteria, such as energy efficiency, coverage, and cost [34]. Meanwhile, TOPSIS ranks alternative WSN solutions based on their similarity to an ideal solution. By employing these methodologies, decision-making processes and optimization in WSN deployments can be significantly enhanced. In WSN, energy consumption is a major issue for several researchers [35,36]. The MCDM approach using TOPSIS has been used to select efficient CHs that enhance accuracy, extend network lifetime, and reduce CH-associated energy consumption overhead [37,38]. Another approach, cluster protocols [39], provides improved energy efficiency, scalability, fault tolerance, data aggregation, extended network lifetime, and efficient routing in WSNs, making them a valuable choice for WSN deployments. There are several clustering protocols, like LEACH, Adaptive Periodic Threshold-based Energy-Efficient Network (APTEEN) [40], Power-Efficient Gathering in Sensor Information Systems (PEGASIS) [41], Centralized LEACH (LEACH-C) [42], Cross-Layered Clustering and Cooperative Communication Hybrid Architecture (C3HA) [43], Hybrid Energy-Efficient Distributed Clustering (HEED) [44], Modified LEACH (LEACH-M) [45], and Adaptive LEACH (ALEACH) [46], have been applied to extend the network's lifetime. LEACH introduced the concept of clustering in WSNs, utilizing a randomized rotation of cluster heads to distribute energy consumption evenly. It offers energy efficiency and scalability. The main issue related to LEACH is that it chooses the CHs randomly, directly impacting the network lifespan. Compared to LEACH, APTEEN uses a dynamic threshold-based approach to select cluster heads, considering residual energy and distance to the base station. It improves network lifetime and energy efficiency. PEGASIS is another popular clustering protocol that optimizes data aggregation and transmission by forming a series of sensor nodes. It reduces energy consumption and extends the network lifetime. Another important factor that improves the quality of WSN communication is reliability. The above protocol omitted the reliability factor introduced by C3HA. C3HA integrates cross-layer information exchange and cooperative communication to enhance network performance, reliability, and energy efficiency. LEACH-M addresses the shortcomings of LEACH by incorporating a mobility-based clustering approach. It adapts to node mobility and improves network stability, whereas ALEACH enhances the LEACH protocol by dynamically adjusting cluster formation based on network conditions, energy levels, and data requirements. The selection of CHs using several network parameters has been introduced by HEED, which incorporates residual energy and node proximity as basic criteria for selecting CHs. Upon reviewing multiple WSN studies focused on extending network lifetime, a clear correlation has been found between clustering mechanisms and selecting suitable CHs. This study aims to extend the network lifetime by dividing the network into an appropriate number of clusters and employing the entropy-weighted TOPSIS technique to select CHs based on six network parameters. Additionally, this study introduces uncertainty using triangular fuzzy numbers (TNF) for defuzzifying experimental parameters, enhancing the research's depth and complexity.

2.2. Basic Concepts of Fuzzy Sets

Let X be a universal set. A fuzzy set is formed by a function $\mu_{\widetilde{A}}(x)$, that corresponds each element x in X to a real number in the interval $[0,1]$. The function $\mu_{\widetilde{A}}(x)$ is designated as a membership function in the fuzzy set $\widetilde{A}$. An α-cut of a fuzzy set $\widetilde{A}$ is a crisp set A_α that covers all the points of X that have a membership grade in $\widetilde{A}$ greater than or equal to the prefixed value α. It is defined as $A_\alpha = \{x \in X : \mu_{\widetilde{A}}(x) \geq \alpha\}$, where $\mu_{\widetilde{A}}(x)$ is the membership function of $\widetilde{A}$, $\alpha \in [0,1]$. A fuzzy set $\widetilde{A}$ is normal if there exists at least one element $x \in X$ such that $\mu_{\widetilde{A}}(x) = 1$. $\widetilde{A}$ is convex if every α-cut of $\widetilde{A}$ is a convex set. A fuzzy set is called fuzzy number when it is convex and normal.

A fuzzy number $\widetilde{A} = (a, b, c)$, where $a \leq b \leq c$ is called a Triangular Fuzzy Number (TFN), and its membership function $\mu_{\widetilde{A}}(x) : X \to [0, 1]$ is as follows:

$$\mu_{\widetilde{A}}(x) = \begin{cases} \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\ 1 & \text{if } x = b \\ \frac{c-x}{c-b} & \text{if } b \leq x \leq c \end{cases}$$

Let $\widetilde{A} = (a, b, c)$ be a triangular fuzzy number, then α-level set of $\widetilde{A}$ is $A_\alpha = \left\{x \in X : \mu_{\widetilde{A}}(x) \geq \alpha\right\} = [A_\alpha^-, A_\alpha^+]$ where $A_\alpha^- = a + (b-a)\alpha$ and $A_\alpha^+ = c - (c-b)\alpha$, $\alpha \in [0, 1]$. Now, we can represent $\widetilde{A}$ as $\widetilde{A} = \underset{\alpha \in [0,1]}{\cup} A_\alpha$. Here, we can derive the signed distance [47] from $[A_\alpha^-, A_\alpha^+]$ to $\widetilde{0}$ as $D(A_\alpha, \widetilde{0}) = \frac{1}{2}(A_\alpha^- + A_\alpha^+)$. If $\widetilde{A} = (a, b, c)$ is the TFN, then we have $D(\widetilde{A}, \widetilde{0}) = \frac{1}{2}\int\limits_0^1 (A_\alpha^- + A_\alpha^+) d\alpha = 0.25(a + 2b + c)$.

2.3. Computation of Criteria Weights Based on Entropy Measure

To determine the criteria weights, we have used the entropy weighted approach. The entropy weighted approach measures the capacity of each criterion to contain decision information in order to estimate the relative importance of characteristics. The amount of entropy value reflects how unpredictable a message is. One could investigate the work of Clausius [48] and Shannon [49] for additional information.

If $\Pi = \left(\pi_{ij}\right)_{m \times n}$ is the decision matrix and $w = (w_1, w_2, \ldots, w_n)$ be the weight vector, and $0 \leq w_j \leq 1$ and $\sum w_j = 1$ are in relation to the m alternatives and n criteria then the weight w_j, $j = 1, 2, \ldots, n$ can be obtained as follows:

Step 1: calculate $\Omega_j = -\frac{1}{\log(m)} \sum\limits_{i=1}^{m} p_{ij} \log(p_{ij})$, $j = 1, 2, \ldots, n$ where $p_{ij} = \frac{\pi_{ij}}{\sum\limits_{i=1}^{m} \pi_{ij}}$.

Here, it is stated that $\lim\limits_{p_{ij} \to 0} p_{ij} \log p_{ij} \to 0$;

Step 2: calculate $\Psi_j = 1 - \Omega_j$, $j = 1, 2, \ldots, n$;

Step 3: calculate $w_j = \frac{\Psi_j}{\sum\limits_{j=1}^{n} \Psi_j}$, $j = 1, 2, \ldots, n$.

2.4. Finding the Best Alternative Using TOPSIS Method Based on TFNs

To overcome an issue involving MCDM, this section describes how to use the TOPSIS strategy when the weights of the criteria are unknown and can be estimated by using Shannon entropy method.

Assume that there exist m alternatives $A_1, A_2, \ldots, A_m$ and n criteria $C_1, C_2, \ldots, C_n$ with a weight vector $w = (w_1, w_2, \ldots, w_n)$, where $0 \leq w_j \leq 1$ and $\sum w_j = 1$. A decision matrix $\widetilde{Z} = \left(\widetilde{z}_{ij}\right)_{m \times n}$ might be used to convey an alternative's characteristics in relation to the criteria expressed by a TFN $\widetilde{z}_{ij} = (z_{ij}^1, z_{ij}^2, z_{ij}^3)$ where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. Employing the signed distance method, mentioned in Section 2.2, the MCDM decision matrix (1) has been formed as follows:

$$(D(\widetilde{Z}, \widetilde{0}))_{m \times n} = \begin{pmatrix} D(\widetilde{z}_{11}, \widetilde{0}) & D(\widetilde{z}_{12}, \widetilde{0}) & \cdots & D(\widetilde{z}_{1n}, \widetilde{0}) \\ D(\widetilde{z}_{21}, \widetilde{0}) & D(\widetilde{z}_{22}, \widetilde{0}) & \ldots & D(\widetilde{z}_{2n}, \widetilde{0}) \\ \vdots & \vdots & \vdots & \vdots \\ D(\widetilde{z}_{m1}, \widetilde{0}) & D(\widetilde{z}_{m2}, \widetilde{0}) & \ldots & D(\widetilde{z}_{mn}, \widetilde{0}) \end{pmatrix} \quad (1)$$

Let $I^+ = (1, 1, \ldots, 1)$ and $I^- = (0, 0, \ldots, 0)$ represent consequently, the positive and negative ideal solutions for the m alternatives $A_1, A_2, \ldots, A_m$. Here, we used the following formula to compute the separation measures ${sm_i}^+ = {sm_i}^+(I^+, A_i)$ and ${sm_i}^- = {sm_i}^-(I^-, A_i)$ of each alternative from positive ideal and negative ideal solutions:

$$ {sm_i}^+ = \sqrt{\sum_{j=1}^{n} \left(w_j(1 - D(\widetilde{z}_{ij}, \widetilde{0})\right)^2} \quad (2) $$

and

$$ {sm_i}^- = \sqrt{\sum_{j=1}^{n} \left(w_j D(\widetilde{z}_{ij}, \widetilde{0})\right)^2} \quad (3) $$

Here $D(\widetilde{z}_{ij}, \widetilde{0}) = 0.25(z_{ij}^1 + 2z_{ij}^2 + z_{ij}^3)$, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$, and $w_j, j = 1, 2, \ldots, n$ are calculated using the entropy-weighted method discussed in Section 2.3.

Using Equations (2) and (3), the relative closeness of m alternatives $A_1, A_2, \ldots, A_m$ with respect to the positive ideal solution I^+ is computed as follows:

$$ RC_i(A_i) = \frac{sm_i^-}{sm_i^- + sm_i^+}, \; i = 1, 2, \ldots, m \quad (4) $$

The best alternative among a group of specified possible alternatives can be identified using Equation (4), which also determines the ranking order of all alternatives. The alternatives may then be ranked according to the closeness coefficient, with the alternative with the higher rank being considered the best choice.

3. Some Assertions and Symbols

We have considered a WSN here under the following assertions:

- Nodes are distributed at random places inside a square area;
- The base station is positioned outside the square's bounds, enabling communication with nodes inclined to multi-path attenuation. Multi-path attenuation does not influence communication between nodes;
- The nodes are cohesive because they share the same capabilities and initial battery energy while performing different tasks depending on the time of day;
- Communication between any node, the BS, or any other node is possible.
- The nodes are immobile;
- Every node senses its environment and emits a signal of the same length;
- Numerous aspects of sensor nodes, including the primary energy of nodes, the distance between sensor nodes and receiving stations, the size of information packets, and estimates of voltage and transmission power, among others, have imprecise values due to erratic/dangerous natural conditions.

Table 1 provides a list of symbols used in the paper.

Table 1. List of symbols.

Symbol	Description
db	Distance to the base station
db_0	Fixed measuring distance to the base station
ds	Distance from the sink
dn_c	A node's distance from each node in a cluster or its number of neighbors
(X, Y)	Position of CHs in a WSN
(W_x, W_y)	Position of nodes in a WSN
I_{energy}	Initial energy
EL_e	Electronics energy
ET_e	The energy used for data transmission

Table 1. *Cont.*

Symbol	Description
e_{fs}	Amplification of energy to overcome open space
e_{mp}	Amplification of energy to navigate the multi-path
ED_{rx}	The usage of energy during data receipt
O_c	The optimal number of cluster heads
Z	The dimensions of the square area
N_{node}	The total number of nodes in the network
N_c	The number of nodes in a cluster
R	The reliability of a cluster

4. Cluster Heads Formation Method for WSN

The nodes designated to serve as CHs should inform the rest of the nodes in the network that they have been selected for such a function. To achieve this, each of the chosen CHs transmits an appropriate signal throughout the network announcing their selection as cluster heads. This brief message provides the network node identification and a header, characterizing it as an update message. Each non-cluster head node selects the CH that is closest to it and uses the least amount of transmission energy to form its cluster. The link is connected to the CH with the shortest distance and received signal amplitude. The node and base station (BS) will respond directly if the distance between it and the CH is longer than its distance from the BS. Otherwise, it connects the cluster using the shortest distance. Here, we have considered the shortest distance measure as Euclidean distance.

If db is the distance between CH and a designated node, then db can be measured using the formula as follows:

$$db = \sqrt{(X - W_x)^2 + (Y - W_y)^2} \tag{5}$$

where (X, Y) and (W_x, W_y) are the position of cluster head (CH) and node location.

The BS, which is situated outside of the network area, is a node with improved processing abilities and no limited battery life. In order to obtain an appropriate signal-to-noise ratio (SNR), a k bit of information is transmitted over a distance db using a conventional radio energy dissipation model [23]. During data communication, the data transmission energy consumption (ET_e) and energy consumption due to data reception (ED_{rx}) are approximated using Equations (6) and (7).

$$ET_e = \begin{cases} k \times EL_e + k \times e_{fs} \times db^2 & if\, db \leq db_0 \\ k \times EL_e + k \times e_{mp} \times db^4 & if\, db \geq db_0 \end{cases} \tag{6}$$

$$ED_{rx} = k \times EL_e \tag{7}$$

It is to be noted that the electronic energy EL_e depends on various features, viz. coding of digital devices, modulation, filtering, and bandwidth of the signal, whereas $e_{fs}db^2$ and $e_{mp}db^4$ are dependent on the distance to the receiver and acceptable bit-error rate.

Following the creation of the clusters, the CH, after receiving all CH connect signals from every node, assigns a timeframe for each designated node. The responsibility of gathering information from all cluster nodes belongs to each cluster head. The CH transmits the message to the BS after applying data aggregation when a packet of data from all the individuals is received. It has been observed that several protocols have been used for re-clustering strategy and choosing CHs using a probabilistic approach rather than a deterministic approach. Data transmission and re-clustering proceed for several cycles until all nodes are still alive. As dead nodes begin to appear, the number of active nodes in the cluster diminishes, and the smaller clusters that have lesser power than the predetermined threshold are combined with the larger ones. As a result, the cluster size starts to slow down anytime the number of active nodes diminishes. Determining the number of CHs in each cycle is crucial for increasing the WSN's lifetime and energy efficiency. Here, we have calculated the requisite number of clusters [42] O_c, distance ratio, and reliability using the following equations:

$$O_c = \sqrt{\frac{e_{fs}}{\pi(e_{mp}db^4 - EL_e)}} Z\sqrt{N_n} \tag{8}$$

$$dr = \frac{ds + dn_c}{ds \times dn_c} \tag{9}$$

$$R = 1 - \frac{N_c}{N_{node}} \tag{10}$$

4.1. Node Selection Criteria:

In our experiment, we have calculated reliability, residual energy, the number of neighbor nodes, the distance from the sink (BS), the average distance of cluster nodes, and the distance ratio (see Table 2). Following the first simulation round, the best CHs were chosen based on six criteria: residual energy, number of neighbors, distance from the sink (BS), average distance of cluster nodes, distance ratio, and reliability. Based on our hypothesis, we divided the network into 14 clusters for this study, with a cluster head in each cluster. We have utilized the NSG2.1 simulator and tool command language for this simulation. Here, we have generated 100 nodes within $100 \times 100\,\text{m}^2$ and run the simulation on NS2 for the first round. For the subsequent round, the selection of CHs has been made by using our proposed algorithm (see Section 4.2). We have plotted the node, and it has been depicted in Figure 1.

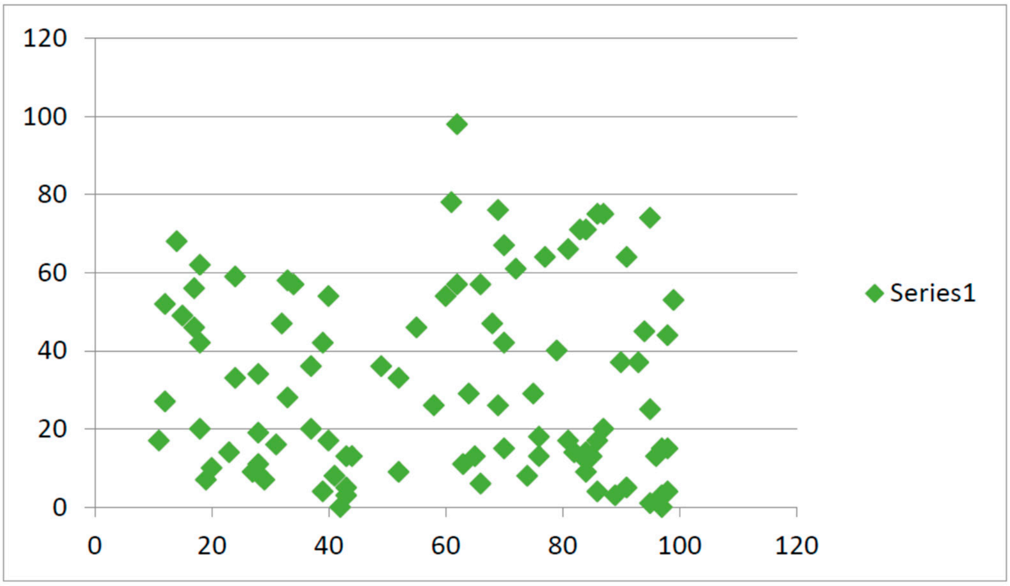

Figure 1. Distribution of 100 nodes over the area $100 \times 100\ \text{m}^2$.

4.2. WSNs Lifetime Extension Algorithm via MCDM and TOPSIS Technique

We proposed an algorithm based on MCDM and TOPSIS techniques to extend the lifetime of WSNs. This algorithm has been termed Algorithm 1. Algorithm 1 is as follows:

Algorithm1. WSN Lifetime Extension Algorithm

Step 1: Distribute 100 nodes in an entire network with BS location (50,175) and spread nodes randomly over 100×100 m^2 areas.
Step 2: In order to find the values of different parameters, all nodes will send the data to BS for the first round of simulation.
Step 3: The network is divided into O_c a number of clusters using Equation (8).
Step 4: Weight is assigned to each node using the entropy-weighted approach. The TOPSIS technique is used to select CHs from each cluster for the second round of simulation based on the weight of predefined parameters for CH selection.
Step 5: Repeat steps 6 to 13 until the residual energy of all the nodes has yet to be finished.
Step 6: When a node's residual energy exceeds all other nodes in the same cluster, the counter increases.
Step 7: When a node's distance from the sink is less than that of all other nodes in the same cluster, the counter increases.
Step 8: When a node's number of neighbors exceeds that of all other nodes in the same cluster, the counter increases.
Step 9: When the average distance of cluster nodes is smaller than that of all other Cluster nodes within the same cluster, the counter increases.
Step 10: When the distance ratio of a node is smaller than the distance ratio of all other nodes within the same cluster, the counter increases.
Step 11: The node with the largest counter value is designated as a CH for the next round.
Step 12: If a cluster has fewer than three nodes, nodes will be added to the closest cluster, considering each cluster's reliability.
Step 13: Jump to the next round.
Step 14: Stop.

5. Numerical Experiment and Discussions

Unsafe or unreliable communication has yielded detrimental consequences, including increased noise and adverse effects on sensor node batteries. The battery life directly affects the network's longevity, which is closely tied to residual energy. Furthermore, the presence of noisy data necessitates extra caution and thorough processing. Lastly, the distance between sensors, logic, and actuators is critical in facilitating replacements. This incident represents the uncertainty of WSNs. For computational experiments, we used a thousand nodes of WSNs where all the nodes were randomly distributed within a $100 \times 100\,\text{m}^2$ area and ran the simulation on NS2 for the first round. In our experiment, we utilized the OPNET modeler to assess the MAC layer functionality of 802.15.4 slotted CSMA/CA. Here, we also considered uncertain parameters for the entire network setup, which has been shown in Table 3. Also, we estimated the optimum range of O_c. Here, we considered $\text{N}_n = 100$ nodes, $\text{Z} = 100\,\text{m}$, $e_{fs} = 10\,\text{pJ}$, $e_{\text{mp}} = 0.0013\,\text{pJ}$, and $76\,\text{m} < db < 168\,\text{m}$. Therefore, the expected optimum number of clusters was in the range (1, 10), i.e., $1 < O_c < 10$.

Table 2. Decision parameter for selecting cluster heads.

Cluster Head	Residual Energy	Number of Neighbors	Distance from the Sink	Average Distance of Clusters Nodes	Distance Ratio	Reliability
CH1	0.9695	8	157.203	13.232	0.0819	0.92
CH2	0.9654	4	77.223	15.527	0.0774	0.96
CH3	0.9698	8	141.173	26.937	0.0442	0.92
CH4	0.9653	7	135.059	31.049	0.0396	0.93
CH5	0.9688	4	92.444	47.752	0.0318	0.96
CH6	0.9641	3	115.069	22.688	0.0528	0.97
CH7	0.9647	4	85.988	22.348	0.0564	0.96
CH8	0.9657	5	106.367	24.433	0.0503	0.95
CH9	0.9649	6	102.181	15.694	0.0735	0.94
CH10	0.9656	10	93.391	33.724	0.0404	0.9
CH11	0.9698	9	119.436	17.016	0.0671	0.91
CH12	0.9688	6	109.224	28.863	0.0438	0.94
CH13	0.9698	2	85.158	29.5	0.0456	0.98
CH14	0.9656	10	147.868	17.706	0.0632	0.9

Table 3. The experimental parameter utilized for WSNs.

Parameters	Parametric Value as per Assumptions	Defuzzified Value
N_n	100	
$\widetilde{I}_i$	(0.7, 1, 1.2)	0.975
Coordinate of BS	(50, 175)	
Size of the data packet	(495, 500, 510)	501.25
Hello/broadcast/CH join message	(22,25,28)	25
$\widetilde{e}_{fs}$	(8, 10, 12)	10
$\widetilde{e}_{mp}$	(0.001, 0.0013, 0.0015)	0.001275
$\widetilde{EL}_e$	(47, 50, 52)	49.75

It ought to be noted that the signed distance method mentioned in Section 2.2 has been used to transform fuzzy parameters into defuzzified values. For example, $I_i = (0.7, 1.0, 1.2)$ and $D(\widetilde{I}_i, \widetilde{0}) = 0.25(0.7 + 2 \times 1.0 + 1.2) = 0.25 \times 3.9 = 0.975$. Other parameters have undergone a similar computation.

Using Equation (8), we have calculated the value of O_c. It is to be noted that the value of O_c lies between $1 < O_c < 10$, and consequently, we have chosen the value of $O_c = 9$ for the purpose of the numerical experiment. Hence, we have selected nine cluster heads based on six criteria: residual energy, number of neighbors, distance from the sink, average distance of cluster node, distance ratio, and reliability using the MCDM approach. Here, Table 3 is a decision matrix of our proposed problem. Using Table 3, we have calculated weight vectors using the entropy method described in Section 2.3. The weight vector w using Section 2.3 has been computed as $w = (0.156, 0.176, 0.167, 0.175, 0.170, 0.156)$. Further, we have calculated sm_i^+ and sm_i^- using Formulas (2) and (3). These are shown in Table 4.

Table 4. Separation evaluates sm_i^+ and sm_i^- of each alternative in relation to positive ideal and negative ideal solutions.

CHs	1	2	3	4	5	6	7	8	9	10	11	12	13	14
sm_i^+	26.20	12.99	23.88	23.02	17.33	19.43	14.69	18.08	17.12	16.53	20.03	18.74	14.92	24.75
sm_i^-	107.11	26.33	88.94	82.68	46.87	58.88	33.65	51.01	45.70	42.65	62.57	54.79	34.70	95.57

Using separation measures of each alternative, we have calculated the closeness coefficient using Equation (4), which has been shown in Table 5.

Table 5. Closeness coefficient of each alternative.

CHs	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$RC_i(A_i)$	0.80	0.67	0.79	0.78	0.73	0.75	0.70	0.74	0.73	0.72	0.76	0.75	0.70	0.79

The alternative with the highest rank is regarded as the best choice. Therefore, we have chosen nine cluster heads based on the closeness coefficient. Table 6 (Option 1) and Table 7 (Option 2) provide these nine cluster heads.

Table 6. Selection of the nine cluster heads as per the highest closeness coefficient of each alternative for Option 1.

$RC_i(A_i)$	0.80	0.79	0.79	0.78	0.76	0.75	0.75	0.74	0.73
Rank	1	2	3	4	5	6	7	8	9
CHs	1	3	14	4	11	6	12	8	5

Table 7. Selection of the nine cluster heads as per the highest closeness coefficient of each alternative for Option 2.

$RC_i(A_i)$	0.80	0.79	0.79	0.78	0.76	0.75	0.75	0.74	0.73
Rank	1	2	3	4	5	6	7	8	9
CHs	1	3	14	4	11	6	12	8	9

The network lifespan is expressed in the number of cycles until its single node exhausts its remaining energy. The experimental results depending on Options 1 and 2 are shown in Figures 2 and 3 respectively. On a setup area, sensor nodes were distributed at random. Network lifetimes, which show the number of active nodes over time in cycles, have been plotted.

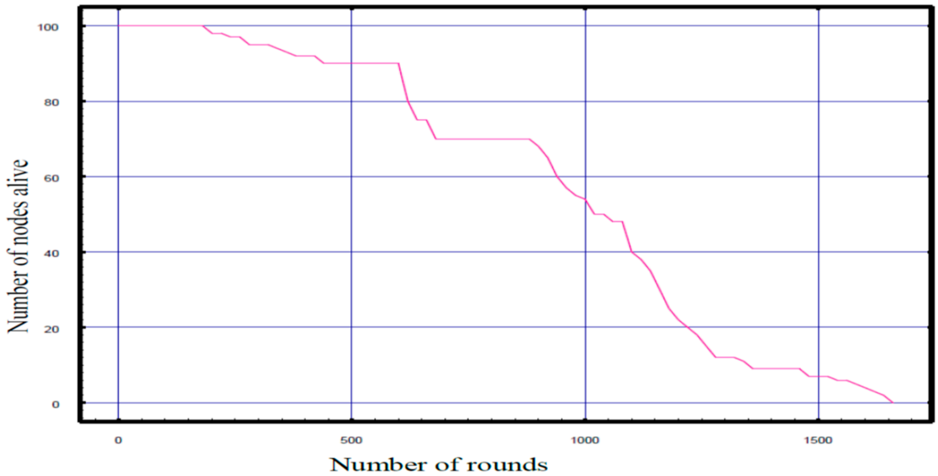

Figure 2. Number of nodes alive vs. number of rounds for Option 1.

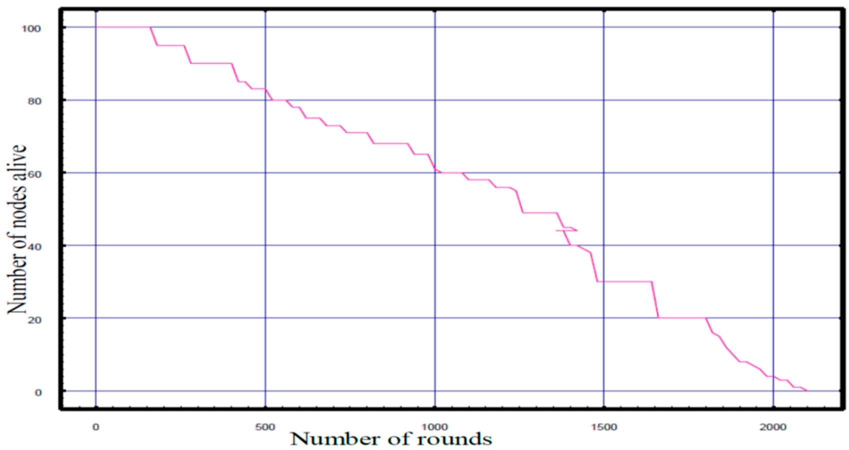

Figure 3. Number of nodes alive vs. number of rounds for Option 2.

Figure 2 shows that the remaining energy diminished after 1900 cycles, whereas Figure 3 shows that the remaining energy diminished completely after 2200 cycles. Consequently, Option 2 is acceptable as compared to Option 1. However, both are acceptable compared to the LEACH protocol. Figure 4 presents comparative results between the LEACH protocol and our proposed method. In this research, it has been found that the proposed strategy with both alternatives shows 31% and 40% network lifetime in comparison with LEACH, where 31% indicates 1900 simulation rounds and 40% to 2200 rounds. The CH selection in LEACH is random, potentially resulting in selecting nodes with low residual energy as CHs. When CHs die after a few simulation rounds, the cluster formation collapses, necessitating data exchange and consuming significant residual energy. This reduces the network's longevity. To address this, our study with uncertain parameter values compares the proposed approach with LEACH regarding cluster residual energy. The findings indicate that in LEACH, the residual energy of all nodes depletes after 1300 rounds, whereas our proposed approach takes 2200 rounds to exhaust all residual energy shown in Figure 5. Compared with energy utilization, our proposed approach consumes 29% less energy than LEACH due to determining the right CHs.

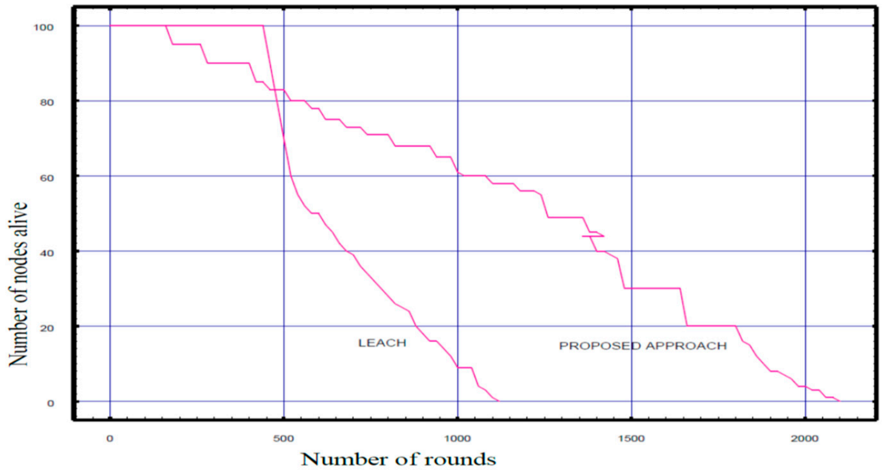

Figure 4. Network lifetime comparison between LEACH and the proposed approach.

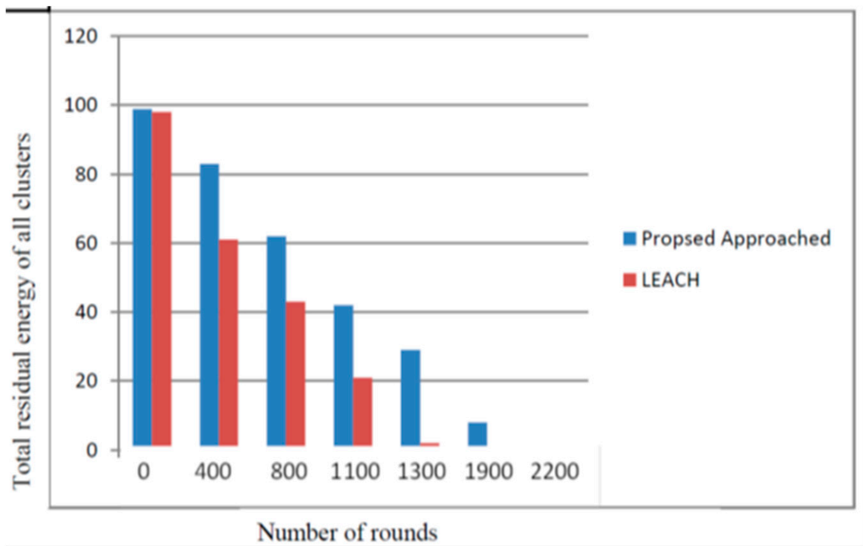

Figure 5. Total residual energy of all clusters vs. number of rounds.

5.1. Time Complexity of Our Proposed Algorithm

In our proposed approach, we have O_c clusters and N_c nodes in each cluster; the algorithm necessitates around $\Theta(O_c)$ operations to access O_c clusters. Determining the reliability of each cluster takes approximately $\Theta({N_c}^2)$ time. Additionally, the algorithm involves constant time operations for calculating residual energy, distance from the sink, number of neighbors, average distance of cluster nodes, and the distance ratio denoted as ∂. Thus, the overall time complexity of the algorithm can be approximated as $\Theta(O_c {N_c}^2 + \partial)$ or simplified as $\Theta(O_c {N_c}^2)$.

5.2. Result Validation

We have validated our proposed result using a statistical hypothesis in this subsection.

Null Hypothesis (H_o)***:*** the average number of simulation rounds falls within the 95% confidence interval, specifically between 1800 and 2300.

Alternate Hypothesis (H_1)***:*** the number of simulation rounds does not fall within the 95% confidence interval.

We set the significance level at $\alpha = 0.05$, and T represents a random variable following the t-distribution. The 95% confidence interval is between 1800 and 2300. The simulation was executed 50 times, and the average result obtained was 2200. Using statistical calculations, we have determined that the *T-Score* is 0.3496 and p (the probability of T being greater than 0.3496) is 0.7968.

Since $(p > \alpha = 0.05)$, we do not have sufficient evidence to reject the null hypothesis (H_o). Therefore, we can conclude that the average number of simulation rounds falls within the 95% confidence interval, i.e., 1800 and 2300.

6. Concluding Remarks

The MCDM method for cluster head selection in WSNs under uncertainty has been examined in this paper. TOPSIS, an entropy-based technique, is used to choose the CHs in WSNs. The number of clusters/cluster heads is optimized by considering six parameters: reliability, residual energy, the number of neighbor nodes, the distance from the sink (BS), the average distance of non-cluster nodes, and the distance ratio. We employed Triangular Fuzzy Numbers to express all the characteristics, including initial node energy, the distance between sensor nodes and base stations, the size of data packets, voltage, and transmission energy measurements, and other matters about sensor nodes (TFNs). For the context of this research, we segregated the entire network into 14 clusters, with a cluster head in each cluster, based on our hypotheses. For this experiment, we used the NSG2.1 simulator and tool command language. We also used the AODV protocol for simulation. The nodes in this network topology were generated using a uniform distribution, and a technique for choosing cluster heads was also proposed. The lifespan achieved by the LEACH protocol was compared to the lifetime achieved by the simulated network. Simulation results show that our suggested approach, based on the entropy-weighted TOPSIS method, significantly extends network lifetime and saves energy compared to the LEACH protocol. Finally, the overall strategy used in this work will serve well enough for the selection of cluster heads as well as other network design aspects associated with WSNs, including uncertain parameters.

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