

Article

Wireless Sensor Network Lifetime Extension via K-Medoids and MCDM Techniques in Uncertain Environment

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Abstract: In this study, the multi-criteria decision-making (MCDM) technique is used in collaboration with K-medoids clustering to establish a novel algorithm for extending the lifetime of wireless sensor networks (WSNs) in the presence of uncertainty. One of the most important problems in WSNs is the energy consumption. Furthermore, extending the network lifetime in WSNs is highly dependent on selecting the appropriate cluster heads (CHs), and this can be a challenging task for the decision makers. In addition, parameters associated with WSNs are completely unexpected due to uncertainty. Therefore, after proposing K-medoids clustering and a MCDM technique, we have developed a novel algorithm for extending the lifetime of WSNs. As criteria, we have taken into account four important aspects of the proposed WSN: the distance from sink, average distance of cluster nodes, reliability of cluster and residual energy. To represent uncertain parameters in this work, we have considered triangular fuzzy numbers (TFNs). Finally, an experiment involving a WSN under uncertainty was investigated, and the findings have been graphically displayed. In this research, it has been observed that the proposed strategy with the novel algorithm exhibits 42% greater network lifetime as compared with a hybrid energy efficient distributed (HEED) algorithm and 11% and 18% with respect to optimal clustering artificial bee colony (OCABC) and particle swarm optimization (PSO) applied to a clustering optimization problem. We have also conducted statistical hypotheses for the purpose of confirming the presented outcomes.

Keywords: lifetime extension; K-medoids; wireless sensor networks; cluster head selection; TOPSIS; multi-criteria decision making; residual energy



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1. Introduction

Wireless sensor networks (WSNs) are among the most popular communication media for many real-time applications due to their size, cost and deployment characteristic [1]. WSNs are made up of self-organizing sensors, which can build an adaptive multi-hop network and send optimized data packets to the base station (BS) for post-processing analysis [2,3]. Some WSN implementations make use of a lot of sensor nodes. The residual energy and memory of these wireless nodes are the biggest challenging task for implementation. Therefore, in order to maximize the benefits of these WSNs, the WSNs nodes must have a system for controlling the interactions with one another as well as an access point [4,5]. Digital data, such as images or videos, are used extensively in WSNs. WSNs are very useful in several real-life applications, viz., agriculture, small scale and/or large-scale industry, military surveillance, weather monitoring, healthcare and smart homes/smart cities [6,7] which all use multimedia data. Multimedia data that contain images and videos are commonly large which generally increase the energy consumption of each sensor node. However, the energy consumption can be optimized by using several algorithms [8,9]. The widespread deployment of large-scale WSNs is being driven by recent developments in

semiconductor, networking and material science technologies. These technologies have enabled a new generation of WSNs that are significantly different from wireless networks created and implemented as recently as five to ten years ago. Modern WSNs are more reliable, cost effective to deploy and maintain and are also more resilient. Although there was no such technology for extensive industrial and consumer application in the 20th century, both academia and industry had seen the possibilities for such networks and collaborated to overcome the engineering barrier. Examples of these academia/industrial initiatives include (i) UCLA wireless integrated network sensors, (ii) University of California at Berkeley Pico radio program, (iii) NASA sensor webs and (iv) the Zigbee alliance. Security is one of the biggest issues with WSNs, which has a significant impact on energy usage. The complexity of a WSN's security increases with node power consumption and vice versa. The two main concerns where new research can make only limited progress are the requirement for reducing energy use and enhancing network security [10,11]. In the study of WSN, energy efficiency has emerged as a key topic. The restrictions imposed by the batteries used to power such devices may be the cause of the interest in energy efficiency. These batteries typically serve as the primary source of energy for these devices, and they have a finite lifespan before needing to be recharged or discarded. For precision agricultural, environmental, disaster, environmental, structural, health, security applications and military surveillance, WSNs are the foundation of ubiquitous computing. Since sensor nodes are typically deployed in harsh environments with low battery capacities, their lifespan is typically a significant concern. Using sophisticated network security protocols and sending and receiving digital information can have a significant impact on network lifetime. Numerous mechanisms, including clustering and routing protocols, are utilized [12–14] to enhance energy efficiency by extending network lifetime. Complex network security and energy conservation have become crucial concerns in WSNs due to the number of sensor nodes and the exchange of digital information. In order to increase energy efficiency and maximize network lifetime, a new algorithm must be developed. Hence, to increase network lifetime, a new optimal algorithm is proposed in this study that is capable of selecting the cluster head (CH) in each round based on specific constraints. Wireless communication in WSNs uses a clustering strategy. Each cluster in the WSN is divided into a controller (or “cluster head”) that aggregates all the data from the sensor nodes in that cluster and sends it to the source (see Figure 1). In every round, the cluster head sends out a message, and the node that receives the message joins the cluster. If there are many nodes in the cluster, the CH turns down the intensity of the message so that fewer nodes can receive it. In the other scenario, if the cluster size is very small, then the cluster head increases the message strength so that more nodes can receive the message. In accordance with the coverage requirement, sensor nodes are deployed very densely, which allows some nodes to be idle which will increase the lifetime of the network. The selection of cluster heads is performed randomly or on the basis of several criteria, such as highest residual energy, maximum number of neighbour nodes, the distance between the cluster head and the base station, rate of charge or discharge over sending data and average distance of cluster nodes. The selections of CHs are very complex procedures and sometimes tedious, which can be reduced by using multiple attribute decision-making (MADM) approaches. The K-medoids clustering algorithm, which promotes energy efficiency in WSNs, is the foundation for cluster selection. Clustering is one of the most challenging works in WSNs. The partitioning around the medoid (PAM) method is one of the successful techniques for creating a cluster. In this research, the K-medoids algorithm, which is an example of the PAM method, is used to divide the entire network into several clusters. Before using segmentation-based approaches, huge scales of data must initially be clustered. Due to its computational effectiveness and directness, the K-means algorithm is the most widely used clustering algorithm across the several researchers in the field of computational intelligence. K-means [15] depends on finding the cluster head in a huge number of datasets. Using a metric based on Euclidean distance, it alternates distinct positions of the entire datasets with the cluster head and re-calculates the cluster head until a convergence condition is

satisfied. However, there are a lot of problems with the K-means algorithm, including the fact that Euclidean distance is the only distance metric utilized in K-means clustering. It has been observed that alternative distance metrics, such as city block distance and cosine distance, can enhance the outcomes of sparse data. When used in applications, such as image processing and other applications, the K-means clustering algorithm has a significant disadvantage that the cluster head need not come from the datasets. When creating clusters, K-means clustering seeks to minimize the distance within the cluster, whereas K-medoids seeks to reduce the dissimilarities between the cluster head and the non-cluster node [16]. On the other hand, reliability, residual energy and distance from the sink node are also dependable factors of WSNs. In this research, key factors, such as distance from base station, average distance of nodes in a cluster and reliability, are also considered with residual energy for CH selection. The entropy method is applied to calculate the weight of each parameter. The TOPSIS technique is applied to each cluster for selection of CHs from each cluster for the first simulation. The proposed algorithm which also takes multiple criteria into account is applied to select the next CHs for the next rounds of simulation. A novel algorithm is introduced to find the cluster head in each round depending on several criteria. Moreover, due to the irregular/hazardous natural circumstances, parameters related to WSNs, such as initial energy of nodes, the distance between sensor nodes and base stations, the size of data packets, measurements of voltage and transmission energy and other factors linked to sensor nodes, is also completely unexpected. Triangular fuzzy numbers (TFNs) are used in this method to express uncertainty or unexpected data [12,13,17,18]. In this paper, we develop a novel algorithm to choose new cluster heads in each successive round. Here, employ K-medoids, TOPSIS techniques and our proposed algorithm to identify the best CHs to enhance network lifetime under uncertainty. It ought to be mentioned that we use TFN datasets to perform the MCDM approach. The implementation of energy-efficient network routing protocols is a major challenge in WSN since it can increase the network's overall lifetime. Clustering is one strategy that can be used for this. Many algorithms, including threshold-sensitive energy-efficient sensor network (TEEN), stable election protocol (SEP) and distributed energy-efficient clustering (DEEC) have been implemented. The selection of CHs and clusters has been the main focus of all these studies. The inter- and intra-cluster distance problem is addressed with these protocols. Numerous optimization techniques, such as PSO (particle swarm optimization) [19], OCABC (optimal clustering artificial bee colony) [20], etc., have been proposed to address this problem. The K-medoids approach is implemented in this paper, together with a novel algorithm, to handle the inter- and intra-cluster distance issue which can lead to extending the network lifetime. The simulation results are compared with OCABC and PSO techniques, and the results section includes an explanation. In this work, it is mentioned that nodes spread over a certain area. We divide the entire network over a number of clusters based on a hyperparameter using the K-medoids algorithm. All the nodes send data to the BS to select the CHs for the first simulation because if a node's position is far from the BS, it will use more residual energy compared to a closer one, which will help choose the CHs for the clusters. By using the entropy method, each parameter is assigned its values. The MCDM topology technique is used to choose CHs from each cluster. After obtaining the optimal number of clusters, which is discussed later in this paper, the optimal number of CHs is chosen over hyperparameter-based CHs by the topology method. The K-medoids algorithm is again applied to create the optimal number of clusters. In the next round of the simulation, a novel algorithm is applied, which selects the next CHs depending on various parameters, such as distance from the sink node, average distance of cluster nodes and reliability. A flowchart of the method used in this study is shown in Figure 2. Table 1 presents a list of acronyms used in this paper. Finally, an experiment with a numerical example is conducted, and the findings are analyzed statistically and graphically.

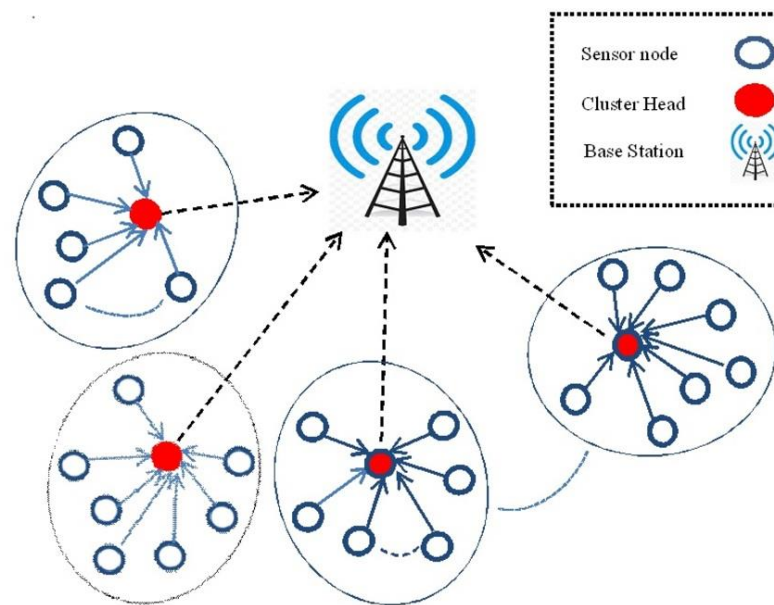


Figure 1. General structure of WSNs.

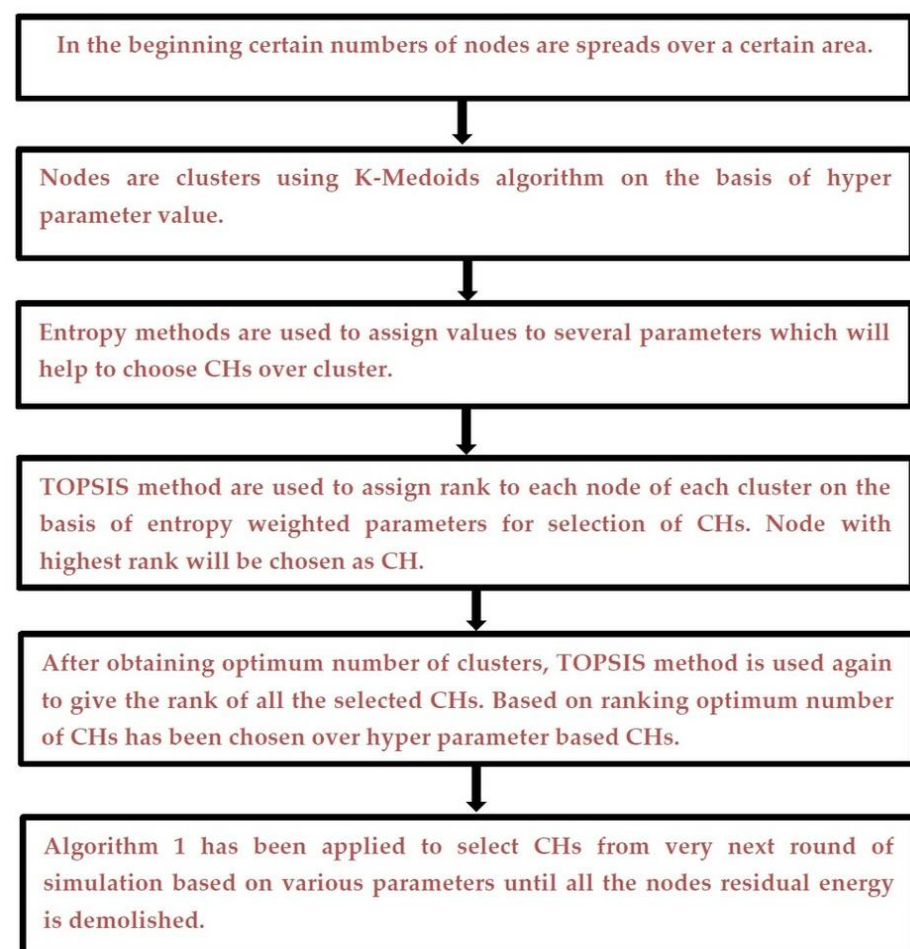


Figure 2. Flowchart of the method used in this study.

Table 1. List of acronyms.

ACO	Ant Colony Optimization
BCDCP	Base-station Controlled Dynamic Clustering Protocol
BS	Base Station
CERP	Cluster-Based Event-Driven Routing Protocol
CHs	Cluster Heads
CLWPA	Clustering Framework for Heterogeneous WSN
DEEC	Distributed Energy-Efficient Clustering
DMs	Decision Makers
EEHC	Energy Efficiency Heterogeneous Cluster
FPCA	Fuzzy-Based PSO Clustering Architecture
HEED	Hybrid Energy-Efficient Distributed Protocol
LEACH	Low Energy Adaptive Clustering Hierarchy
LEACH-C	Centralized Low Energy Adaptive Clustering Hierarchy
MCDM	Multi-Criteria Decision Making
OCABC	Optimal Clustering Artificial Bee Colony
PAM	Partition Around Medoids
PSO	Particle Swarm Optimization
REAC-IN	Regional Energy-Aware Clustering with Isolated Nodes
SEP	Stable Election Protocol
TEEN	Threshold-Sensitive Energy Efficient Sensor Network
TFNs	Triangular Fuzzy Numbers
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
WSNs	Wireless Sensor Networks

Related Work

Making decisions is an important factor in all scientific fields. Using the MCDM approach to solve a problem is a very effective way to find a better solution than all other possible solutions [21]. There have been numerous studies on clustering in WSNs with successful outcomes [22–27]. In addition, heuristic approaches for clustering in WSNs are applied [28,29]. The clustering approach can be divided into two categories: static and dynamic. In a static approach, the cluster head is fixed during the clustering [30–32]. In contrast, in dynamic clustering, the cluster heads are changed periodically during clustering. The low-energy adaptive cluster hierarchy proposed by Heinzelman (LEACH) [33] is one of the examples of dynamic clustering. It relies on randomized CH rotation to uniformly divide the energy load among all sensor nodes in the network. Each node chooses itself as a CH using a probabilistic mechanism and announces its availability to all nearby sensor nodes. Signal intensity is the key factor between the communication nodes to determine the distance between them. The packets received from every node in its cluster are aggregated by the CH. In order to balance the overall energy consumption across the network, each node has a chance to become the CH. In comparison with other methods, LEACH comes with low algorithmic complexity, but it is not energy efficient due to uneven distribution of CHs. An energy efficient heterogeneous cluster (EEHC) was proposed in a heterogeneous environment where some nodes have a higher energy capacity than others. Based on the weighted election probability according to the residual energy, the nodes act as the cluster head. Although the idea of heterogeneity is introduced, this procedure does not take into account various aspects when choosing CHs [34]. A modified version of the LEACH protocol, called LEACH-C (centralized LEACH) [35], was introduced, which reduced the amount of energy used when transmitting data from non-cluster head nodes to their cluster heads by minimizing the total sum of squared distances between all cluster nodes and the closest cluster head. A base-station controlled dynamic clustering protocol (BCDCP) was proposed by Pachlor and Shrimankar [36], which is a centralized routing protocol that uniformly disperses the energy dissipation among all sensor nodes to maximize average energy savings and extend network lifetime. Previous reported methodologies/algorithms used to increase the wireless sensor network lifetime with their timeline and their major weakness and strengths are presented in Table 2.

Table 2. List of previous reported methodologies/algorithms along with their strengths and their major weakness.

Methodology	Year of Development	Strengths	Major Weakness
Low-Energy Adaptive Clustering Hierarchy (LEACH)	2002	(i) Each node has equal probability to be cluster head. (ii) The energy dissipation of each node is relatively balanced.	There are no selection criteria of CHs.
Hybrid Energy-Efficient Distributed (HEED)	2004	(i) The nodes are well distributed. (ii) Energy consumption between intra-cluster nodes is minimized.	It increases control message overhead at the time of cluster formation.
Power-Efficient Gathering in Sensor Information Systems (PEGASIS)	2012	(i) The distribution of energy with the chain is uniform. (ii) It reduces the number of transmissions between the sender and receiver.	Its take lots of time for sending and receiving information.
Cluster-Based Event-Driven Routing Protocol (CERP)	2014	(i) It reduces the energy consumption by finding the shortest path between CHs and BS.	There is a Node isolation problem in the network and unequal cluster formation.
Regional Energy-Aware Clustering with Isolated Nodes (REAC-IN)	2015	(i) The problem of node isolation has been solved. (ii) The network lifetime and the stability of the entire network have been enhanced.	The different stages of the network cannot be expressed based on the network average energy.
Fuzzy-Based PSO Clustering Architecture (FPCA)	2016	(i) Cluster deformation and energy efficiency are enhanced. (ii) The network lifetime is also improved.	Performance measurement is a little bit difficult because of its complex approach.
Ant Colony Optimization (ACO)	2019	(i) It reduces data loss. (ii) It extends the network lifetime.	This algorithm is only appropriate with mobile nodes.
Clustering Framework for Heterogeneous WSN (CLWPA)	2020	(i) It enhances the network lifetime.	The implementation of this model is very challenging.

A TOPSIS method centered on the election of cluster leaders using a “Multiple Attribute Decision Making” approach was proposed by Azada and Sharma [37]. For CH selection in WSN, Alami et al. [38] introduced an energy-efficient fuzzy approach. The primary goal of the work was to use fuzzy parameters to minimize energy consumption and improve the life of the network. Using four criteria, the fuzzy-TOPSIS-based cluster head election in mobile networks was proposed by Khan et al. and compared to the conventional LEACH and fuzzy [39]. On the basis of several research works, it can be seen that the fuzzy MCDM method can be applied to derive the rank from the various criteria for CH selection. In this research work, the network is divided into several clusters depending on the value of the hyperparameter using K-medoids. In addition, based on the MCDM method, rank is given to several cluster heads which will help find the optimal number of cluster heads by their rank value. In the existing literature, many studies use only residual energy as the primary criteria for the selection of CHs.

The rest of the work is presented as follows. Section 2 presents basic mathematical foundations and methodologies to develop the entire paper. In order to accomplish the study, Section 3 provides some symbols and notations. The system model definition and formulation are discussed in Section 4. The experimental setup and results are examined in Section 5. The concluding remarks of the research are included in Section 6.

2. Preliminaries

This section explains the entropy weighted method and the TOPSIS technique based on the fuzzy numbers used in this work.

2.1. Entropy Weighted Method

In 1865, German physicist R. Clausius first proposed the notion of entropy [40]. It is a phase characteristic of matter and characterizes the disorder or chaos of a thermodynamic process. Information entropy, a concept introduced by Shannon in 1948, is a quantification of the communication uncertainty in sources of information [41]. The entropy weight technique is used to determine the relative importance of features by measuring the capacity of every judgment criterion to carry decision information. It basically employs the quantity of the entropy value to indicate the degree of message unpredictability. The entropy weight can be estimated from the decision matrix.

Assume that $Z = (z_{ij})_{m \times n}$ is the decision matrix, and $w = (w_1, w_2, \dots, w_n)$, where $0 \leq w_j \leq 1$ and $\sum w_j = 1$ are the weight vector with regard to the m alternatives $A_i (i = 1, 2, \dots, m)$ and n criterion $C_j (j = 1, 2, \dots, n)$. Now, we can calculate the weight $w_j, j = 1, 2, \dots, n$ using the following steps:

$$\text{Step 1: Compute } p_{ij} = \frac{z_{ij}}{\sum_{i=1}^m z_{ij}}$$

$$\text{Step 2: Compute } E_j = -\frac{1}{\log(m)} \sum_{i=1}^m p_{ij} \log(p_{ij}).$$

It is to be that $p_{ij} \log p_{ij} \rightarrow 0$, when $p_{ij} \rightarrow 0$

$$\text{Step 3: Compute } U_j = 1 - E_j$$

$$\text{Step 4: Compute } w_j = \frac{U_j}{\sum_{j=1}^n U_j} = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)}$$

2.2. TOPSIS Method Based on Triangular Fuzzy Numbers (TFNs)

This section covers how to use the TOPSIS technique involving MCDM problems, where the criteria weights are unknown and the decision-makers' (DMs') preference insight, expressed in the form of TFNs, can be estimated by using the Shannon entropy method [42,43].

Assume that there exist m alternatives $A_1, A_2, \dots, A_m$ and n criterion $C_1, C_2, \dots, C_n$ with a weight vector $w = (w_1, w_2, \dots, w_n)$, where $0 \leq w_j \leq 1$ and $\sum w_j = 1$. The characteristics of an alternative A_i with respect to the criteria C_j can be expressed by a TFN $\tilde{z}_{ij} = (z_{ij}^1, z_{ij}^2, z_{ij}^3)$, ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$), and the decision matrix $\tilde{Z} = (\tilde{z}_{ij})_{m \times n}$ might be used to convey an alternative's characteristics in relation to the criteria expressed by $\tilde{z}_{ij}$, where $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$. As a result, the MCDM problem can be expressed using the following decision matrix: $\tilde{Z} = (\tilde{z}_{ij})_{m \times n}$. Now, using the signed distance measure, we convert the decision matrix into the following decision matrix:

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

where $D(\tilde{z}_{ij}, \tilde{0})$ is the defuzzified value of the triangular fuzzy number $\tilde{z}_{ij}$, and $D(\tilde{z}_{ij}, \tilde{0}) = \frac{1}{4}(z_{ij}^1 + 2z_{ij}^2 + z_{ij}^3)$, ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$). $D(\tilde{z}_{ij}, \tilde{0})$ is derived using the signed distance method [44]. Here, Equation (1) is the required decision matrix of our proposed problem.

Let $I^+ = (1, 1, \dots, 1)$ and $I^- = (0, 0, \dots, 0)$ represent, respectively, the positive and negative ideal solution for the m alternatives $A_1, A_2, \dots, A_m$. Therefore, the following formula can be used 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.

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

and

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

where the weight vector $w = (w_1, w_2, \dots, w_n)$ is calculated using the entropy weighted method described in Section 2.1. Using Equations (2) and (3), we calculate the relative closeness of m alternatives $A_1, A_2, \dots, A_m$ with respect to the positive ideal solution I^+ which are as follows:

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

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

2.3. K-Medoid Algorithm

A popular medoid-based technique is the K-medoid algorithm, commonly referred to as the partitioning around medoid (PAM) algorithm [45]. This algorithm consists of three steps which are as follows:

- (i) Initial medoid selection;
- (ii) Medoid swapping;
- (iii) Object labeling.

The first medoid is selected at random. Then, medoids are exchanged for randomly chosen $(q - k)$ potential medoids, where k is the number of clusters, and q is the number of data points. A medoid is a location in the cluster whose differences from all other points in the cluster are at their lowest.

The dissimilarities of the medoid (M_i) and data points (P_i) is calculated by $|P_i - M_i|$. The cost of K-medoids is given by $\sum_{M_i} \sum_{P_i \in M_i} |P_i - M_i|$. For more details about the K-medoids algorithm, one may refer to the work of Budiaji and Leisch [46].

3. Symbols and Notations

We have taken into account a WSN here under the following assertions:

- Nodes are placed uniformly distributed and at random locations inside a square.
- At the highest level of the hierarchical WSN is the base station (BS). It serves as a channel for communication between the sensor network and the user. The BS is situated beyond the boundaries of the square, allowing communication with the nodes liable to multi-path attenuation.
- Multi-path attenuation does not influence communication between nodes.

- The nodes are cohesive since they possess the same capacities and initial battery energy while having varying functions at every specific time.
- Each node has the ability to communicate with the BS and any other node.
- The nodes are static. i.e., stationary.
- Each node detects its surroundings and gives a signal that has the same length.

The initial energy of nodes, the range between sensor nodes and BS, the size of data packets, measurements of voltage and transmission energy and other factors linked to sensor nodes are also completely unexpected due to the irregular/hazardous natural circumstances and are fuzzy valued. Table 3 presents a list of symbols used in this paper.

Table 3. Table of symbols.

Symbol	Description
d	Distance to base station
d_0	Fixed measuring distance to base station
(C_x, C_y)	Coordinate of cluster head in a WSNs
(N_x, N_y)	Coordinate of node in a WSNs
$E_{initial}$	Initial energy
E_{elec}	Electronics energy
E_{TX}	Data transmission energy consumption
ϵ_{fs}	Energy amplification to overcome open area
ϵ_{mp}	Energy amplification in order to navigate the multi-path
ϵ_{amp}	The amplifier energy consumption during transmission phase
E_{RX}	Energy consumption while data reception
K_{opt}	Number of cluster heads that is optimal
L	Length of data
N	Number of nodes in the network as a whole
H	Distance between the special node and the common node
N_c	Number of clusters
$X - Axis$	Direction of length of the base station
$Y - Axis$	Direction of breadth of the base station
m	Number of alternatives
n	Number of criteria

4. System Model Definition and Formulation

One base station (BS) and a large number of sensor nodes comprise the system infrastructure. Two categories are used to categorize all sensor nodes. Common nodes and cluster head nodes are the two kinds of nodes. Common nodes' duties include keeping track of environmental data and sending sensing data to the cluster head node. The cluster head node is systematically chosen from the common nodes. The cluster head receive the data from common nodes, aggregates the data and transmits the data to the BS.

The energy model is the first-order radio model. We just take into account energy use during the communication phase. The energy dissipation caused by data transmission, reception and aggregation makes up the total energy usage. In this paradigm, a common node and a cluster head node exchange L -bit data, and Equation (5) can be used to determine the data transmission energy consumption, whereas Equation (6) is used to determine energy consumption during receiving the data.

$$E_{TX}(L, d) = (E_{elec} + \epsilon_{amp})L \quad (5)$$

$$E_{RX}(L) = E_{elec}L \quad (6)$$

$E_{TX}(L, d)$ is the energy consumption during the transmission of L -bit of data, and $E_{RX}(L)$ is the energy consumption during receiving the data. Equation (7) can be used to

determine the amplifier's energy usage during the transmission phase, where ε_{amp} is the amplifier energy consumption during the transmission phase.

$$\varepsilon_{amp} = \begin{cases} \varepsilon_{fs}d^2 & \text{if } d \leq d_0 \\ \varepsilon_{mp}d^4 & \text{if } d > d_0 \end{cases} \quad (7)$$

If the value of d less than or equal to d_0 , then the sensor node will use the free-space propagation model. On the other hand, if the system uses a multipath fading channel which uses an ε_{fs} and ε_{mp} communication energy parameter, it can be used to calculate the value of d_0 by Equation (8).

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (8)$$

Determining the number of cluster heads in each cycle is crucial for increasing the WSN's lifetime and energy efficiency. We determine the optimal cluster size k_{opt} [33] using Equation (9).

$$k_{opt} = \sqrt{\frac{\varepsilon_{fs}}{\pi(\varepsilon_{mp}d_{toBS}^4 - E_{elec})}} M\sqrt{N} \quad (9)$$

where M , N are represented as an area covered and the number of nodes in the system. BS defines the base location.

5. Experimental Setup and Results

In order to obtain a general clustering algorithm, we present a clustering algorithm based on K-medoids. This will reduce energy consumption and increase network lifetime. In our proposed approach, the base station is used to collect data from all nodes that are sensing through cluster head nodes. We first gather data on node positions and residual energy, after which we compute the cluster number k . By computing the mean locations for the central circle and the residual energy, we improve the K-medoids algorithm to shorten the iteration time. To find the cluster head in each iteration, we implement an algorithm, taking three parameters, residual energy, distance from base station and reliability, into account. In our studies, we deployed a 100-node network with the BS at (50,100) and nodes randomly spread between (100,100). The distribution of 100 nodes around the $100 \times 100 \text{ m}^2$ network is depicted in Figure 3. Each data message is 4000 bits long, and the packet header for every type of packet is 25 bytes long. The channel's bandwidth is set at 1 Mb/s. The optimal value k_{opt} is used to fix the initial number of clusters, and once nodes begin to die, the number of clusters varies with node density. Greater clusters combine with smaller ones. The base station (BS) is a node with greater computational capabilities along with no energy constraints. It has been observed that irregular/hazardous communication can increase noise level in communication and affect the batteries of sensor nodes. Batteries are directly related to residual energy which will impact the network lifetime. Secondly, noisy data are troublesome and need additional careens. For replacement, distance between the sensors, logic and actuators is very significant. So, we have considered the following fuzzy parameters given in Table 4.

In order to group all sensor nodes into k clusters, we employ the K-medoids technique. The K-medoids algorithm, in contrast to the K-means algorithm, represents the cluster head node using a real node rather than a hypothetical mean point. As a result, the partition approach relies on minimizing the distance between the special node and the common node.

$$H = \sum_{i=1}^k \sum_{x \in C_i} \text{dist}(x, r_i) \quad (10)$$

where C_i stands for cluster i , and x is a common node in the cluster C_i . H is the total distance between all representative nodes and common nodes. The primary goal of the K-medoid is to reduce H . Here, we apply the K-medoids algorithm over 100 nodes and

divide the entire network into 14 clusters which is based on the value of hyperparameter N . Table 5 shows the 14 cluster heads along with their all-parametric values. It is to be noted that in our experiment there are fourteen cluster heads that can be used as alternatives, and the four criteria are distance from sink, average distance of cluster nodes, reliability of clusters and the residual energy. The distribution of 100 nodes into 14 clusters after applying the K-medoids algorithm is depicted in Figure 4. Now, we plot a box plot which is commonly referred to as a box and whisker plot, a form of chart that is frequently used in explanatory data analysis in descriptive statistics. Box plots use the data's quartiles (or percentiles) and averages to visually depict the distribution of numerical data and skewness of the whole data. Box plots display a dataset minimum score, viz., (i) first quartile (ii), second quartile which is known as median and (iii) third quartile as well as maximum scores in a five-number summary. The minimum score is the result after removing outliers. Twenty-five percent of the scores are below the first quartile value. Half of the scores are higher than or equal to this number, while the other half are lower. We applied the box plot on the co-ordinate of each node to check whether any outlier position of the node is either present or not in the range. Figure 5 shows the analysis of data points for outliers using the box plot.

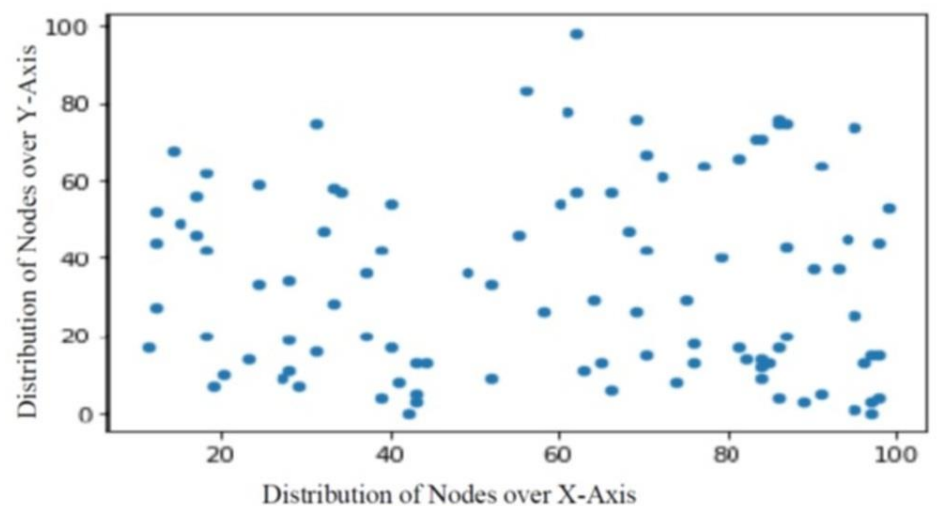


Figure 3. Distribution of 100 nodes around the $100 \times 100 \text{ m}^2$ network.

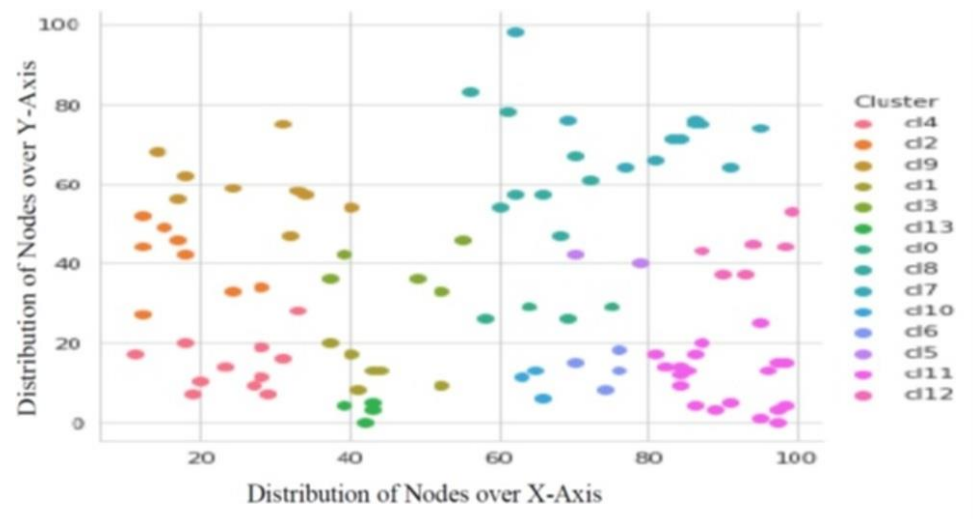
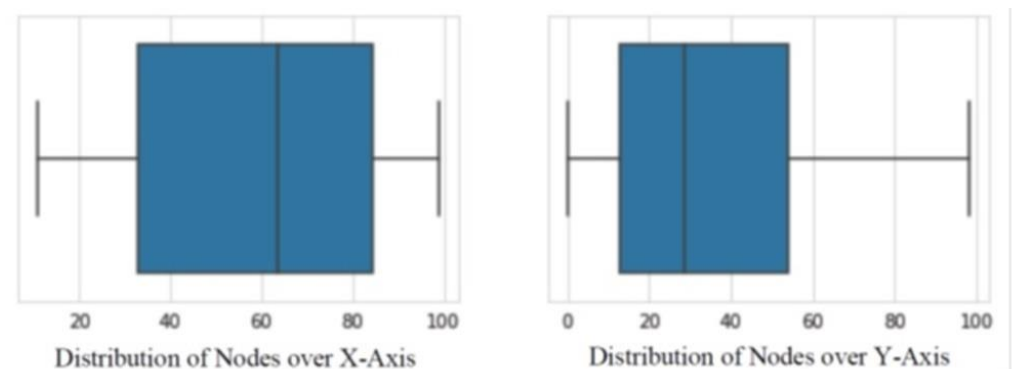
Table 4. Values considering different simulation parameters.

Parameters	Parametric Value as per Assumptions	Defuzzified Value
N	100 [#]	100
$E_{initial}$	(0.7, 1.0, 1.2) J/bit/m ²	0.975 J/bit/m ²
Coordinate of BS	(50,100) [#]	(50,100)
Size of the data packet	(495,500,510) byte	501.25 byte
Hello/broadcast/CH join message	(22,25,28) byte	25 bytes
ϵ_{fs}	(8,10,12) J/bit/m ²	10 J/bit/m ²
ϵ_{mp}	(0.001,0.0013,0.0015) J/bit/m ²	0.001275 J/bit/m ²
E_{elec}	(47,50,52) J/bit/m ²	49.75 J/bit/m ²
K_{opt}	10 [#]	10

[#] Not considered as fuzzy valued.

Table 5. The 14 cluster heads along with their all-parametric values.

Cluster Head	Distance from Sink	Average Distance of Cluster Nodes	Reliability of Cluster	Residual Energy
Cluster 0	76.400	7.864	0.210	0.9695
Cluster 1	87.281	6.097	0.315	0.9654
Cluster 2	66.242	9.929	0.421	0.9698
Cluster 3	64.008	9.891	0.263	0.9653
Cluster 4	90.139	8.721	0.578	0.9688
Cluster 5	66.641	1.000	0.105	0.9641
Cluster 6	90.802	5.569	0.210	0.9647
Cluster 7	44.688	10.353	0.578	0.9657
Cluster 8	45.880	12.618	0.421	0.9649
Cluster 9	48.549	11.96	0.473	0.9656
Cluster 10	89.944	4.329	0.157	0.9698
Cluster 11	93.776	9.286	0.947	0.9688
Cluster 12	70.434	7.568	0.315	0.9698
Cluster 13	97.252	3.095	0.210	0.9656

**Figure 4.** Distribution of 100 nodes into 14 clusters after applying the K-medoids algorithm.**Figure 5.** Analysis of data points for outliers using the box plot mechanism.

For the purpose of our experiments, we estimated the optimum range of k_{opt} using (9). Here, $N = 100$ nodes, $M = 100$ m, $\epsilon_{fs} = 10$ pJ and $\epsilon_{mp} = 0.0013$ pJ. In addition, we considered unpredicted initial energy of each node and unexpected size of data packets as (0.7, 1, 1.2) and (495, 500, 510) which are triangular fuzzy numbers. When dealing with fuzzy parameters, we used the equivalent de-fuzzified values obtained by the signed

distance method. Hence, the expected optimum number of clusters to be considered was between 6 and 11, i.e., $6 < k_{opt} < 11$.

Using Section 2.1, we calculated weights using the entropy method. The weights of different cluster heads are given in Table 6. As the value of k_{opt} lies between 6 and 11, in our experiment we took the value of k_{opt} as 10 which is the optimum value. In order to choose the top 10 cluster heads, we selected the corresponding heads as per their higher values (see bold faces in Table 6). The distribution of 100 nodes into the top 10 selected clusters after applying the K-medoids algorithm based on their weights is displayed in Figure 6.

Table 6. The 14 cluster heads along with their corresponding weights.

Cluster Head	Weights
CH13	0.4968
CH5	0.4965
CH10	0.4962
CH6	0.4958
CH1	0.4953
CH4	0.4947
CH11	0.4946
CH0	0.4940
CH12	0.4933
CH2	0.4919
CH3	0.4918
CH9	0.4883
CH8	0.4879

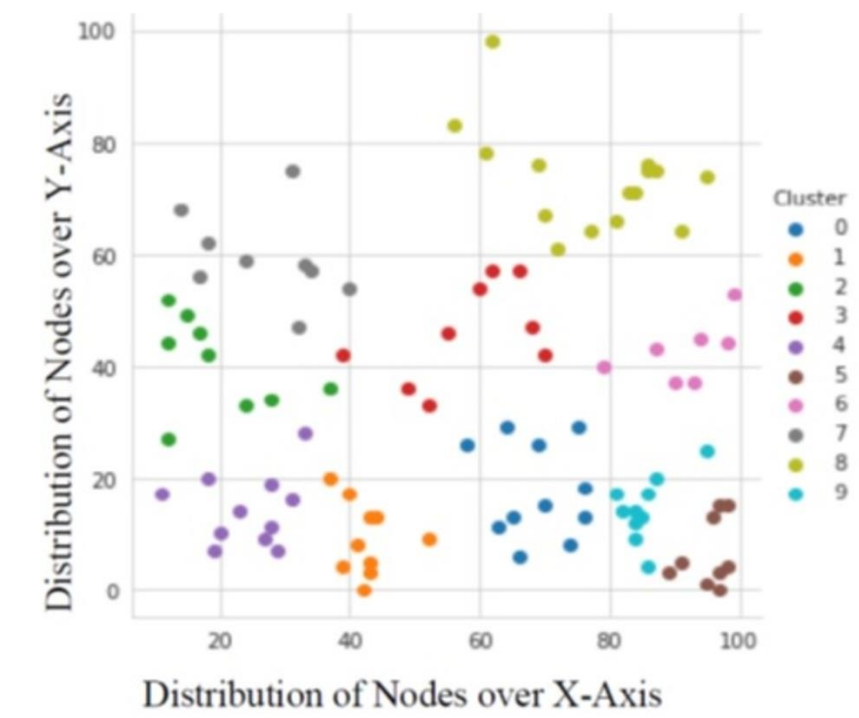


Figure 6. Distribution of 100 nodes into top 10 selected clusters based on their weights.

5.1. Node Selection Criteria

Initially, we selected the best CHs using the K-medoids algorithm over 100 nodes. For this selection, we coded the algorithm in Python and executed it on a Python Jupiter notebook (Version: Python 3 (ipykernel)) in a Linux operating system. Now, we apply our proposed algorithm (see Algorithm 1) for selection of CHs for the next round, depending

on different parameters, such as reliability, residual energy, the distance from the sink (BS) and the average distance of cluster nodes. Algorithm 1 is given below:

Algorithm 1 CHs Selection Algorithm

Step 1: Initially, i.e., in the first round, create N_c number of clusters using the K-medoids algorithm.
Step 2: In the next round, select nodes and calculate their distance from the sink node as well as calculate average distance of cluster nodes, reliability and residual energy.
Step 3: Repeat Steps 4 to 9 for the next round for every cluster until all the nodes diminish their residual energy for finding the next cluster node in every new round.
Step 4: For all nodes in a cluster, compare its residual energy with other nodes in a cluster and increment the counter it encounters as a greater value in comparison to another node.
Step 5: For all nodes in each cluster, compare its distance from the sink with other nodes in a cluster and increments the counter it encounters small value in comparison to other node as the nodes are movable.
Step 6: For all nodes in a cluster compare the average distance of nodes in a cluster with other nodes in a cluster and increment the counter it encounters small value in comparison to other node as the nodes are movable.
Step 7: Choose the node in a cluster as a cluster head with the highest counter value.
Step 8: If a cluster has fewer than three nodes, nodes will be added to the nearest cluster based on the reliability of each cluster.
Step 9: Jump to the next cluster.
Step 10: Stop.

The term which has been used in the algorithm can be calculated as follows:

- (a) Average distance of nodes: distance of one node with respect to all other node in a cluster/number of neighbor's node. If d is the distance between CH and a designated node, then d can be measured using the formula as follows:

$$d = \sqrt{(C_x - N_x)^2 + (C_y - N_y)^2} \quad (11)$$

- (b) Reliability: $1 - \frac{\text{No. of Neighbors in a cluster}}{\text{Total number of nodes in the experiments}}$

5.2. Simulation Results

For the purpose of simulation, we developed Algorithm 2 which is as follows:

Algorithm 2 WSN Lifetime extension Algorithm

Step 1: Deployed 100 nodes in a network with the BS at (50,100) and nodes are randomly spread over (100,100)m² areas.
Step 2: Box plot mechanism was employed to check whether any outlier presents in the data (node) or not.
Step 3: Nodes are divided into number of clusters based on hyperparameter values using the K-medoids algorithm.
Step 4: The TOPSIS technique was applied to choose CHs from clusters using criteria such as distance from sink, average distance of cluster nodes, reliability of cluster and residual energy.
Step 5: Based on the values of k_{opt} , nodes are again divided into k_{opt} number of clusters. Then, CHs of each cluster were chosen by the TOPSIS approach, and clustering is performed by applying the K-medoids algorithm for the first round of the simulation.
Step 6: Applying Algorithm 1 to choose the CHs for the very next rounds until residual energy of all the nodes has not been diminished, and we have counted the number of rounds throughout the complete simulation process.
Step 7: Stop.

We coded Algorithm 2 in the C++ programming language, and the pictorial representations have been completed using the Python programming language on the basis of the

numerical results obtained. After 2600 rounds, the residual energy of all nodes alive has been diminished. Figure 7 illustrates this situation graphically.

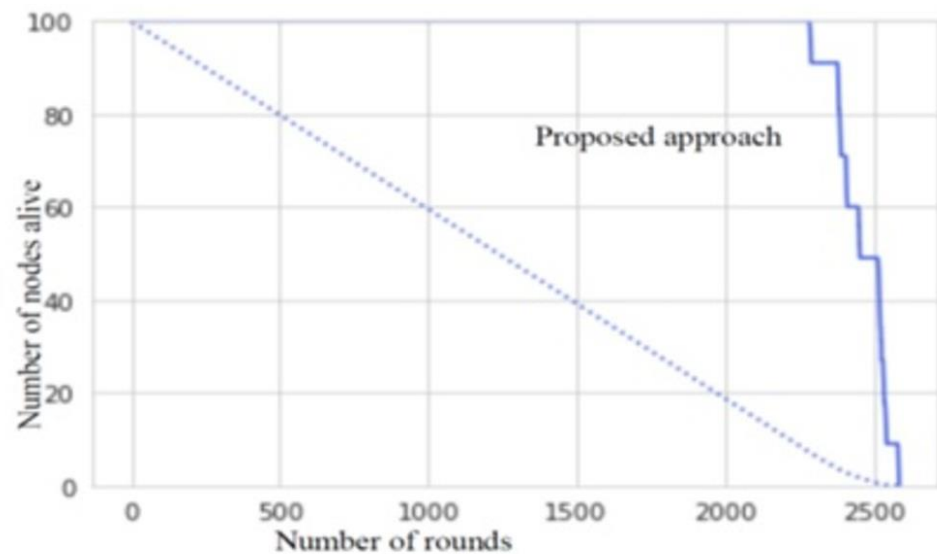


Figure 7. Number of rounds vs. number of nodes alive.

The dotted line in Figure 7 depicts a similar circumstance in which the residual energy must be diminished if the clustering mechanism is being utilized. From Figure 7, it has been seen that after 2600 cycles, the residual energy is completely diminished. So, our proposed schemes have a greater residual energy which in turn extends the network lifetime more than the LEACH-C and HEED schemes, which are depicted in Figure 8. The red line shows the network lifetime of LEACH-C [35] and the blue line for HEED [47].

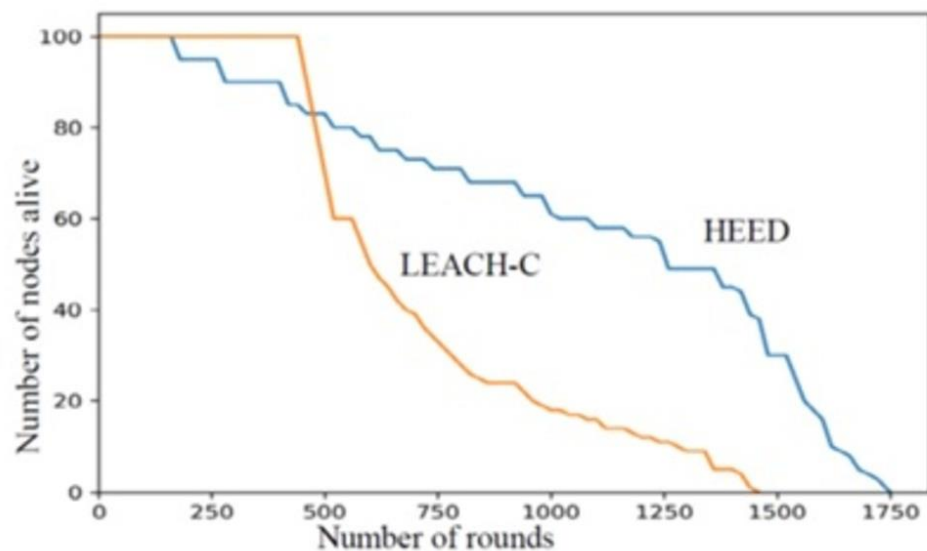


Figure 8. Number of rounds vs. number of nodes alive using the LEACH-C and HEED algorithms.

HEED (hybrid energy efficiency distributed clustering) protocol is an energy-efficient clustering protocol. Node degree and distance to neighbors are used as secondary parameters, with residual energy as the key parameter. The algorithm employed in this study is designed to extend network lifetime, and residual energy is included as a parameter with equal priority to other parameters. First, a comparison between the proposed approach and HEED was made on the basis of these differences. In comparison to HEED, our suggested algorithm exhibits 32% more network lifetime. The LEACH-C (centralized low

energy adaptive clustering hierarchy) protocol is based on residual energy. When forming a cluster, it takes into account the residual energy of each node as well as the distances between different nodes and eligible cluster heads. In contrast, the cluster in the proposed approach is created using the K-medoids algorithm, and the CHs are chosen using the MCDM approach. The proposed strategy with the novel algorithm exhibits 42% greater network lifetime when the two approaches are compared. The K-medoids algorithm is a very popular optimized clustering algorithm which tries to optimize the problem of inter- and intra-cluster distance for cluster creation. The optimized clustering model of WSN is further studied and tried to solve with the very popular optimization technique. In this study, experimental results were compared with OCABC (optimal clustering artificial bee colony) and PSO (particle swarm optimization) as applied to the clustering optimization problem in WSN. It was discovered that the proposed approach outperformed the two algorithms by 11% and 18% in terms of network lifetime (see Figure 9).

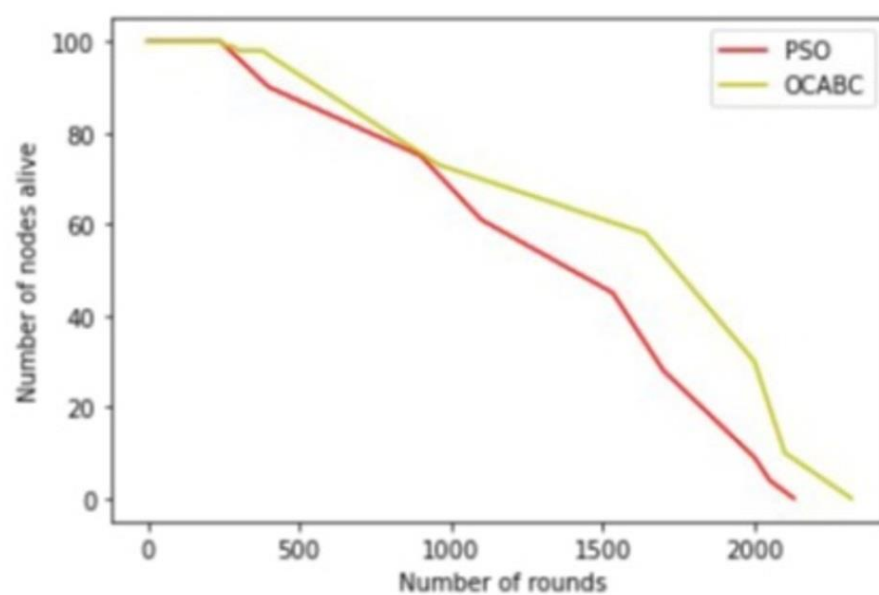


Figure 9. Number of rounds vs. number of nodes alive using the PSO and OCAB algorithms.

Again, the clustering strategy in WSN maximizes the network's lifetime and energy efficiency. The clustering algorithm may often select two CHs for two distinct clusters, even if one of the clusters has just one node or if the two selected CHs are sometimes quite close to one another. The energy efficiency is decreased when certain kinds of CHs are chosen. Some protocols completely disregard other criteria and select CH based only on the residual energy and neighbor's degree of distance. This technique reduces the network lifetime as well. The distance from the sink, the average distance between cluster nodes and residual energy were some of the characteristics used in this proposed algorithm to choose the CHs. Using the reliability parameter, which is also introduced in this algorithm, the problem of a cluster with a single node is also resolved. Let the number of clusters be N_c and the total number of nodes be N . For accessing N_c number of clusters, $\Theta(N_c)$ times are required and within each cluster to find the average distance between every pair of nodes present in the cluster, it needs $\Theta(N^2)$ time. The time needed to calculate the residual energy and distance from the sink are constant ρ_1 (say). Hence, the time complexity of the algorithm is $\Theta(N_c N^2 + \rho_1) \approx \Theta(N_c N^2)$. In the situation where the number of clusters and nodes are equal, the maximum running time (worst-case time complexity) will be $\Theta(N^3)$.

Now, to validate the results, we conduct a statistical hypothesis. We have stated the hypothesis as follows:

Hypothesis H₀. *The average number of simulation rounds ends with a 95% confidence interval, i.e., the simulation round is between 2570 to 2630.*

Hypothesis H₁. *The number of simulation rounds will not end up with 95% confidence interval.*

Let the level of significance be $\alpha = 0.05$, and T is a random variable having t distribution. Here, 95% a confidence interval is [2570, 2630]. The simulation has been performed 50 times. The average simulation result has been considered for the final simulation result which is 2600. Using t statistics, we calculated $T - \text{Score}$ as 0.4691 and $p = \text{Prob}(T > 0.4691)$ as 0.6460. As $p > \alpha = 0.05$, then we do not have enough evidence to reject the null hypothesis H_0 . Therefore, average number of simulation rounds ends with a 95% confidence interval.

6. Conclusions

In order to maximize network lifetime under uncertainty, in this paper we used K-medoids and MCDM techniques to determine the most suitable CHs. After that, we developed a novel algorithm for the purpose of simulation to extend network lifetime under uncertainty. The amount of data in today's digital content is massive, and it is all being transmitted via network channels. In addition, we used WSNs for the purpose of communication. The extension of network lifetime is a challenging task. Therefore, in order to reduce energy usage as much as possible, we must compress these data in the form of images or videos and provide effective routing algorithms. In this paper, we presented a K-medoids-based clustering algorithm along with a novel algorithm for wireless sensor networks to reduce the usage of residual energy and enhance performance. Finding the optimal number of clusters is a very difficult task. Clustering is based on inter- and intra-cluster distance between nodes which is an optimization problem. The problem may be single objective or multiple objective. In a multiple-objective optimization problem, PSO and OCABC are very popular optimization models. Much research has been conducted on cluster optimization using these two techniques which increase the network lifetime dramatically, but the execution time and the complexity of this algorithm are much higher compared to the proposed approach. In this research, a comparison was made between the proposed approach, PSO and OCABC with respect to network lifetime. It was found that the proposed approach shows greater network lifetime by 11% and 18% with respect to OCABC and PSO applied to the clustering optimization problem. Research based on network lifetime extension mainly depends on optimal clustering and CHs selection. In our proposed approach, optimal clustering was performed by the K-medoids algorithm, and CHs were selected by the proposed algorithm. The implementation using the PSO and OCABC algorithms only concentrated on optimal clustering. No CH selection criteria were applied to choose the best CHs from each cluster. As a result, deformation of clusters starts after a few simulations compared to the proposed approach. Diagrams of the occurrence are shown in Figures 7 and 9. The experimental findings and analysis of our suggested scheme which have been presented graphically show that the entire network uses less energy and extends the network lifetime better than the other two well-known algorithms: LEACH-C and HEED. In this research, the node position was assumed to be two-dimensional, but in reality, the node position will be multi-dimensional which is not considered in this research. This may also affect the lifetime of the entire network. The distance between any two nodes is calculated without considering any obstacle, but in a real-life situation, there will be many obstacles between any pair of nodes that will reduce the effectiveness of the algorithm. Further studies need to be considered to develop a new algorithm that will consider the obstacle when calculating the distance between pairs of nodes as well as energy used to transfer the data over the network that takes obstacles into account. The proposed methodology can be used in future research to identify CHs based on multi-criteria decision making, which will improve the network lifetime. For further research,

one may use this proposed approach to solve other WSNs problems considering different parameters and models.

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