Karbala International Journal of Modern Science

Volume 8 | Issue 4 Article 2

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Keywords

IoT; WSNs; Clustering; Energy consumption; Fuzzy C-Means.

This research paper is available in Karbala International Journal of Modern Science: https://kijoms.uokerbala.edu.iq/home/vol8/iss4/2

RESEARCH PAPER

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Abstract

Sensor nodes in Wireless Sensor Network (WSN)-based Internet of Things (IoT) networks are often battery-powered, resulting in supplying relatively low energy. Energy efficiency in WSN-based IoT systems is a critical challenge as the IoT becomes more sophisticated owing to its widespread adoption. Clustering-based routing approaches are well-known approaches that have distinct benefits in terms of efficient communication, scalability, and network lifespan extension. In this research, we present a novel clustering technique for WSN-based IoT systems based on Fuzzy C-Means (FCM). To pick the best Cluster Head (CH), the method uses an FCM technique to build the clusters and a reduction in the total energy spent on each cluster. Rather than replacing CHs for dynamic clustering at each period in this study, we plan to use an energy threshold to hypothesize the dynamicity of CH dependent on existing energy levels, therefore increasing the sensor network lifespan.

Keywords: IoT, WSNs, Clustering, Energy consumption, Fuzzy C-Means

1. Introduction

MANETs (mobile ad-hoc networks), WSNs (wireless sensor networks), and IoT (Internet of Things) are three types of networks that distribute low-resource nodes and nodes that must be deployed quickly. These IoT devices not only assist in data transmission and reception but also link a variety of devices to the Internet. Those devices might be fixed or mobile, based on the use for which they are intended. WSNs have proven their value in a variety of applications in the IoT era [1,2]. WSN is made up of small sensor nodes (SNs) that are arbitrarily deployed and are utilized to control and monitor applications such as battlefield monitoring, forest fire monitoring, house monitoring, environmental monitoring, surveillance, industrial control systems, and vehicle automation, amongst many others [3,4]. Processing, memory, radio, and energy units are all included in these sensor nodes. These SNs capture data about the surrounding environment, such as acoustics, vibration, light, humidity, and temperature. The data is sent to a base station (BS) once it has been preprocessed using wireless communication [5,6]. In WSNs, the transmission of data is the most energy-depleting function for SNs. As a result, making fewer data transfers or lowering the power of transmission is required to reduce energy use [7]. Furthermore, in order for WSNs to be used, a number of conditions in the network's architecture and operation must be met. Because SNs are powered by a finite amount of energy, energy saving is often regarded as the most critical challenge in ensuring network connectivity and extending SN lifetime, particularly if the deployment area is harsh or hostile and the battery is not replaceable [8,9].

Although such sensor nodes are simple to deploy, the limitations of restricted energy significantly stifle the use and growth of WSNs. As a result, several studies on WSNs have been conducted, such as on how to extend the network's survival period and balancing the network energy usage. Numerous researchers have conducted extensive studies on more energy-efficient network architectures,

Received 8 March 2022; revised 10 August 2022; accepted 14 August 2022.
Available online 10 November 2022

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https://doi.org/10.33640/2405-609X.3259

routing algorithms, and protocol development, and a variety of techniques are utilized in the WSN energy strategy. In comparison to the planar routing algorithm, the use of a hierarchical clustering routing algorithm has superior flexibility and energy efficiency [10].

Clustering is one feasible method for resolving these challenges and making the best use of available energy. This is due to clustering, which divides the network into clusters and requires SNs in each cluster to submit data to a cluster head (CH) [11]. Because of the sensors' closeness to the CHs, the sensors can reduce their powers of transmission, lowering energy consumption and extending the network lifespan. CHs are chosen from among the SNs to manage data gathering from sensors inside their clusters, aggregate it, and send it to the BS [12].

To extend the lifetime of WSN-based IoT, we introduce a novel clustering protocol dependent on fuzzy c-means with distance- and energy-limited termed (FCMDE) for clustering, CH selection, and data transmission. FCMDE clusters SNs using the fuzzy c-means technique, but instead of choosing the node closest to the fuzzy c-means centroid as the CH, as in previous studies [11,13], FCMDE chooses the node closest to the majority of nodes in the network. The closeness rule guarantees that nodes in each cluster are constantly close to their CH, enabling them to send at significantly lower power levels. Rather than replacing CHs for dynamic clustering at each period in this study, we plan to use an energy threshold to hypothesize the dynamicity of CH dependent on existing energy levels. The network's energy usage is considerably influenced by the modification in how the CH is picked.

The remaining portions of the paper are described below. Section 2 includes the related works. Section 3 briefly introduces the network concept and energy consumption model. Section 4 contains a full overview of the suggested protocol. The simulation findings and discussions are presented in section 5. Section 6 outlines the paper's conclusion.

2. Related works

A significant amount of research in sensor networks has focused on energy-efficient clustering-based routing methods [14−21]. In this study, we looked at a variety of strategies, highlighting a few of them. In the network, the sensor nodes can be chosen to act as CH either centrally or distributedly. The first makes use of a BS to manage CH choice, whilst the second is entirely self-organized.

Machine learning is progressively being used to partition the network into clusters, from which CHs are chosen based on predetermined factors. This may be accomplished through the employment of algorithms such as k-means [12,13,22] and fuzzy c-means [11,13], which are increasingly being used in WSNs, the IoT, and crowd-sensing applications. To deal with the uncertainty in WSNs [23,24], used clustering methods based on fuzzy logic. The authors in [23] introduced data processing and clustering for WSNs based on fuzzy logic. This method takes into account each node's energy level, bandwidth, and connection efficiency. The suggested work aims to increase network performance regarding the lifetime of the network, the number of live nodes, CH selection time, throughput, and energy usage.

The authors in [24] presented an energy-efficient clustering technique based on the fuzzy logic system to extend the WSN lifespan in a probabilistic approach model. With the support of an efficient CH selection approach, this effectively tackles the issue of low sensor node residual energy usage. The authors of [25] recommended three protocols: enhanced DEEC (EDEEC), developed DEEC (DDEEC), and DEEC. The rates of CH energy minimization and network longevity were investigated for each clustering strategy. In terms of sensor network longevity, the EDEEC protocol surpasses both the DECC and DDEEC protocols, according to the data. In [26], the authors introduced a load balancing method that works intelligently dependent on a controller of fuzzy logic and the queue of priority to reduce and disseminate energy usage, resulting in an improvement in network lifespan.

In [27], the authors firstly offer an analytical approach for determining the ideal number of clusters in a WSN. Next, they present a centralized clustering approach dependent on the spectral division method. Following that, they offer a decentralized solution to the clustering technique based on the fuzzy C-means approach. Eventually, they ran extensive simulations, and the findings revealed that the suggested approaches beat the HEED clustering method in regards to energy cost and network longevity. The paper's authors [28] suggest a Scalable Energy-Efficient Clustering Hierarchy (SEECH) for selecting CHs. High-degree SNs are categorized as CHs in this approach, whereas low-degree SNs are used as relays. It employs a distance-based method to assess the homogeneity of CHs for balancing clusters. As compared to the LEACH and TCAC methods, the suggested algorithm shows improved SEECH protocol performance in terms of sensor network lifespan.

In [29], the authors presented an energy -efficient distribution -independent network clustering algorithm. The authors discussed the energy-hotspot (hole) problem by taking into account each of the non-uniformly and uniformly distributed networks. The proposed algorithm called Multi-Objective Fuzzy Clustering Algorithm (MOFCA). The results showed that MOFCA has superiority to other known techniques in terms of Total Remaining Energy (TRE), First Node Dies (FND), and Half of the Nodes Alive (HNA). Authors in [30] presented multi-criteria zone head selection in grid-based WSN to build an improved grid-based hybrid network deployment (IGHND) algorithm. IGHND is a developed version of the GHND algorithm by optimize the zone head selection where considering five instead of three parameters. The effectiveness of the suggested method was proven compared with existing methods.

In [10], the authors suggested UCNPD as a unique unequal clustering routing protocol for WSNs that considers the balancing of energy depending on the network partition and distance. They created a circle by making a ring region with the BS as the center, then the area of the network is partitioned depending on the distance between nodes and the BS in the protocol's design model. These node portions are responsible for connecting to the BS, while the rest adhere to the optimal clustering routing service protocol, which elects the cluster head using a timing strategy. Cluster rebuilding consumes less energy as a result. They also created uneven clusters by establishing varied competitive radiuses, which aids in balancing network energy use. To decrease and balance energy utilization, they examined all of the energy of the cluster head, the distances to BS, and the degrees of the node while choosing a message route.

The paper [17] proposed a new passive multi-hop clustering technique (PMC). The PMC technique is built on the notion of a multihop clustering algorithm, which guarantees that the cluster is covered and stable. A priority-based neighbor-following technique is given for selecting the best neighbor nodes to join the same cluster during the cluster head selection stage. This method ensures that the inter-cluster nodes are highly reliable and stable. The stability of clustering is considerably enhanced by assuring the stability of the cluster members and picking the most stable node in the N-hop range as the cluster leader. The cluster's dependability and resilience are increased further during the cluster maintenance stage by implementing the cluster merger method.

DECA (differential evolution based clustering algorithm) [31] is a new clustering method that relies on DE. The researcher included a vector encoding approach for assigning nodes to respective CHs, as well as a local optimization stage to increase the performance of the network.

Some authors proposed using mobile edge computing (MEC) instead of traditional solutions that introduce cloud computing to address issues with IoT devices, such as limited computation and energy resources [32–42]. Since edge servers are installed nearer to the devices on the edge of the network in MEC systems and have significantly more processing capability than IoT devices, offloading computing duties to them can minimize latency and energy usage.

Table 1 shows a categorization of several clustering techniques as well as clustering features.

3. Preliminaries

The energy consumption model and the network model are presented in this section. Table 2 lists the nomenclature of all the variables that were utilized.

3.1. Network model

In this part, we demonstrate a common IoT monitoring environment for WSN-based IoT applications. We use a cluster-based design to ensure the system's energy efficiency. The BS is positioned in the middle of a square sensing field with N sensor nodes distributed at random. The nodes continually monitor the environment and send the findings of their observations to the CH, which sends the data collected to the BS (also known as the gateway or sink) on a periodic basis as shown in Fig. 1.

For our network model, we make the following assumptions:

- The topology of the network remains static throughout the network operation.
- Sensor nodes based on the IoT are deployed in a uniform pattern but at random.
- The sensor nodes are all homogeneous.
- All sensor nodes are energy-restricted and start with the same amount of energy.
- The BS is supposed to be free of energy, computation, and network coverage limitations.
- Radio interference, as well as any obstruction or signal attenuation caused by the existence of physical objects, are not taken into account.
- We believe that the suggested protocol is extremely secure. This work's security considerations are outside the scope of this paper.

Table 1. Clustering techniques are classified based on several clustering characteristics.

Reference	Clustering objectives	Clustering methodology	Cluster count	Nodes mobility	Inter-cluster communication	CH selection approach	CH selection parameters	Outcomes
UCNPD [10]	Balancing the network energy consumption	Distributed	Variable	Static	Mutli hop	Timing time	Residual energy, node degrees, competition radius	Better performance of network energy balance and provides a longer effective working life comparing with LEACH, EEUC and I_EEUC protocol
FLCP [23]	Improve the energy consumption, throughput, and network lifetime.	Distributed	Variable	Static	Mutli hop	Fuzzy logic	Residual energy, link efficiency	In comparison to the LEACH protocol, the suggested model outperformed it in the network lifetime.
DDEEC [25]	Increases network lifetime	Distributed	Predetermined	Static	Single hop	Probability	Initial and residual energy levels	DDEEC protocol enhances the network lifetime
SEECH [28]	Increases network lifetime	Distributed	Variable	Static	Mutli hop	Probability	The degree of nodes	SEECH protocol, lifetime is 118% better than TCAC protocol and 136% better than LEACH protocol
PCM [17]	Stability and reliability of the cluster	Distributed	Variable	Mobile	Mutli hop	Priority-based neighbor-following strategy	Number of followers, node relative mobility	The suggested algorithm increases node's reliability and stability.
DECA [31]	Maximize the network lifetime	Centralized	Fixed	Static	Single hop	Differential evolution	Standard deviation of the life time of the CHs, standard deviation of average cluster distance	DECA outperforms traditional DE and GA, LBC in terms of network lifetime and energy consumption
DESA [43]	Prolonging the network lifetime	Distributed	Variable	Quasi-stationary	Single hop	hybrid differential evolution and simulated annealing	Total Euclidean distance of a node from every other node in the cluster, remaining energy	70% better performance than LEACH in terms of number of alive nodes
ECAFG [44]	To form balanced clusters and to improve network lifetime	Distributed	Fixed	Static	Single hop	Genetic fuzzy system	Node's distance from CH as well as from the cluster center, node's residual energy	Prolonged network lifetime by 54, 37, 33% in terms of first node death compare with LEACH, CHEF, LEACH-ERE reduces energy consumed

FUCA [45]	Extends the lifetime of the network	Distributed	Fixed	Static	Mutli hop	Fuzzy logic	The distance to base station, residual energy, and density	It extends the lifetime of the network as compared with its counterparts.
Our proposed (FCMDE)	Energy-efficient clustering to improve network lifespan	Centralized	Predetermined	Static	Single hop	Fuzzy C-Means	Position inside the cluster, level of residual energy	FCMDE enhances the lifetime by roughly 250% and 168% compared to DDEEC and SEECH

3.2. Radio model

Sensor nodes need energy for remaining awake, network maintenance, data processing, packet receiving, packet transmission, and sensing, among other things. The amount of energy required to send a packet is proportional to the size of the packet and the distance traveled. In terms of energy usage, we utilize the same radio model that was employed in [46] and is shown in Fig. 2.

The transmitter demands a quantity of energy to send an $w - bit$ packet across a distance of d, as given:

$$E_{TX}(w,d) = \begin{cases} E_{elec} \times w + \epsilon_{fs} \times w \times d^2 \; if \; d < d_0 \\ E_{elec} \times w + \epsilon_{mp} \times w \times d^4 \; if \; d \geq d_0 \end{cases} \tag{1}$$

Receiving an $w - bit$ packet consumes the following amount of energy:

$$E_{RX}(w) = E_{elec} \times w \tag{2}$$

The energy utilized per bit by the receiver or transmitter circuits is denoted by E_{elec} in (1) and (2). In a free space model and a multi-path fading channel model, we utilize ϵ_{fs} and ϵ_{mp}, respectively, to describe the energy usage of the amplifier per bit. The distance between the receiver and transmitter is indicated by the letter d. The d_0 threshold is formulated as having

$$d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}} \tag{3}$$

The data aggregation power consumption, which is denoted as E_{da}, is another factor that is considered. We suppose that each cluster member delivers $w - bit$ packet to its CH during each period of data collection, and that the energy spent by a CH during one period of collecting data may be expressed as

$$E_{CH} = \frac{N}{c} \times E_{elec} \times w + \frac{N}{c} \times E_{da} \times w + \epsilon_{mp} \times w \times d_{BS}^4 \tag{4}$$

The CH wastes energy by collecting packets from nodes, aggregating them, and transferring the resulting packets to the BS. The number of clusters is given by c, while the average distance between a CH and a BS is given by d_{BS}.

4. The FCMDE protocol

In this part, the suggested protocol for clustering based on the fuzzy for the WSNs' saving energy issue is presented. The protocol is centralized in which the FCM algorithm in the BS establishes the architecture of a specific WSN. During the initial stage of building, the fuzzy c-means method is in charge of distributing sensor nodes to the closely relevant clusters depending on the geographic

Table 2. The nomenclature of the variables.

Variable	Description
N	*Sensor Nodes No.*
N'	*No. of alive Sensor Nodes*
SN	*Sensor Node*
CH	*Cluster Head*
T_{CH}	*The network's total number of CHs*
BS	*Base Station*
c	*Clusters No.*
w	*Packet Size*
w^*	*Control Packet Size*
d	*Distance*
d_0	*Distance Threshold*
E_{TX}	*Energy of Transmission*
E_{RX}	*Energy of Receiving*
E_{elec}	*Energy used by the Receiver Electronics*
ϵ_{fs}	*Free Space Amplifier Energy*
ϵ_{mp}	*Multipath Fading Amplifier Energy*
E_{da}	*Data Aggregation Power Consumption*
d_{BS}	*Distance from SN to the BS*
SC	*Silhouette Coefficient*
λ	*Distance Cost Functions*
E_{Co}	*Energy Cost Function*

positions of these sensors during this stage of building. The BS performs this step just once at the start of the protocol, and it stays unaltered across the lifetime of the network. To put it another way, once the network architecture has been created, no sensor can be relocated from one cluster to the next.

Subsequently, the proposed protocol is divided into numerous rounds, each of which includes two stages: CH selection and transmission of data (Fig. 3). The CH selection phase considers the nodes' remaining energy as well as their cluster's position (with regard to other nodes). Instead of using the sensor node closest to the centroid, FCMDE uses a novel measure in which the sensor node closest to all other nodes is chosen as the CH. After BS has chosen the CHs, it broadcasts a control packet including the essential information for nodes, such as node id, related CH, and centroid of the cluster. The transmission of data stage entails data interchange between SNs, CHs, and their BS, with the strategy for all of these transmissions being determined by the SNs', CHs', and BS's residual energy and relative distance. The CH selection and the transmission of data are iterative in each round. Figure 3 depicts the flowchart of the proposed FCMDE.

4.1. Building a WSN topology

Clustering is an unsupervised learning approach that groups consistent data points based on a certain

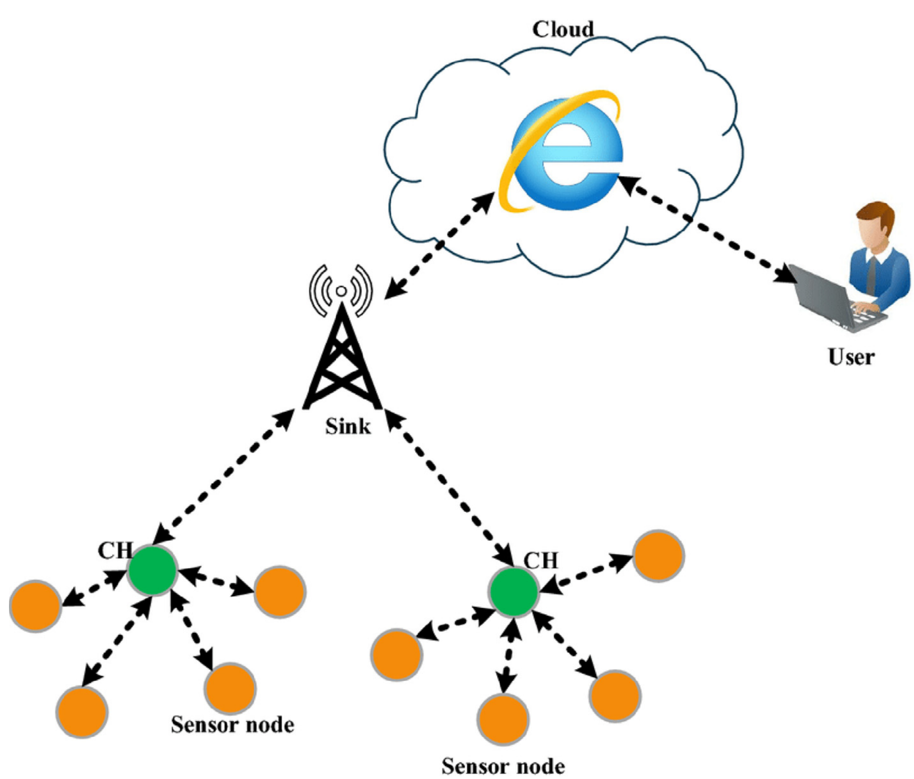

Fig. 1. Network model.

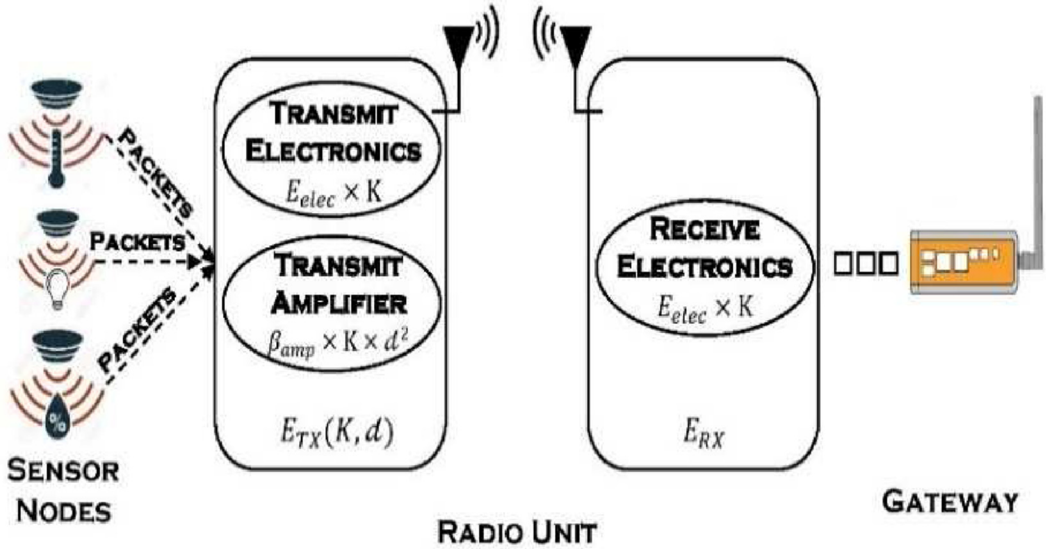

Fig. 2. Radio model.

similarity measure that increases inter-cluster similarity whilst reducing intra-cluster similarity. Following the sensor nodes have been deployed, each node communicates its position and energy information to the BS in order for the network's CHs to be selected in each round. There are two phases in the initial stage of building the FCMDE protocol. The first phase is to decide on the best number of clusters to use. The second phase is WSN clustering using the fuzzy c-means method.

4.1.1. The optimal number of clusters

Since the quantity of inter-cluster communication rises with c, determining the ideal number c of clusters is crucial. However, when c is lower, the number of intra-cluster communications increases considerably. Using the silhouette coefficient (SC) or silhouette score approach [47], we will determine the ideal number of clusters as in the following: (5)

$$SC(n_i) = \frac{b(n_i) - a(n_i)}{\max\{a(n_i), b(n_i)\}} \tag{5}$$

where, $SC(n_i)$ is the silhouette coefficient of the sensor node n_i; $a(n_i)$ denotes the average intra-cluster distance, that is, the average distance between sensor node n_i and all other sensor nodes in the cluster to which n_i belongs. The minimal average inter-cluster distance between sensor node n_i and all clusters to which n_i does not belong is denoted by $b(n_i)$.

The SC's value ranges from (−1, 1). A score of 1 indicates that the sensor node is highly compact inside the cluster to which it belongs and is far distant from the other clusters. The poorest possible value is −1. Near-zero values indicate overlapping clusters.

4.1.2. FCM clustering

To split the network into a fixed optimal number of clusters, we suggest a centralized clustering algorithm based on the fuzzy c-means [25] approach in this section. We presume that the BS node is fully aware of the network architecture. The BS node connects all CHs. The BS uses the FCM method to compute the cluster centroids and assign *SNs* to the clusters $c = \{C_1, C_2, \ldots, C_c\}$ based on the information received from the SNs. Instead of being a complete member of only one cluster, every node is allocated a degree of membership u_{ij} to a cluster C_i.

FCM is an iterative process that seeks to decrease the following objective function at a local level:

$$J_{min} = \sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^{m} d_{ij}^{2} \tag{6}$$

where, u_{ij} is the degree of membership to cluster i of sensor node SN_j, d_{ij} denotes the distance between sensor node SN_j and the cluster $C_i's$ center point. With the actual parameter $m > 1$.

The FCM-based clustering algorithm's behavior is determined by the clusters' number c in addition to

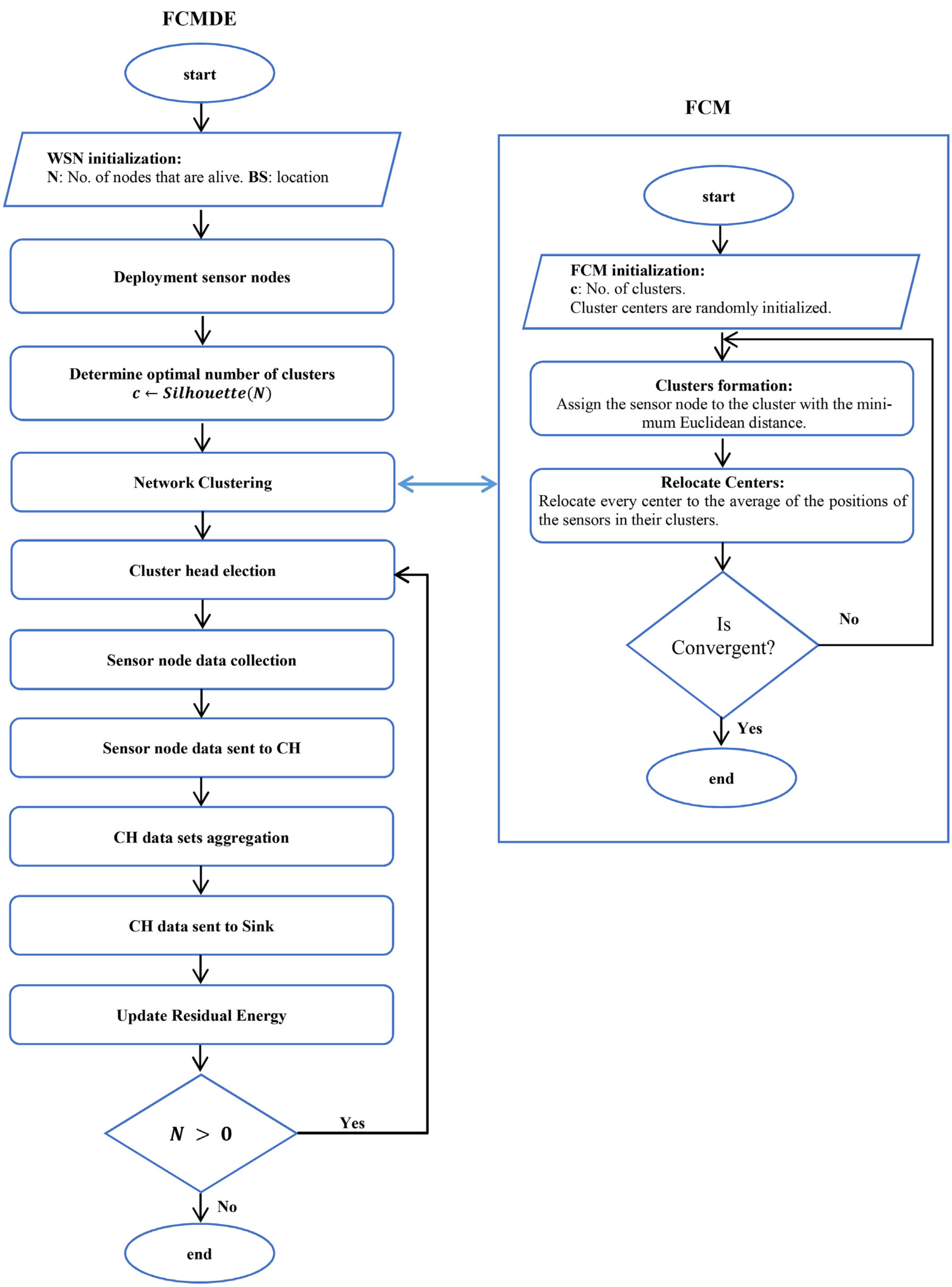

Fig. 3. The flowchart of the proposed FCMDE.

the sensor nodes' number. During the clustering phase, the following activities are taken:

1. Set the fuzzy clusters' number to c.
2. Assign c initial cluster centers at random.
3. Compute the matrix of membership using

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}} \tag{7}$$

4. Compute the center of the cluster using

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} n_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{8}$$

5. Steps 3 and 4 should be repeated until all nodes' membership values converge, which is written as:

$$max\left\{U_{ij}^{I+1} - U_{ij}^{I}\right\} < \beta \tag{9}$$

where U_{ij}^{I} is the I^{th} iteration's membership matrix, and β is the terminating indicator, which has a value between 0 and 1. When U_{ij}^{I} converges, every node with the greatest membership amongst clusters is allocated to that cluster.

The FCM algorithm associates the cluster center coordinates with their sensor members; only the sensor node's membership is taken into account by our protocol as shown in Algorithm 1.

Following the establishment of the WSN topology, the protocol runs its rounds, with each round separated into the previously described CH selection and data transmission stages. These two stages are explained in the following sections.

4.2. CH selection

Clustering is conducted prior to CH selection in this study to decrease the energy consumed in the process of cluster creation. After FCM creates the clusters, the CH is picked as the sensor node that is nearest to the most other nodes (i.e., is the best place for a CH). This is due to the fact that the CH mediates among SNs inside the cluster, reducing the energy consumption needed by cluster nodes to deliver data.

Moreover, at this phase, every node has about equal energy levels, that is consistent with the assumption established in Section 3.1. Two factors must be met by the CH selection policy:

4.2.1. Position inside the cluster

Rather than the node closest to the cluster's center, the CH is chosen based on its proximity to the most other nodes. Because the aim of the proposed protocol is to minimize the energy required by sensors for sending to the CH, rather than to choose the node at the cluster's center, this requirement, which we call the closeness rule, is more beneficial than closeness of the possible CH to the cluster's center. We develop a cost function, λ, that calculates the Euclidean distance between the selected node and all other in-cluster nodes to discover the sensor that is closest to the most other nodes and costs the least amount of energy to broadcast to inside its cluster.

Algorithm 1: Fuzzy c-means

Input: N: *Sensor nodes No.*
Output: C: *Number of clusters created*

/* Network Initialization */

for $i \leftarrow 1$ *to* N ***do***
  Deployment sensor nodes randomly
  Set SN-id, SN initial energy
end for

/* Bootstrapping Process */

/* SNs sending their geographical position and id to the BS */

for $i \leftarrow 1$ *to* N ***do***
  Compute the Euclidean distance between the SNs and the BS
end for

/* Fuzzy C Means */

$\boldsymbol{C} \leftarrow$ *Calculating optimal No. of clusters using Eq.* (5)
for $j \leftarrow 1$ *to* N ***do***
  SN_j *is given the coefficient* u_{ij} *for being a member of cluster* i
end for
Initially selecting the centroid within per cluster formed
for $j \leftarrow 1$ *to* C ***do***
  while $\beta < max\{U_{ij}^{I+1} - U_{ij}^{I}\}$ ***do***
    assigning the SN to C^{th} *with the largest member−ship value*
    calculating the objective function
    updating the cluster centroid using Eq. (8)
    updating the membership value using Eq. (7)
  end while
end for

$$\lambda = \sum_{j=1}^{c} \sum_{n_i \in C_j} d(n_i, X_j) \tag{10}$$

where n_i denotes the i^{th} node in the network, and X_j indicates the centroid of the sensor nodes in a specific cluster, and C_j comprises N_j nodes and the Euclidean distance $d(n_i, X_j)$ is given by:

$$d(n_i, X_j) = \|n_i - X_j\|^2 \tag{11}$$

4.2.2. The level of residual energy

A node's remaining energy should be over a certain threshold E_{TH} in order for it to be considered for CH selection. This criterion is required to prevent the CH from dying too soon, resulting in the network being disconnected. For every CH selection, we create an energy-related cost function that describes the total energy usage for all sensor cluster members. When sensor node X_i is designated as CH, the energy-related cost functions $E_{Co}(CH_i)$ for each cluster of n_c sensor nodes are expressed as the total consumed energy of all sensor nodes.

$$E_{Co}(CH_i) = \sum_{j=1, j\neq i}^{n_c} E_{TX}(x_j \rightarrow X_i) + (n_c - 1) \times E_{RX}(X_i) + E_{TX}(X_i \rightarrow BS) \tag{12}$$

where,

- $E_{TX}(x_j \rightarrow X_i)$: the amount of energy expended by sensor node x_j to send a data packet to CH X_i.
- $E_{RX}(X_i)$: the amount of energy utilized by the CH X_i when it receives a data packet from a sensor node.
- $E_{TX}(X_i \rightarrow BS)$: the amount of energy expended by CH node X_i during the transmission of the aggregated data packet to the BS.

The BS calculates the cost functions relating to energy and closeness for each cluster and chooses the node with the lowest $E_{Co}(CH)$ and λ as the CH. The BS transmits a packet of information to every node in the network once the CH has elected, which includes the CH ID, and the cluster ID. Following the CH election, the BS changes the state of the nodes in its system (energy levels of nodes).

Following the completion of the initial configuration of the network, the CHs in the next period will compare their energy levels ($E_{CH-Th}(i)$) to the energy threshold function E_{TH}. The CH can maintain intra-cluster communication with member nodes of a cluster if the present CH remaining energy levels ($E_{CH-Th}(i)$) are equivalent or higher than the energy threshold level E_{TH}; otherwise, the CH must discontinue and demand the creation of a new cluster. Therefore, the CH could remain without change for consecutive periods until its residual energy falls below the threshold.

4.3. Transmission of data

The sensor nodes begin transmitting data packets to the CHs when the CHs are identified. Each SN is sensing its region of interest at a fixed rate, so the sensed data will constitute a data packet. At the end of each round, each cluster member node will send its data packet to their CH. Then, all CHs perform data aggregation on the received data packets from their cluster members, reducing the quantity of data and then transmitting the aggregated data to the BS directly. Due to the obvious shortest geographic distance to the CHs attained by the FCM algorithm, the transmitting power of cluster member nodes is enhanced.

We've also presented a novel technique for SN packet routing, in which all SNs submit their data packets in a single hop. Depending on the Euclidean distance between the SN and its CH (d_{SN-CH}) and the SN and the BS (d_{SN-BS}), each SN sends its data packets either to the CH or to the BS as shown in Fig. 4. The distances d_{SN-CH} and d_{SN-BS} have the following equations:

$$d_{SN-CH} = EUC_{Dis}(SN, CH) \tag{13}$$

$$d_{SN-BS} = EUC_{Dis}(SN, BS) \tag{14}$$

The SN's destination can be specified as follows:

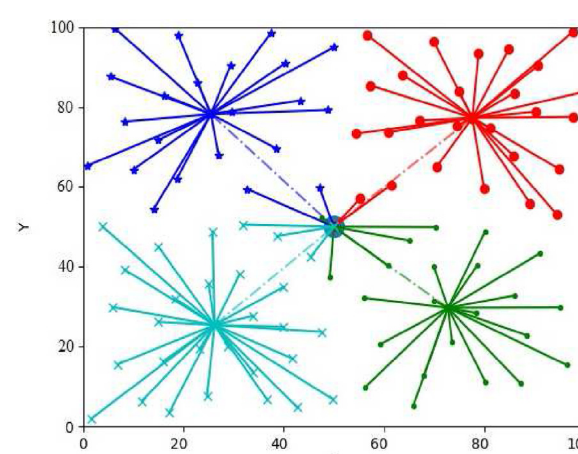

Fig. 4. Display of various forms of nodes with their distances.

$$SN_{Dist.} = \begin{cases} CH, & d_{SN-CH} < d_{SN-BS} \\ BS, & Otherwise \end{cases} \tag{15}$$

When the SN fulfills $d_{SN-CH} < d_{SN-BS}$, it sends its data packet to its CH; otherwise, it sends it to the BS directly.

5. FCMDE energy consumption (cost)

The suggested work's energy consumption is separated into two stages: setup energy and data transmission energy.

5.1. The setup Stage's energy consumption

The setup stage comprises the creation of clusters and their members, and the energy spent during these operations is referred to as setup-stage energy ($setup_E$). The energy used by every node to send a $w^* - bit$ control packet to the BS is calculated as follows:

$$E_{SN'TX}(w^*, d_{SN-BS}) = \begin{cases} E_{elec} \times w^* + \epsilon_{fs} \times w^* \times d_{SN-BS}{}^2 \text{ if } d_{SN-BS} < d_0 \\ E_{elec} \times w^* + \epsilon_{mp} \times w^* \times d_{SN-BS}{}^4 \text{ if } d_{SN-BS} \geq d_0 \end{cases} \tag{16}$$

where, d_{SN-BS} denotes the distance measure (i.e., Euclidean) between the SNs and the BS. Once the clusters have been formed (i.e., the CHs have been chosen), the BS sends out a control message to the network, that contains all of the crucial data for all SNs. Every SN expends energy in order to receive this data, which may be expressed as,

$$E_{SN'RX}(w^*) = E_{elec} \times w^* \tag{17}$$

Every CH then communicates the TDMA schedule to its SNs and consumes energy as

$$E_{CH'TDMA}(w^*, d_{SN-CH}) = \begin{cases} E_{elec} \times w^* + \epsilon_{fs} \times w^* \times d_{SN-CH}{}^2 \text{ if } d_{SN-CH} < d_0 \\ E_{elec} \times w^* + \epsilon_{mp} \times w^* \times d_{SN-CH}{}^4 \text{ if } d_{SN-CH} \geq d_0 \end{cases} \tag{18}$$

The greatest distance measure (i.e., Euclidean) connecting CH and the cluster's constituent SNs is d_{SN-CH}. Energy usage by every SN to acquire the aforesaid TDMA schedule is specified as,

$$E_{SN'TDMA}(w^*) = E_{elec} \times w^* \tag{19}$$

Equations (16), (17) and (19) may be used to calculate energy usage by typical SNs.

$$E_{SN'} = \sum_{i=1}^{N'} E_{SN'TX} + E_{SN'RX} + \sum_{i=1}^{N'-T_{CH}} E_{SN'TDMA} \tag{20}$$

where, T_{CH} is the network's total number of CHs. Equation (18) may be used to calculate the energy usage of CH nodes as follows:

$$E_{CH'} = \sum_{i=1}^{T_{CH}} E_{CH'TDMA} \tag{21}$$

As a result, equations (20) and (21) may be used to calculate the overall energy usage during the setup stage of a round.

$$setup_E = E_{SN'} + E_{CH'} \tag{22}$$

5.2. The data transmission Stage's energy consumption

According to the criteria specified in Equation (15), every SN sends its data packet toward either CH or BS. SN's energy usage every round will be calculated as follows:

$$E_{SN}(w,d) = \begin{cases} E_{elec} \times w + \epsilon_{fs} \times w \times d^2_{SN-CH}, \text{ if } d_{SN-CH} < d_{SN-BS} \\ E_{elec} \times w + \epsilon_{fs} \times w \times d^2_{SN-BS}, \text{ Otherwise} \end{cases} \tag{23}$$

As every CH uses single-hop communication, it sends its own data packet straight to the BS. As a result, CH's energy usage every round would be calculated as follows:

$$E_{CH}(w, d_{CH-BS}) = \begin{cases} w(E_{elec} + E_{da})(n_c - n_b) + \epsilon_{fs} \times w \times d^2_{CH-BS}, \text{ if } d_{CH-BS} < d_0 \\ w(E_{elec} + E_{da})(n_c - n_b) + \epsilon_{fs} \times w \times d^4_{CH-BS}, \text{ if } d_{CH-BS} \geq d_0 \end{cases} \tag{24}$$

where n_c is the number of SNs in a certain cluster, n_b is the number of SNs that transmit their data packet straight to the BS rather than to the CH, and d_{CH-BS} is the distance between CH and BS.

As a result, Equations (23) and (24) may be used to calculate the overall energy consumption throughout a round's data transmission stage:

$$D - TRAS_E = \sum_{i=1}^{N'-T_{CH}} E_{SN} + \sum_{i=1}^{T_{CH}} E_{CH} \tag{25}$$

Thus, equations (22)−(25) may be used to calculate the overall energy usage per round, that comprises the setup and data transmission stages:

$$Round_E = setup_E + D - TRAS_E \tag{26}$$

6. FCDME complexity

In this part, the analysis of the suggested protocol's time complexity is described. The proposed FCMDE technique is divided into two stages, as previously described. FCM builds the infrastructure for the provided WSN in the first stage, which is only executed once at the start of the protocol. The FCM has a time complexity of $O(nd^2ci)$, in which n represents the total number of SNs, d is the number of dimensions (set to 2 in FCMDE, which reflects the $x-$ and $y-$ axis position of every SN), c denotes the number of clusters, and i is the number of FCM iterations over all SNs in the specified WSN. Furthermore, the time required to perform one complete cycle of FCMDE is the same as the time required to complete the CH election and data transmission stages. By closely evaluating these two stages, it is clear that the CH-election stage dominates the entire time. As a result, the analysis is centered on this stage and divided into the message complexity and the time complexity.

6.1. Message complexity

Every SN can only send one control message every round. SNs chosen as CHs must send CH_ADV messages to each of the neighbors within the cluster to market them as CHs, while cluster member nodes shall broadcast CH_JOIN messages to join the CH. So, given a network of N nodes, there are a maximum number of N messages broadcast. As a result, the message complexity for each SN is $O(1)$, and it is $O(N)$ for the entire network.

6.2. Time complexity

At the moment of the CH election, every SN in a network separately determines its likelihood of becoming a CH. Hence, the time complexity for this stage is $O(1)$ for the whole network. After cluster creation, each cluster member node chooses one CH out of its list of nominees for CHs to join a cluster. In the worst-case scenario, a cluster member node may be required to handle $(N-1)$ CHs. Hence, $O(N)$ is the worst-case of complexity. As a result, given N nodes in a network, the time complexity of FCMDE is $O(N)$.

7. Simulation and performance evaluation

The simulation findings used to assess our suggested protocol (FCMDE) are presented in this section. The FCMDE supposes that the sensor nodes are deployed in a $100m \times 100m$ region for building the network model as shown in Fig. 5. No two nodes may be at the same position at the same time in these simulations. This indicates that each sensor's vertical and horizontal coordinates are chosen at random between 0 and the dimension's maximum value (i.e., 100).

The sink node is positioned at the center of the network $(50, 50)$. Table 3 lists the factors that were utilized in the simulations. The FCMDE protocol is compared to the DDEEC [25], MOFCA [29], IGHND [30], SEECH [28] and FUCA [45] protocols in five aspects: network lifetime, throughput, energy consumption, end-to-end delay, and reliability.

Because the FCM method requires the clusters count to be known beforehand, we set the optimal number of clusters to 4, as computed by Equation (5) and illustrated in Fig. 6. As illustrated in Fig. 7, our suggested technique divides 100 sensor nodes into four clusters, each represented by a different color.

7.1. An evaluation of lifetime

It is critical that all sensor nodes remain operational as long as feasible since the performance of the network suffers when a node dies. As a result, knowing the death time of the first node is critical.

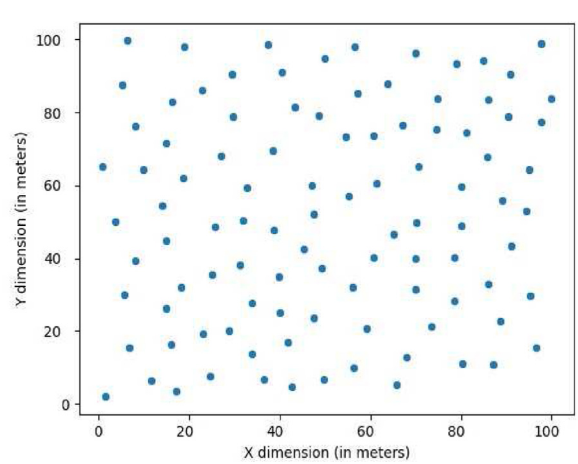

Fig. 5. Sensor nodes deployment in the region of interest.

Table 3. Simulation factors.

Factors	Value
WSN Size	100 $m \times$ 100 m
SNs No.	100
BS location	(50, 50)
Initial Energy	10 J
Clusters No.	4
Simulation time	600 s
Transmission channel	*Wireless channel*
E_{da}	$5nJ/bit/signal$
ϵ_{fs}	$10pJ/bit/m^2$
ϵ_{mp}	0.0013 $pJ/bit/m^4$
E_{elec}	50 nJ/bit
d_o	88 m
Packet Size	512 *bytes*
Control Packet	400 *bit*

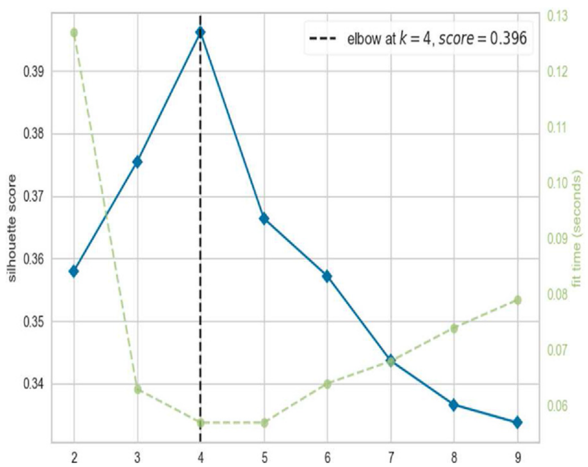

Fig. 6. Silhouette score.

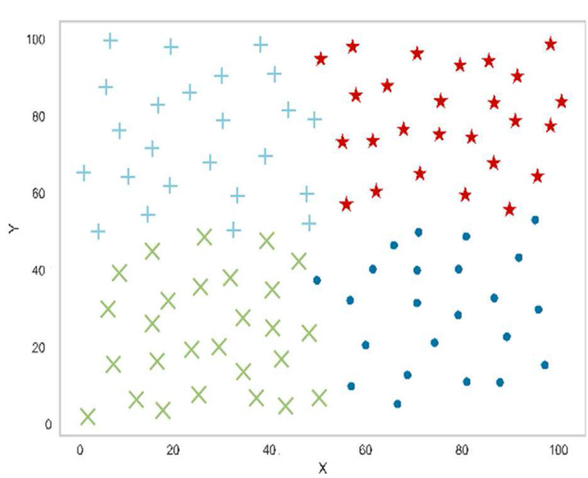

Fig. 7. Cluster formation with FCMDE.

The period of time during which the network's first node dies is described as the network's lifetime.

First-SN, Half-SN, and Last-SN (periods' number during which the network's first, half, and last node die, respectively), are all being included in the study as shown in Fig. 8. Figure 9 shows the comparison of FCMDE with DDEEC, MOFCA, SEECH, IGHND, and FUCA simulation results. We discovered that, when compared to previous works, the suggested work's network lifespan has been significantly increased, and this is due to our work's consideration of energy and distance.

It is shown by the results obtained in Fig. 8, the suggested protocol (FCMDE) has a first-SN enhancement of roughly 150%, 79%, 68%, 48%, and 7% when compared to DDEEC, MOFCA, SEECH, IGHND, AND FUCA, respectively. The Half-SN and Last-SN are also superior in comparison.

7.2. Consumption of energy

In the next experiment, the FCMDE protocol investigates how much energy is lost on average

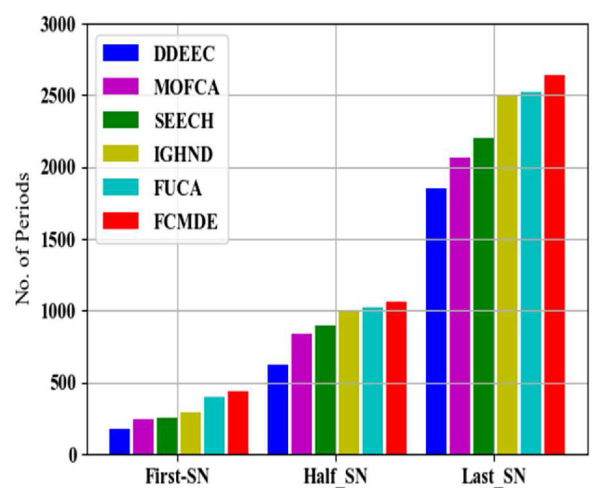

Fig. 8. First-SN, Half-SN and Last-SN stages of the network.

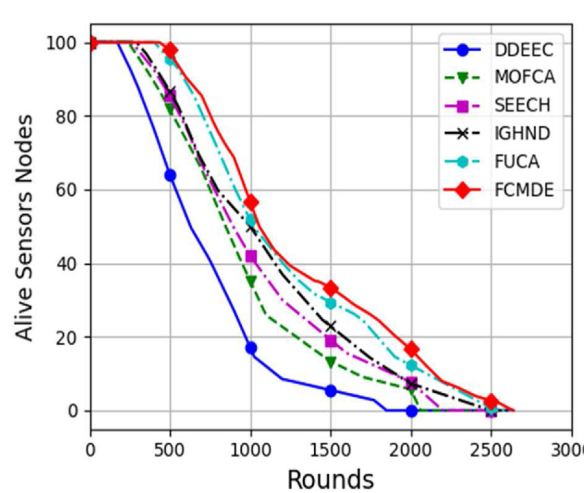

Fig. 9. Sensor nodes lifetime.

inside the network. Consumption of energy is among the ultimate important factors to consider when determining WSN's effectiveness. Figure 10 compares the suggested FCMDE protocol to the DDEEC, MOFCA, SEECH, IGHND, and FUCA strategies in terms of energy usage. Experimental results demonstrate that the energy consumption during every period was already lowered. The FCMDE protocol uses energy roughly 55%, 53%, 50%, 28% and 24% less than the DDEEC, MOFCA, SEECH, IGHND, AND FUCA protocols, respectively, throughout the transmission of data. The findings demonstrate that the FCMDE protocol performs best and saves more energy in comparison to the other two protocols.

7.3. Analyze the throughput

Another simulation experiment was conducted to assess the network's throughput. Throughput is defined as the ratio of the packets that the CH acknowledges to the delay of the communication of packets in the process of transmitting, which is defined as:

$$Throughput = \frac{total\ No.\ of\ packets\ received\ by\ CH}{delay\ in\ process\ of\ communication} \quad (27)$$

The analysis of the throughput of the suggested FCMDE protocol compared to DDEEC, MOFCA, SEECH, IGHND, and FUCA protocols is shown in Fig. 11. When compared to the DDEEC, MOFCA, SEECH, IGHND, and FUCA protocols, the quantity of packets sent to the CH in the suggested FCMDE protocol is 41%, 45%, 21%, 10%, and 5% faster, respectively. As a result, as compared to previous techniques, throughput measuring has grown over time.

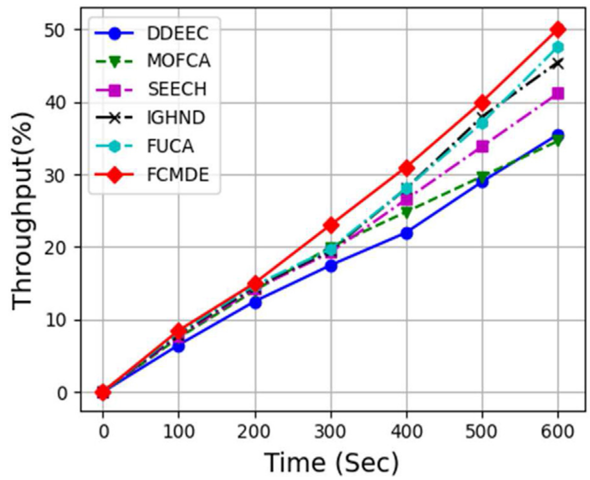

Fig. 11. The Throughput of the network.

7.4. End to end delay

It's computed by dividing the total time it takes to deliver a data packet to the CH by the number of data packets it receives.

$$delay = \frac{\boldsymbol{Total\ time\ to\ deliver\ packet\ to\ CH}}{\boldsymbol{No.\ of\ packets\ recieved\ by\ CH}} \quad (28)$$

The suggested technique's end-to-end delay measurement is shown in Fig. 12. At most times, FCMDE takes less than 65 ms to send data packets from SNs to the CH, which is faster than DDEEC, MOFCA, SEECH, IGHND, and FUCA transmission times. When compared to conventional protocols, the FCMDE approach reduces latency considerably by optimizing data transmission rates.

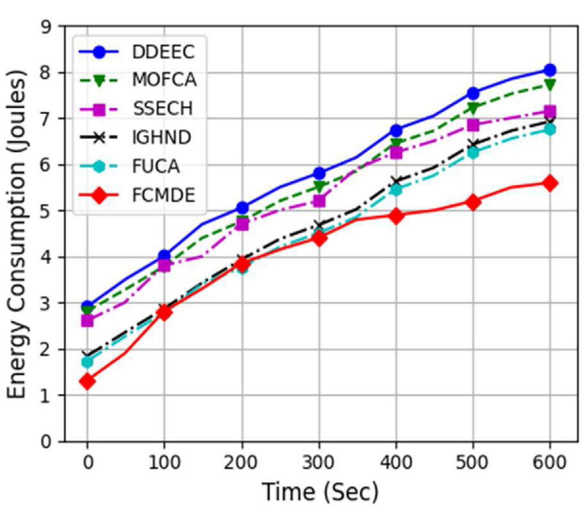

Fig. 10. The energy consumption of the network.

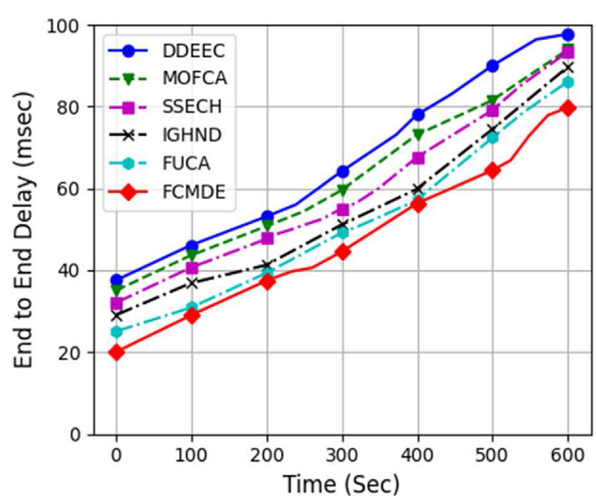

Fig. 12. The end-to-end delay vs. Time.

7.5. Analyze the reliability

It calculates the sensor network's lifespan over a period of time. The formula is as follows:

$$Reliability = 1 - \frac{t}{mean\ time\ between\ failure} \quad (29)$$

Figure 13 compares the FCMDE approach to the DDEEC, MOFCA, SEECH, IGHND, and FUCA techniques in terms of reliability. The results demonstrate that FCMDE is anywhere between 11% and 7% more reliable than the other protocols.

7.6. FCMDE's influence on large- and small-scale networks

The findings for average energy consumption for each round for the whole network are analyzed as given in Table 2 below to highlight the FCMDE's influence on large- and small-scale networks.

The nodes count used in the simulation ranges from 100 to 400. Table 4 indicates that when compared to DDEEC, MOFCA, SEECH, IGHND, and FUCA, the total network's average energy consumption per round for FCMDE is much lower for all situations. These findings demonstrate that FCMDE has a considerable influence in both large- and small-scale networks.

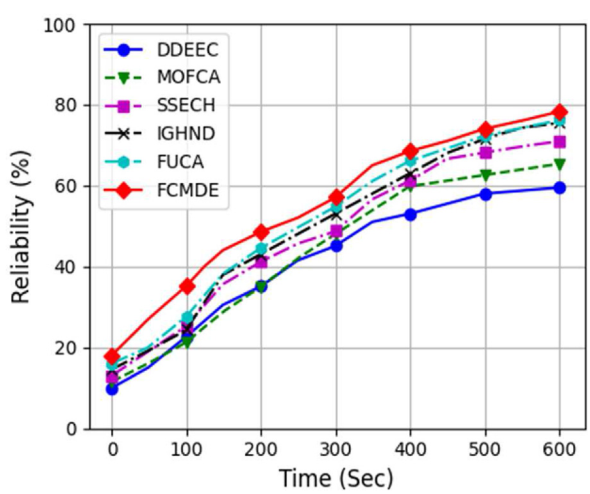

Fig. 13. The Reliability of the network.

7.7. Discussion

Since it has a longer number of rounds until the die of the first node, our suggested method outperforms DDEEC, MOFCA, SEECH, IGHND, and FUCA in terms of network lifetime. The figures also show that when the density of nodes and initial energy grows, our methods become more efficient. Our methods are also proved to be robust since the death time of the first node can indicate the robustness of the method. This is due to the fact that the lifetime, scalability, and efficiency of the entire network are all dependent on the appropriate cluster count and the geographic location of the cluster head. It's worth mentioning that the silhouette coefficient determines the optimal cluster count. In comparison to DDEEC, MOFCA, SEECH, IGHND, and FUCA, our method can find the ideal cluster count and give an ideal CH election approach to save energy.

As we noted in the literature review, there are some researchers who have adopted other ideas to address the problems associated with sensors, whether in WSNs, MANETs, IoV, or IoT. One of these methods is the use of mobile edge computing to take advantage of its resources in the process of reducing energy consumption.

8. Conclusions

In this study, FCMDE was introduced as a clustering protocol for WSN-based IoT. The suggested FCMDE reduces energy drain and increases longevity while minimizing overhead costs. FCDME chooses a CH during clustering by combining fuzzy c-means, node location, and residual power. In an attempt to reduce transmission overhead costs and unnecessary CH changes for every transmission period, FCMDE uses functions of thresholds, namely the threshold of energy and the closeness rule. The effectiveness of the suggested FCMDE protocol has been demonstrated through thorough simulation using a variety of possible assessment performance indicators. Average energy usage, network longevity, and throughput are all examples of these indicators. A comparison analysis of

Table 4. Per-round energy consumption average.

Nodes No.	The total network's energy consumption average per round, *Joule*					
	DDEEC	MOFCA	SEECH	IGHND	FUCA	FCMDE
100	2.912	2.80	2.608	1.83	1.72	1.312
200	3.8071488	3.36	3.4096992	2.50	2.488	1.7153088
300	5.54853936	3.90	4.96929624	3.456	3.07	2.49989136
400	7.18653936	4.10	6.43629624	4.036	4.026	3.23789136

SEECH and DDEEC procedures was also conducted, demonstrating the superiority of the FCMDE approach.

Future studies will focus on developing a novel CH selection function (e.g., utilizing metaheuristic optimization approaches) for grouping the network system of multitier heterogeneous sensor networks. Future research in this area may yield better results, which will be valuable for multimedia and heterogeneous sensor networks.

Acknowledgement

The authors wish to express their gratitude to the University of Babylon in Iraq for their support.

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