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A Fuzzy Logic Based Cluster Head Election Technique for Energy Consumption Reduction in Wireless Sensor Networks

Catherine Onyango[1], Kibet Lang'at[2] and Dominic Konditi[3]

[1]Research Scholar, Department of Electrical Engineering, Pan African University Institute for Basic Sciences, Technology and Innovation, 62000-00200 Nairobi, Kenya; cathyonyango@gmail.com
[2]Associate Professor, Department of Telecommunication and Information Engineering, Jomo Kenyatta University of Agriculture and Technology, 62000-00200 Nairobi, Kenya; kibetlp@jkuat.ac.ke
[3]Professor, School of Electrical and Electronic Engineering, Technical University of Kenya, 52428-00200 Nairobi, Kenya; dominic.konditi@tukenya.ac.ke

*__Correspondence:__ cathyonyango@gmail.com; Tel.: +254721865111

ABSTRACT- Wireless sensor networks deploy sensor nodes to different areas for data collection. The small size of these sensor nodes allows limited energy storage capacity, and most applications of the networks do not support recharging the batteries once their energy is depleted. Research on energy efficiency in wireless sensor networks is thus an active area that seeks to minimize energy consumption so that the sensor nodes can live longer. Clustering, one of the energy consumption optimization techniques, is employed in this research. It splits the network into smaller groups for data collection and forwards the data to the base station via appointed cluster heads. A fuzzy-based cluster head election strategy is proposed here to improve energy efficiency in wireless sensor networks. The input parameters of the fuzzy inference system are chosen as the residual energy, the node centrality, and the mobility factor. The system generates an output of the chance of a node being selected as a cluster head based on the combination of the values of the given inputs. The simulation results show that the proposed model reduces the network's overall energy consumption and extends the sensor nodes' lifetime.

Keywords: clustering; energy consumption; fuzzy logic; network lifetime; wireless sensor networks.

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1. INTRODUCTION

Small sensing devices are used in Wireless Sensor Networks (WSNs) to collect data in a target environment and process it for use in a specific application. Based on the sensing area, the sensors are deployed using different techniques. For easily accessible areas, the sensors can be set up manually by human beings at desired locations; inaccessible areas use aerial vehicles to deploy the sensors randomly. Based on the types of sensors in use and where they are deployed, WSNs can be terrestrial, underground, underwater, or multimedia. When a network comprises sensors with equal processing capabilities, sensing capabilities, and the same energy consumption rate during sensing, transmission, and reception, it is referred to as a homogeneous network, while a heterogeneous network is one whose sensors are of different capabilities. Sensors deployed in a network can either be static (not changing location after deployment) or mobile (moving around the network area). WSNs are used in diverse applications, including health monitoring, precision agriculture, military tracking, home automation, environmental monitoring, and industrial applications [1]. The small size of sensors limits their energy, memory, and computing capability capacity. They are powered by batteries, which means that once the energy in the batteries is depleted, the nodes can no longer participate in the network and are said to be dead. In several applications, access to the sensor nodes to replace or recharge their batteries is impossible. Therefore, Energy efficiency is a significant area of focus in WSNs to ensure that the limited energy resource is utilized to extend the network lifetime. Solutions that have been researched include energy-saving methods like scheduling sleep and wake–up times for sensor nodes; energy harvesting techniques like solar rechargeable batteries; use of chemical batteries, power control, wireless power transfer, data aggregation, and design of energy-efficient clustering and routing protocols [2]–[6].

Cluster-based protocols have been widely used in WSNs to efficiently utilize limited energy resources [7], [8]. The main concept behind these is splitting the network area into smaller regions called clusters, in which the sensed data is aggregated by one of the sensor nodes before being forwarded to the base station (BS). The sensor node that takes up this role is called the cluster head (CH). All other nodes within the cluster forward their sensed data to the CH to save energy that would have

Research Article | Volume 11, Issue 4 | Pages 1136-1146 | e-ISSN: 2347-470X

otherwise been consumed to forward the data to the BS directly. Energy consumed in transmission is directly proportional to the distance between the transmitter and receiver. Therefore, a sensor node forwarding data to a CH closer to it than the BS utilizes less energy. Several CH selection strategies have been reviewed in [9], where the main objective is to ensure that the best nodes are selected for this role.

Fuzzy logic-based clustering is one of the popular methods used in energy-aware CH selection. It involves different variables describing sensor node characteristics being fed as inputs to a fuzzy inference system (FIS) that takes them through a fuzzification and defuzzification process to obtain outputs. Such input parameters include residual energy, distance to BS, node centrality, node concentration, neighbor nodes energy, and node degree. The FIS generates outputs that aid in deciding the most suitable node to act as CH in every cluster region.

This research proposes a fuzzy logic-based model for cluster head election in WSNs. Parameters defining sensor node properties determine the chance of a node being elected as CH for the cluster it belongs to. The motivation of this study is to extend the lifetime of sensor nodes in a network by minimizing the energy consumed during the transmission of sensed data to the BS. The contributions of this work are explained as follows:

I. A cluster head selection model is designed based on fuzzy logic that accepts residual energy, node centrality, and mobility factor as inputs to the FIS and gives an output of the chance of a node being elected as CH.

II. The accuracy of the choice of CH is increased by avoiding the random selection of initial CHs and instead considering the three inputs using fuzzy logic at the very initial selection.

III. An improvement in the CH selection strategy reduces energy consumption per transmission round. The combination of the three inputs ensures a selection of CHs that last longer due to possession of sufficient energy, balance the energy consumption within a local cluster by being centrally located and thus averaging the distances of transmission from all nodes in the cluster, and stay within the same cluster during the transmission round as a low mobility factor is preferred.

IV. A performance analysis is carried out to demonstrate the reduction in energy consumption and extension of network lifetime. The energy consumption is monitored throughout the transmission rounds, and the network's residual energy is measured at different times. The network lifetime is measured by an analysis of the number of alive and dead nodes at different rounds of transmission and an analysis of the rounds at which the first node dies, half the nodes die, and all nodes die.

The approach taken in this research is key to energy management in WSNs. It saves energy during data transmission by balancing energy consumption during intra-cluster communication. The energy saving is achieved by considering the centrality of nodes within a cluster in addition to the energy and mobility. As opposed to some techniques that randomize the initial selection and consider the above in subsequent transmissions, this approach combines the three properties at the very initial appointing of CHs, reducing possible errors associated with probabilistic selection.

The organization of the remaining part of the paper is as follows: section II describes previous research related to the work presented here. Section III explains the methodology followed to develop the proposed model, and the simulation results are presented in Section IV. Section V concludes the paper.

2. RELATED WORKS

The design of cluster-based protocols for WSNs is a research area that has attracted a lot of attention to achieve high levels of energy efficiency to prolong the network lifetime. The earliest hierarchical algorithm, the LEACH algorithm, is based on the clustering technique where nodes are grouped into clusters with one acting as a head [10]. The protocol involves a setup stage where CHs are elected, clusters are formed, and a TDMA schedule is created. The second stage is the data transmission stage. LEACH's main shortcoming is the random selection of CHs without considering energy in the nodes, which can lead to a node with low residual energy being appointed as CH. The node would then deplete its energy before successful transmission. The basic LEACH did not consider the mobility of nodes, but several of its variants have considered sensor node mobility as one of the criteria for CH selection. The LEACH-mobile (LEACH-M) in [11] confirms that a sensor node has not moved out of its cluster during the steady state phase. It allocates one of the TDMA time slots to check whether sensed data is received from a node, and if not received, the node is removed at the end of the next frame, and the time slot is allocated to a newly joined node. The advantage is that it reduces packet loss in the steady-state phase. However, it does not consider mobility during CH selection, which could lead to choosing a CH that leaves its cluster before data forwarding. LEACH-ME [12] extends the LEACH-M by introducing a check on the remoteness of a node before it is considered during the CH rotation phase in the steady state phase. However, it does not address the mobility issue during the initial CH selection. The LEACH-MF algorithm developed in [13] extends the LEACH-ME algorithm by considering the mobility of sensor nodes during the initial CH selection, which was previously not considered. The research achieves an extended network lifetime and reduced energy consumption. However, this algorithm still adopts random values in the initial selection of CH candidates, which could lead to candidates with less energy and higher mobility qualifying as candidates before the second selection that employs the FIS. The LEACH-MF/EH in [14] is an extension of the LEACH-MF that introduces the aspect of energy harvesting in nodes. The protocol can prolong the network lifetime, especially in the morning, since it considers solar energy harvesting nodes. Random number generation at the beginning of the CH election still leaves room for a node with relatively low residual energy or higher mobility compared to neighbor nodes qualifying as candidates for the second CH selection. Authors in [15] developed a distributed algorithm that shatters the chance of a node being a CH using a FIS with inputs such as residual energy, node centrality, and distance to the BS. The probabilistic approach selects

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probationary CHs, which are then subjected to the FIS to select the final CHs. The algorithm performs better than those it is compared with, especially as the network grows. The authors in [16] proposed a model that divides the network area into unequally-sized clusters to alleviate the hotspot problem experienced by nodes closest to the BS. The radius of each cluster is chosen by use of fuzzy logic. The node's residual energy, concentration, and base station distance are the input parameters to select CHs and determine the cluster radius. The research achieves reduced energy consumption and prolonged network duration compared to several existing protocols. However, the probabilistic approach in arriving at a provisional CH in both [15] and [16] would risk starting with a non-optimal selection. CHEETAH's algorithm is proposed in [17] that performs cluster head selection based on a type-2 fuzzy logic system. The probability of CH selection given as output by the system is combined with a random number generated for each node to arrive at the choice of CH. The input values considered are the residual energy, distance to the BS, the historical contribution as a CH, and the estimated power saved by the nodes when they transmit via CHs. The convenient selection of the CH and the reduction of control packets that this model achieves help to improve the network lifetime, as the authors demonstrate with the previous works it is compared to. A centralized fuzzy logic approach is proposed in [18] that elects CHs based on three input parameters: node residual energy, node concentration, and node centrality. The algorithm developed in [19] uses fuzzy logic to select the most suitable node for the CH role. The input parameters are the residual energy, the node distance to BS, and the node centrality. The authors set a new threshold for the CH selection probability, considering a ratio between the number of clusters and the total number of nodes. For a node to qualify as CH, it has to achieve a lower threshold and the highest CH chance generated by the FIS. A fuzzy-based clustering protocol is designed in [20] that uses the number of neighbors and the residual energy as inputs to determine the node that qualifies as the header node. A header node is selected from among the chosen CHs by considering the distance to BS and residual energy and is used to route data gathered by other CHs to the BS. This model minimizes the number of control packets transferred, as clustering is not done in each round. A hierarchical routing protocol is proposed in [21] that uses a fuzzy-based clustering technique to reduce energy consumption in WSNs. Residual energy, communication cost, and position of nodes are the inputs to the FIS, which generates an output of the best node to act as a cluster leader. The energy consumption is significantly reduced when compared to the cited research, and the network lifetime of the nodes is increased. These fuzzy-based algorithms reviewed in [17]–[21] achieve improved network lifetime and energy consumption performance due to the optimal CH selection. The use of fuzzy logic at the first instance of CH appointment instead of applying a probabilistic approach can be attributed to this improvement. However, none of these models consider the mobility of nodes. They can thus be extended to consider sensor node mobility in the CH selection stage since most real-world applications use mobile nodes. We propose a model in this research which considers the energy in the sensor nodes, their position relative to the cluster center, and their mobility in the very first selection of CHs as opposed to assigning random values and setting a threshold for qualification of a node. This increases the chances of optimal selection of the CH nodes. The fuzzy logic model is split into two to help reduce the complexity of the computation required as fewer rules are used in the FIS. The model is aimed at reducing the energy consumption in the network and subsequently extending the lifetime of the sensor nodes.

3. THE PROPOSED FUZZY MODEL

In the proposed model, sensor node deployment is done in a two-dimensional network square area. The entirely simulated data utilized in this article is generated through the MATLAB platform. Simulation allows a controlled environment to assess the model's performance. The widely adopted platform in the academic and research community has a rich set of toolboxes, including communication systems and optimization, providing ease of use and rapid prototyping for WSNs. The deployed network consists of 100 sensor nodes within a 100m X 100m network area, randomly distributed with the mobility following a random waypoint model. All nodes are homogenous with an initial energy of 1J. A single stationary base station is situated at the center of the network (50, 50). A single transmitted packet is 4000 bits long. The simulated data also includes parameters like sensor node location, energy levels, and communication distance.

After deployment, the network area is split into predetermined regions using a k-means clustering algorithm. Fuzzy logic selects a node that is most suitable as a CH for every region. The choice of fuzzy logic over probabilistic and metaheuristic algorithms is informed by its simplicity and ease of implementation, allowing for less computational requirements. This computational efficiency is advantageous to sensor nodes where computing resources are limited. In addition, sensor node properties like energy and distance are represented in qualitative terms. Fuzzy logic allows a natural way to model such by using linguistic variables and rules.

Data transmission follows from member nodes within a cluster to their corresponding CHs, and after the CHs receive, they aggregate the data from the member nodes and forward it to the sink node. The following subsection describes how each input parameter to the FIS is computed.

3.1 Parameter Computation

3.1.1 Residual energy

Residual energy is the remaining battery level in a sensor node during data transmission. The node dies and can't transmit data if the battery is depleted and not rechargeable. Choosing cluster heads based on energy is important as nodes with low energy reserves may die before completing transmission, causing data loss. When a node's energy reaches a threshold value greater than zero, it is marked as dead and doesn't participate in communication. Residual energy is calculated by subtracting energy consumed at a given instance from the initial or previously calculated residual energy. The first-order radio model presented in *equation (1)* from [5] is used to calculate the consumed energy per transmission round.

$$E_{T_X}(l,d) = \begin{cases} E_{elec} \times l + \varepsilon_{fs} \times l \times d^2, d \leq d_0 \\ E_{elec} \times l + \varepsilon_{mp} \times l \times d^4, d \geq d_0 \end{cases}, \quad (1)$$

E_{T_X} is the energy dissipated to transmit and is a function of the distance d and length of the message l in bits; E_{elec} is the energy needed to process l-bit data with the electronic circuits. ε_{fs} and ε_{mp} are the energy parameters for free space and multipath models, respectively. Energy dissipation is proportional to d^2 in free space and d^4 for the multipath model. A reference distance, denoted as d_o, determines whether the free space or multipath model is used to compute energy consumed. The free space model is used for distances shorter than the reference distance, while the multipath model is used for longer distances. The reference distance is computed using *equation (2)* below:

$$d_o = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}, \quad (2)$$

The energy that is dissipated when a node receives an l−bit message is given by *equation (3)*

$$E_{R_X} = E_{elec} \times l, \quad (3)$$

Where the symbols have the same meaning described above. The transmission and reception energy thus contributes to the total energy consumption per round of transmission as in *equation (4)*

$$E_{total} = E_{T_X} + E_{R_X}, \quad (4)$$

To compute the residual energy in a node after the first round of transmission, the energy consumed in that round is deducted from the initial energy of the node. For subsequent rounds, the energy consumed per round is deducted from the residual energy of the previous round, as in *equation (5)*

$$E_{res_{n+1}} = E_{res_n} - E_{total_{n+1}}, \quad (5)$$

$Eres_{n+1}$ is the residual energy after the current round, $Eres_n$ is the residual energy of the previous round, and $Etotal_{n+1}$ is the energy consumed in the current round. During the first round of transmission, $Eres_n = E_{init}$, where E_{init} is the initial energy in the node. This residual energy value is passed to the fuzzy inference system as input parameters for determining the most suitable candidate for the CH election.

3.1.2 Node centrality

The node centrality described in this research refers to the position of the sensor nodes relative to the center of the region of interest where a cluster is expected to be formed. It is computed by getting the Euclidean distance between the nodes and the centroids of the clusters to which the nodes are assigned. The closer a node is to the center of the region, the more likely it is to remain within the cluster during the entire transmission duration, as it has a longer distance to cover before it gets to the edge of the cluster compared to other nodes further away from the center. The mobile nodes move randomly within the network area at different speeds and directions.

The node at the center will need to cover a longer distance to reach the cluster's edge, which describes a high centrality. In contrast, a node further away from the center, which defines a lower centrality, can easily move out of the current cluster as it will need to cover a shorter distance. In addition, when a node is centrally located compared to the other nodes within the cluster, the cost of all other nodes sending data to it is reduced. Therefore, the efficiency of communication is increased.

3.1.3 Node mobility factor

The mobility factor is a parameter that describes the degree to which a sensor node is mobile. The concept applied in the Random waypoint model is borrowed here to determine this mobility factor. The model describes a mobile node as pausing at different points for a given duration within a set interval and then moving at a different direction and speed to its new destination at a speed that ranges between set intervals. It is, therefore, dependent on the speed of the sensor node and the pause time. A high speed and short pause time translates to a high mobility factor, while a low speed and long pause time translates to a low mobility factor.

Figure 1 illustrates the FIS structure, with the speed and the pause time as the fuzzy input variables and the mobility factor as the output. Each input and output have three linguistic values; hence, the numeric value 3 is against each. The Mamdani FIS is chosen as the inference system. Compared to Sugeno, the Mamdani is more robust to noise and performs better in non-linear mapping of inputs to outputs. The output is defuzzified using the centroid method to obtain crisp mobility factor values. The membership functions for the inputs to the FIS are shown in *figures 2 and 3*, and the output variable is shown in *figure 4*. Triangular membership functions are chosen due to their simplicity and computational efficiency. *Figure 2* shows the speed input variable, which is defined by the linguistic variables: Low (L), Average (A), and High (H). The simulated speed values range from 1-5 m/s, which defines the horizontal axis, and the degree of membership ranges from zero to one, defining the vertical axis. Every instance of speed value is assigned a degree of membership based on the three possible values.

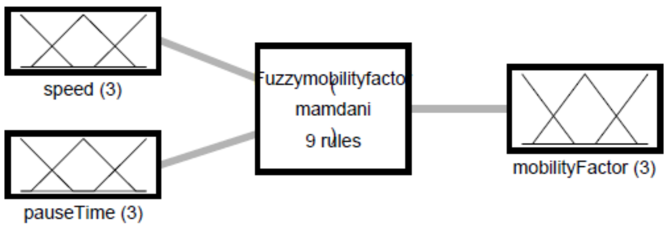

Figure 1. FIS structure for computation of mobility factor

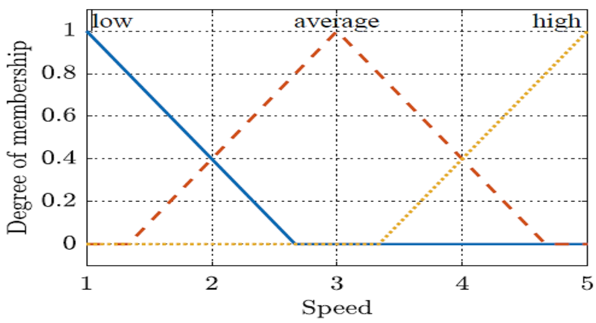

Figure 2. Membership function of the speed variable

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Research Article | Volume 11, Issue 4 | Pages 1136-1146 | e-ISSN: 2347-470X

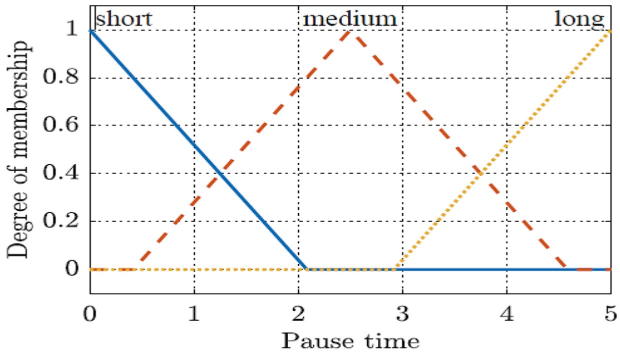

Figure 3. Membership function of the pause time variable

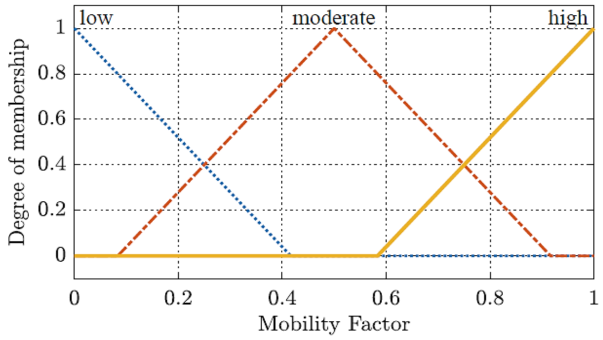

Figure 4. Membership function of the mobility factor output

Figure 3 represents the pause time input, which is defined by the linguistic variables: short (S), Medium (M), and Long (L). Pause time values range from 0 – 5 s, with every instance of pause time for a node being assigned a degree of membership based on the three possible values. The mobility factor membership function, shown in *figure 4*, has three possible values: low (L), moderate (M), and high (H). The MF is a constant whose value ranges between 0 and 1.

Table 1 shows the fuzzy rule base, comprised of nine rules, to give the output value based on the combination of the linguistic values of the input variables. The system has two inputs, each with three possible values. That results in nine unique combinations of the rules to give different output values, as listed in the table.

Table 1. Fuzzy rule base for mobility factor FIS

Rule	Speed	Pause time	Mobility factor
1	Low	Short	Moderate
2	Low	Medium	Low
3	Low	Long	Low
4	Average	Short	Moderate
5	Average	Medium	Moderate
6	Average	Long	Low
7	High	Short	High
8	High	Medium	High
9	High	Long	Moderate

Two instances of the rule viewer are shown in *table 2* to illustrate the outcome of the FIS. At a speed of 4.61m/s and a pause time of 0.614s, the mobility factor is 0.817, indicating that a high moving speed with short pause times describes a high mobility factor. The second instance shows a low speed of 1.35m/s and a long pause time of 4.39s, giving a low mobility factor of 0.158. The mobility factor determined for each node is passed to the second FIS as one of the three inputs for determining the chance of being elected as CH of the cluster to which the node belongs.

Table 1. Sample instances of the rule viewer output

	Speed(m/s)	Pause time(s)	Mobility factor
1	4.61	0.614	0.817
2	1.35	4.39	0.158

3.2 Network Split into Cluster Regions

The initial split of the network area is done using k-means clustering that divides it into a predetermined number of clusters. First, initial cluster centroids are obtained for the different clusters; these are the midpoints of every cluster. Euclidean distances are then computed between all the sensor nodes and the initial cluster centroids as in *equation (6)* from [22]

$$d = \sqrt{(N_x - C_x)^2 + (N_y - C_y)^2}, \tag{6}$$

Where *d* is the Euclidean distance between a node and the cluster center, and $N_{x,y}$, and $C_{x,y}$ are the node and cluster center coordinates, respectively. The computation is done for all sensor nodes and all cluster centers, after which sensor nodes are allocated to clusters whose centroids are closest to them. The algorithm then recalculates new cluster centers, allocating sensor nodes to the closest ones. This cycle is repeated until a stopping criterion that assumes the best clusters have been achieved is met [22].

3.3 Fuzzy Logic-Based CH Selection

A FIS is designed to determine the chance of a sensor node becoming a CH. The FIS is made up of three input variables and one output variable. These inputs are residual energy, centrality, and mobility factor, as described in the previous section, while the output variable is the CH chance. Human heuristics are applied to determine the values of the variables and to develop fuzzy rules that describe how the inputs are mapped onto the outputs. The nodes with the highest residual energy, the lowest centrality value, and the lowest mobility factor have the highest chance of being elected as CHs. The effect that higher residual energy has is that a node can transmit for a longer period before the battery dies than nodes with lower energy. Therefore, a node whose lifetime is longer based on energy is more desirable as a cluster head than a node whose life would be shorter in terms of residual energy possessed. As for centrality, the lower its value, the closer the node is to the cluster's center. Such a node would need to cover a longer distance to leave the current cluster and join another compared to nodes further away from the center or closer to the edge of the cluster, which are characterized by higher centrality values. It is thus desirable to elect a node with a higher chance of remaining within the same cluster during a round of transmission since departure from the cluster before complete data forwarding translates to energy wasted. Mobility, however, requires management and should first be considered when selecting nodes to act as CHs to ensure that the nodes with

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the least mobility have a higher chance. The nodes would most likely remain within a cluster during transmission.

Figure 5 is the membership function of the residual energy. The initial energy of the nodes is 1J, which marks the maximum value on the horizontal axis, with the vertical axis indicating the degree of membership for every instance of the variable. The linguistic variables are Low, Medium, and High, as shown in the figure. *Figure 6* shows the centrality membership function. Based on the 100m X 100m network area, and assuming no clusters formed, the maximum value of Euclidean distance between a node and the center is 70.7m. This value informs the choice of 70 as the maximum value of the horizontal axis since that distance is shorter with clustering. The linguistic variables are Close, Average, and Far.

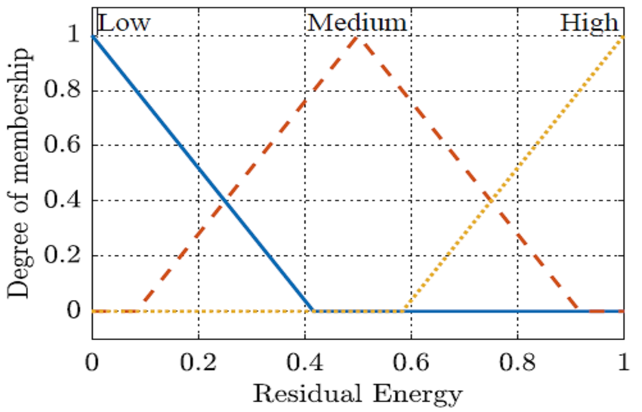

Figure 5. Membership function for residual energy

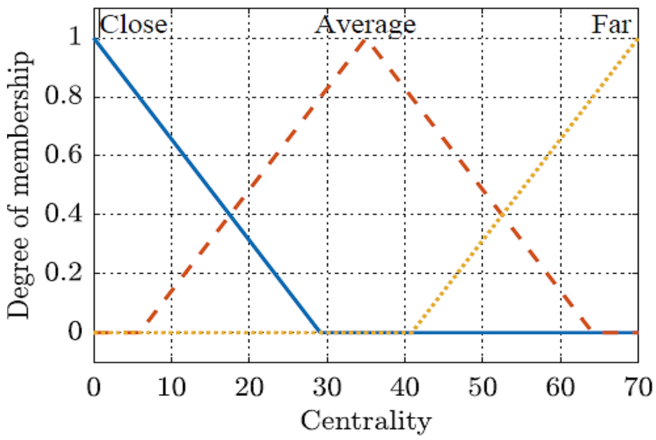

Figure 6. Membership function for the centrality

Figure 7 is the membership function for the mobility factor, obtained from the first FIS stage output described in *section 3.1.3*. The output of this FIS is the CH chance, whose membership function is shown in *figure 8*. The output consists of five linguistic variables, namely Very low, Low, Medium, High, and Very high, as labeled at the top of the figure. The value of the CH chance ranges from 0 to 1, as in the vertical axis, and each instance is assigned a degree of membership, which also ranges between 0 and 1.

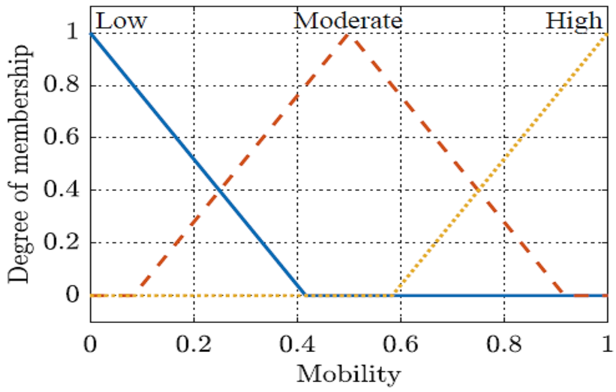

Figure 7. Membership function for mobility

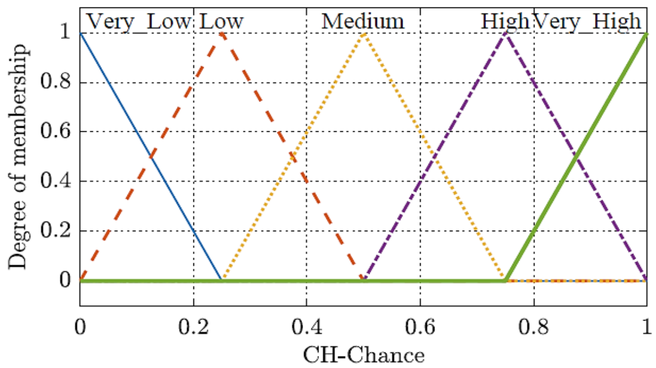

Figure 8. Membership function for CH chance

The rule base set up to achieve the above criteria consists of 27 rules, as shown in *table 3*. Human heuristics develop the output values for each combination of the three input variables. The structure of the FIS is illustrated in figure 9. The inputs fed into the inference system at the center are the residual energy, centrality, and mobility factor. The numeric value indicated against each represents the number of linguistic variables, in this case, three. The Mamdani FIS is chosen due to its robustness to noise and non-linear mapping of inputs to outputs, which gives more accurate results. The centroid method is used to defuzzify the fuzzy output to obtain crisp values of the CH chance, which is the system output, as illustrated.

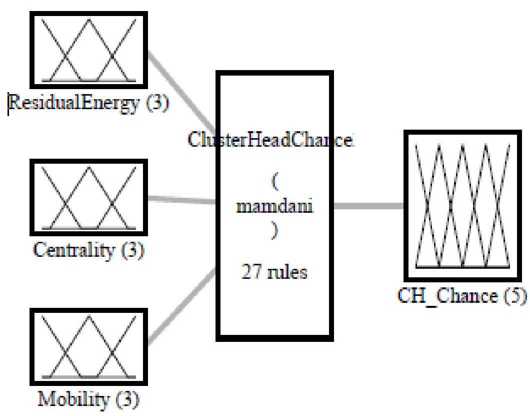

Figure 9. Fuzzy inference system for CH chance

International Journal of
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3.3 Performance Evaluation

The performance of the proposed model is monitored based on energy consumption and network lifetime parameters. The energy consumption per round, the total energy consumed at a given round, and the residual energy in the network are measured.

Table 2. Fuzzy rule base for CH chance FIS

Rule	Residual energy	Centrality	Mobility	CH chance
1	Low	Close	Low	Medium
2	Low	Close	Moderate	Low
3	Low	Close	High	Very low
4	Low	Average	Low	Medium
5	Low	Average	Moderate	Low
6	Low	Average	High	Very low
7	Low	Far	Low	Low
8	Low	Far	Moderate	Very low
9	Low	Far	High	Very low
10	Medium	Close	Low	Very high
11	Medium	Close	Moderate	High
12	Medium	Close	High	Medium
13	Medium	Average	Low	High
14	Medium	Average	Moderate	Medium
15	Medium	Average	High	Medium
16	Medium	Far	Low	Low
17	Medium	Far	Moderate	Low
18	Medium	Far	High	Very low
19	High	Close	Low	Very high
20	High	Close	Moderate	High
21	High	Close	High	Medium
22	High	Average	Low	Very high
23	High	Average	Moderate	High
24	High	Average	High	Medium
25	High	Far	Low	Low
26	High	Far	Moderate	Low
27	High	Far	High	Low

These help to check the energy utilization rate by the sensor nodes. Less energy consumption by the sensor nodes implies an improvement in energy utilization. Network lifetime, on the other hand, is measured by analyzing the duration of time that a network lasts, having active nodes. The number of alive nodes and the number of dead nodes are monitored. The number of alive nodes is tracked to determine when the network is no longer functional because nodes have depleted their energy. The first node dead (FND) is a metric that indicates the point at which the first node to deplete its energy resource is detected. The FND plays a significant role in evaluating the network's lifetime as it indicates the point at which the stability of the network is disrupted. An increase in transmission rounds before the first node dies shows an improvement in energy utilization and, thus, a more stable network. Monitoring subsequent node deaths is critical to track how long the network remains functional. Here, the half-nodes dead (HND) and the last node dead (LND) are recorded. Half nodes dead (HND) is a metric that describes the point at which half the nodes in the network have their energy depleted and are thus no longer participating in the data transmission. The LND shows the point at which all nodes in the network are dead, and no data transmission occurs after that point. A comparison of the studies cited in the related works [14]–[26] shows that the authors in [21] achieved the best results in terms of network lifetime and energy consumption based on fuzzy logic. On this basis, the simulation results of the proposed model are compared with those of the HROCF model developed in [21].

4. RESULTS AND DISCUSSION

4.1 Simulation Setup

The proposed model is simulated using the Fuzzy Logic Tool Box in the MATLAB platform. The parameters used, whose definitions are given in *sub section 3.1.1.*, and their corresponding values are given in *table 4.*

Table 3. Simulation Parameters

Parameter name	Value
Number of sensor nodes	100
Size of Network	100X100m^2
Location of Base station	50 X 50
Data packet size (l)	500 bytes
E_0	1J
E_{elec}	50nJ/bit
ε_{fs}	10pJ/bit/m^2
ε_{mp}	0.0013pJ/bit/m^4
E_{DA}	5nJ/bit/signal

Figure 10 shows the sensors' random distribution in the described network area, with the base station, also referred to as the sink node, located at the center of the network area. The 100 nodes are randomly distributed in the 100m X 100m network area with the stationary base station at the coordinates (50, 50).

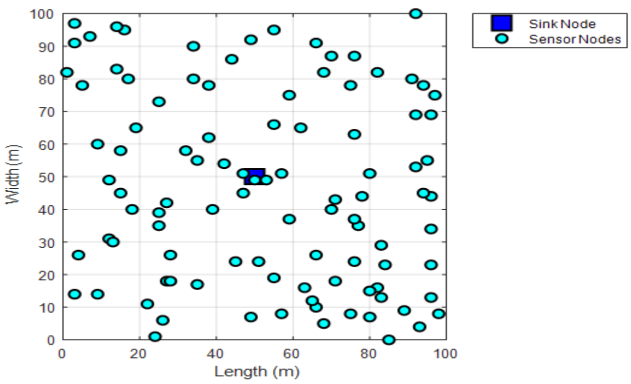

Figure 10. Sensor nodes deployed in the network area

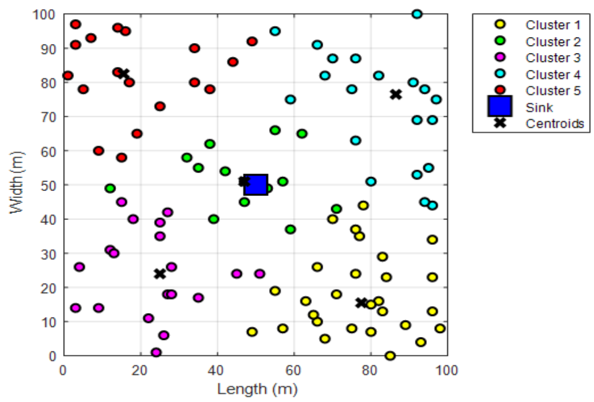

Figure 11. Network Area Split into five regions

The k-means algorithm's network split yields the cluster regions displayed in *figure 11*. Different colors of the nodes are used to show the five distinct regions into which they are grouped. The cluster centroids are highlighted for every cluster, and these are the basis for the computation of the centrality of the member nodes in every cluster region.

4.2 Cluster Head Selection

After splitting the network region, Fuzzy logic is used to select the CH for each region based on the three input parameters: the residual energy of the sensor nodes, the centrality of the nodes per cluster, and the mobility factor of the nodes. For the first round of transmission, the residual energy of the nodes is the initial energy, which reduces in subsequent rounds as energy is dissipated during data transmission.

Table 5 shows two instances of the output of the rule viewer. These indicate the output of the FIS structure, given the combination of input values shown. The input values are parameters of nodes in the network; in this case, two are sampled. The first instance is a case of low residual energy (0.0672), high centrality value (63.6), and a high mobility factor (0.928), giving a very low value of CH chance (0.15), meaning that the node is very unlikely to be selected as CH. The second instance has inputs of high residual energy (0.934), low centrality value (4.64), and a low mobility factor (0.0904), which gives a high CH chance (0.845) as the output, which means that the particular node has a high chance of being selected to act as the CH of the cluster in which it belongs. These results show that the rule base set up for the FIS gives the expected results. These rules are applied to all the sensor nodes in the network, and for each cluster region, the node with the highest CH chance is elected as the CH.

Table 4. Sample instances of the rule viewer output

	Residual energy(J)	Centrality	Mobility factor	CH chance
1	0.0672	63.6	0.928	0.15
2	0.934	4.64	0.0904	0.845

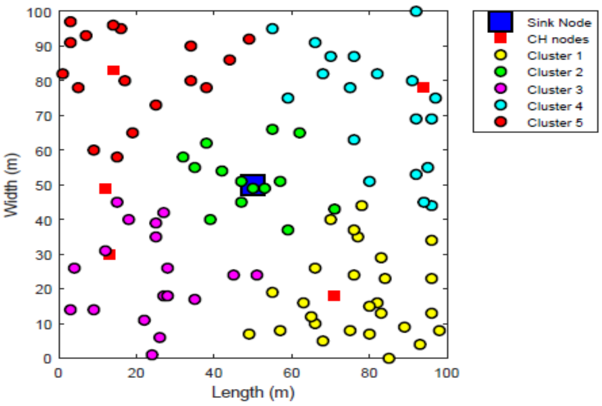

Figure 12. Member nodes and elected CHs

Figure 12 shows the elected CH nodes in the network. In every cluster region, the node that achieves the highest CH chance and is elected as the CH is highlighted in red for illustration. These nodes have the best combination of residual energy values, centrality, and mobility factor based on the rules defined for the FIS structure.

4.3 Network Lifetime

The network lifetime is a measure of how long a network is functional. It is determined by analyzing the number of alive and dead nodes at different rounds, the FND, HND, and LND.

4.3.1 Analysis of the number of alive nodes

Figure 13 shows the network's total number of nodes alive during the different transmission rounds. Initially, both protocols have the same number of alive nodes, and then the HROCF model has nodes depleting their energy earlier than the proposed model. The proposed model has more alive nodes than the HROCF throughout the transmission rounds.

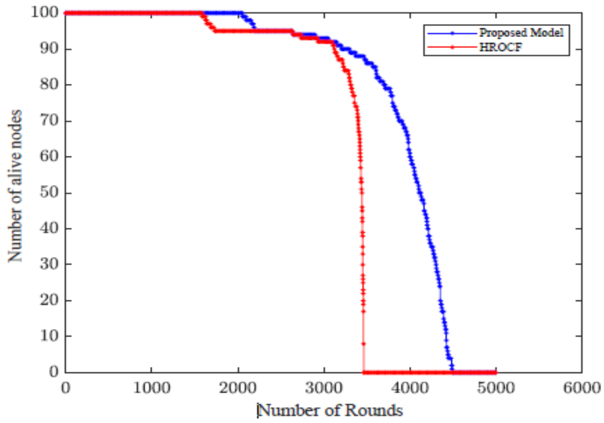

Figure 13. Alive nodes analysis

At just over 2000 rounds, the proposed model experiences its first death of nodes, while the same happens for the HROCF at just over 1500 rounds, explaining the drop in the curve from the 100-node mark. Over the transmission rounds, more nodes deplete their energy, thus reducing the number of alive nodes, which explains the descending profile of the curve up to the point where there is no node alive.

4.3.2 Analysis of Death of Nodes

The number of dead nodes in the network at every transmission round is recorded, and a plot comparing the two protocols is shown in *figure 14*. Initially, all nodes are alive; therefore, the graph starts at zero dead nodes. At the point where the first dead nodes are experienced for both protocols, the graph curves upward, indicating an increase in the dead nodes. It can be seen from the gradients of the curves that the nodes in HROCF die at a faster rate than those in the proposed model, which leads to the network nodes being marked dead several rounds earlier in HROCF compared to the proposed model. The difference can be attributed to the HROCF protocol's higher energy consumption during transmission than the proposed model. The optimal choice of CHs reduces energy consumption per round for the proposed model, leading to fewer dead nodes per round.

4.3.3 FND, HND, and LND

The bar graph in *figure 15* shows the different points at which there was the first node death (FND), 50% node deaths, also referred to as half nodes dead (HND), and when the last node (LND) in the network died. The comparison is made between

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the proposed model and previously published protocols [17], [21], [24]. The FND signifies the point at which network stability is affected. It occurs at round 2054 for the proposed model compared to round 1580 for the HROCF model, which previously outperformed the other two protocols. Since the death of the first node marks the point at which network stability is disrupted, the proposed model, whose FND occurs, after more rounds of transmission , is more stable than HROCF,

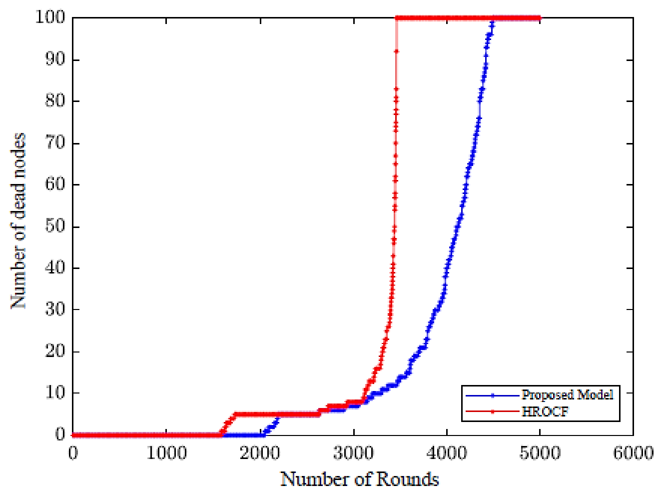

Figure 14. Dead nodes analysis

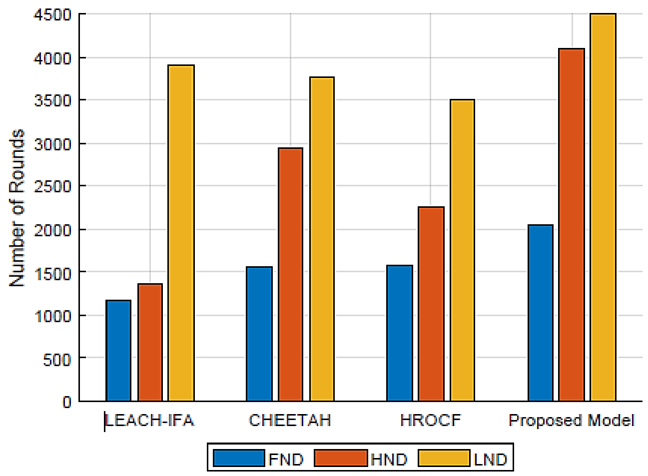

Figure 15. Network lifetime comparison

CHEETAH, and LEACH-IFA, whose FND occurs during earlier transmission rounds. The values of the transmission rounds at which FND, HND, and LND occur for the three protocols are summarized in *table 6*. The improvement noted in the proposed model compared to the HROCF is attributed to considering nodes centrally located as candidates for the CH role, thus ensuring that no node has an extremely high communication cost compared to the rest of the nodes within the same cluster.

The HND occurs at 4103 for the proposed model compared to 2250 for HROCF, which confirms that nodes in the network using the HROCF die faster than those using the proposed model. A protocol that runs for more rounds before half the nodes in the network are dead for the same network area, density, and load has more efficient energy utilization. The LND occurs at round 4500, marking the proposed model's entire network lifetime, which is higher than the 3500 rounds at which the LND occurs for HROCF. An improvement of 28.57% is noted in the overall network lifetime.

It is important to note that the network lifetime defined here is when the last node dies. However, depending on the application that a WSN is used in, the network will cease to be functional at some threshold before the last node dies. That threshold would be used to define the total network lifetime of that particular network.

4.4 Energy Consumption

4.4.1 Total Residual energy

Figure 16 shows a plot of the total energy remaining in the network against the round of transmission for the two protocols. In the beginning, the total residual energy is equivalent to the total initial energy of all the nodes in the network. In subsequent rounds, the residual energy gradually reduces as nodes consume energy in transmission and reception. At any given round, it can

Table 5. Network lifetime comparison with other protocols

	LEACH-IFA	CHEETAH	HROCF	PROPOSED MODEL
FND	1170	1564	1580	2054
HND	1370	2943	2250	4103
LND	3900	3758	3500	4500

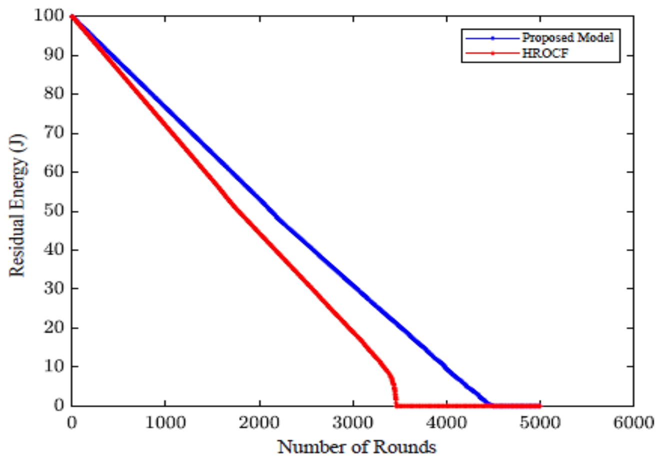

Figure 16. Total Residual Energy in the network

be seen that the energy in the HROCF network is less than that of the proposed model. This shows the proposed model's reduced energy consumption per transmission round. A higher amount of energy in the network means that the network will remain functional for longer.

4.4.2 Energy consumption per round

Total energy consumed in the network per round of transmission is a metric that, when monitored, demonstrates the energy efficiency of the network. *Figure 17* plots the energy consumed in every round for the proposed and the HROCF models. Initially, the energy consumed for both models remains constant, hence the flat section of both curves. The constant energy consumption is because all the nodes participate in the sensing and transmission of data, and they consume the same amount of energy, being a homogenous network. However, the proposed model's energy consumption level is lower than that of HROCF during that period. When nodes' energy gets depleted, the nodes no longer contribute to the energy consumption in the network, hence the reduction in the energy consumed starting from the point at which the first node dies. This explains the drop in the curve as less energy is consumed, based on the reduced number of total nodes participating in the network. The energy consumed per round for the proposed model is less than that of the HROCF, thus showing an improvement in performance since less energy spent translates to the longevity of the network operation.

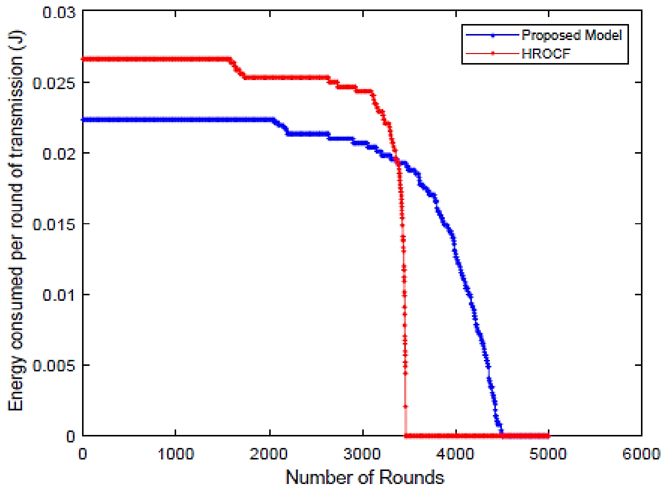

Figure 17. Energy consumed during every round of transmission

4.4.3 Total Energy Consumption

The cumulative energy consumed during the network operation is plotted in *figure 18*, showing how much total energy has been consumed since the network launch.

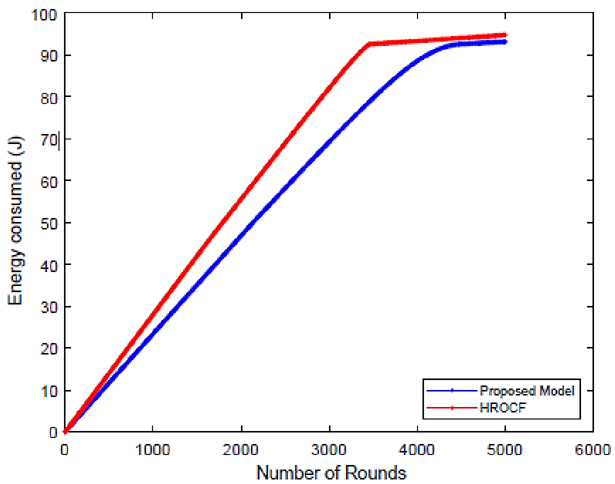

Figure 18. Total energy consumed in the network measured at every round of transmission

The rate of energy consumption increase is higher in HROCF when compared to that of the proposed model, thus causing a steeper gradient of the curve for the HROCF protocol, which means that the available energy in the network will be depleted faster in the HROCF model. In contrast, the proposed model takes longer before the energy in the network gets depleted. It can be seen that the total energy consumed does not get to 100J, which is the total initial energy in the network. A minimum energy threshold is set for every node to qualify to participate in the network instead of allowing the nodes to deplete their energy 100%, which would lead to loss of packets during transmission.

5. CONCLUSION

A model is proposed in this research that uses fuzzy logic to select appropriate nodes to take up the CH role in a WSN. The network is split into cluster regions using the k-means algorithm, and a CH is selected to head each cluster region. All member nodes in each cluster forward their sensed data to their CHs, which then aggregate the data per cluster and forward it to the base station at the network area's center. The proposed model increases network stability as it takes longer before the first node death and achieves an extended network lifetime, running for more rounds before the last node dies. The 28.57% improvement is a contribution towards energy saving in WSNs. It is important to note that depending on the WSN application, a network can be deemed dysfunctional upon the death of a certain percentage of the total nodes and not necessarily the death of the last node. Investigating the threshold value of the number of nodes per cluster would greatly benefit implementing specific WSN applications. An increase in the transmission rounds before this percentage of dead nodes is arrived at means a prolonged network lifetime due to increased efficiency in energy utilization. Residual energy is also a metric that is monitored in the network. Higher residual energy means that the network will be alive longer. A higher amount of residual energy for longer transmission periods is desired in the network. It demonstrates more efficient energy utilization as nodes within the network consume less energy in data forwarding. However, it is important to note that the available, total residual energy may be contained in a few alive nodes but may not be an assurance of connectivity. It is, therefore, necessary to analyze the connectivity of the still-alive nodes further. This research will also be extended by analyzing the optimal number of clusters that the network region should be initially split into and the effect that a higher or lower number of clusters has on the energy efficiency of the protocol.

REFERENCES

[1] R. E. Mohamed, A. I. Saleh, M. Abdelrazzak, and A. S. Samra, "Survey on Wireless Sensor Network Applications and Energy Efficient Routing Protocols," *Wirel. Pers. Commun.*, vol. 101, no. 2, pp. 1019–1055, 2018, doi: 10.1007/s11277-018-5747-9.

[2] S. B. Prathibha and M. C. Supriya, "A Novel Hybrid Energy Efficient Model using Clustering in Wireless Sensor Networks," *Int. J. Electr. Electron. Res.*, vol. 11, no. 2, pp. 451–456, 2023, doi: 10.37391/ijeer.110227.

[3] R. Praveenkumar, Kirthika, D. Arumugam, and Dinesh, "Hybridization of Machine Learning Techniques for WSN Optimal Cluster Head Selection," *Int. J. Electr. Electron. Res.*, vol. 11, no. 2, pp. 426–433, 2023, doi: 10.37391/IJEER.110224.

[4] S. Srinivasa Rao, K. C. Keshava Reddy, and S. Ravi Chand, "A Novel Optimization based Energy Efficient and Secured Routing Scheme using SRFIS-CWOSRR for Wireless Sensor Networks," *Int. J. Electr. Electron.*

Res., vol. 10, no. 3, pp. 644–650, 2022, doi: 10.37391/IJEER.100338.

[5] H. Azarhava and J. Musevi Niya, "Energy Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks," *IEEE Wirel. Commun. Lett.*, vol. 9, no. 7, pp. 1000–1003, 2020, doi: 10.1109/LWC.2020.2978049.

[6] B. A. Muzakkari, M. A. Mohamed, M. F. A. Kadir, and M. Mamat, "Queue and Priority-Aware Adaptive Duty Cycle Scheme for Energy Efficient Wireless Sensor Networks," *IEEE Access*, vol. 8, pp. 17231–17242, 2020, doi: 10.1109/ACCESS.2020.2968121.

[7] S. El Khediri, "Wireless sensor networks: a survey, categorization, main issues, and future orientations for clustering protocols," *Computing*, vol. 104, no. 8, pp. 1775–1837, 2022, doi: 10.1007/s00607-022-01071-8.

[8] P. Rawat and S. Chauhan, "Clustering protocols in wireless sensor network: A survey, classification, issues, and future directions," *Comput. Sci. Rev.*, vol. 40, p. 100396, 2021, doi: 10.1016/j.cosrev.2021.100396.

[9] R. Ramya and D. T. Brindha, "A Comprehensive Review on Optimal Cluster Head Selection in WSN-IoT," *Adv. Eng. Softw.*, vol. 171, no. June, p. 103170, 2022, doi: 10.1016/j.advengsoft.2022.103170.

[10] I. Daanoune, B. Abdennaceur, and A. Ballouk, "A comprehensive survey on LEACH-based clustering routing protocols in Wireless Sensor Networks," *Ad Hoc Networks*, vol. 114, no. July 2020, p. 102409, 2021, doi: 10.1016/j.adhoc.2020.102409.

[11] D. S. Kim and Y. J. Chung, "Self-organization routing protocol supporting mobile nodes for wireless sensor network," *First Int. Multi- Symp. Comput. Comput. Sci. IMSCCS'06*, vol. 2, pp. 622–626, 2006, doi: 10.1109/IMSCCS.2006.252.

[12] G. S. Kumar, V. P. Mv, and K. P. Jacob, "Mobility metric based LEACH-Mobile protocol," *Proc. 2008 16th Int. Conf. Adv. Comput. Commun. ADCOM 2008*, pp. 248–253, 2008, doi: 10.1109/ADCOM.2008.4760456.

[13] J. S. Lee and C. L. Teng, "An Enhanced Hierarchical Clustering Approach for Mobile Sensor Networks Using Fuzzy Inference Systems," *IEEE Internet Things J.*, vol. 4, no. 4, pp. 1095–1103, 2017, doi: 10.1109/JIOT.2017.2711248.

[14] J. S. Lee and H. T. Jiang, "An Extended Hierarchical Clustering Approach to Energy-Harvesting Mobile Wireless Sensor Networks," *IEEE Internet Things J.*, vol. 8, no. 9, pp. 7105–7114, 2021, doi: 10.1109/JIOT.2020.3038215.

[15] B. Balakrishnan and S. Balachandran, "FLECH: Fuzzy logic based energy efficient clustering hierarchy for nonuniform wireless sensor networks," *Wirel. Commun. Mob. Comput.*, vol. 2017, 2017, doi: 10.1155/2017/1214720.

[16] M. Adnan, L. Yang, T. Ahmad, and Y. Tao, "An Unequally Clustered Multi-hop Routing Protocol Based on Fuzzy Logic for Wireless Sensor Networks," *IEEE Access*, vol. 9, pp. 38531–38545, 2021, doi: 10.1109/ACCESS.2021.3063097.

[17] J. C. Cuevas-Martinez, A. J. Yuste-Delgado, and A. Trivino-Cabrera, "Cluster Head Enhanced Election Type-2 Fuzzy Algorithm for Wireless Sensor Networks," *IEEE Commun. Lett.*, vol. 21, no. 9, pp. 2069–2072, 2017, doi: 10.1109/LCOMM.2017.2703905.

[18] S. Lata, S. Mehfuz, S. Urooj, and F. Alrowais, "Fuzzy Clustering Algorithm for Enhancing Reliability and Network Lifetime of Wireless Sensor Networks," *IEEE Access*, vol. 8, pp. 66013–66024, 2020, doi: 10.1109/ACCESS.2020.2985495.

[19] E. Al-Husain and G. Al-Suhail, "E-FLEACH: An Improved Fuzzy Based Clustering Protocol for Wireless Sensor Network," *Iraqi J. Electr. Electron. Eng.*, vol. 17, no. 2, pp. 190–197, 2021, doi: 10.37917/ijeee.17.2.21.

[20] Z. Alansari, M. Siddique, and M. W. Ashour, "FCERP: A Novel WSNs Fuzzy Clustering and Energy Efficient Routing Protocol," *Ann. Emerg. Technol. Comput.*, vol. 6, no. 1, pp. 31–42, 2022, doi: 10.33166/AETiC.2022.01.002.

[21] R. S. Kumaran, A. Bagwari, G. Nagarajan, and S. S. Kushwah, "Hierarchical Routing with Optimal Clustering Using Fuzzy Approach for Network Lifetime Enhancement in Wireless Sensor Networks," *Mob. Inf. Syst.*, vol. 2022, pp. 1–11, 2022, doi: 10.1155/2022/6884418.

[22] M. Gamal, N. E. Mekky, H. H. Soliman, and N. A. Hikal, "Enhancing the Lifetime of Wireless Sensor Networks Using Fuzzy Logic LEACH Technique-Based Particle Swarm Optimization," *IEEE Access*, vol. 10, pp. 36935–36948, 2022, doi: 10.1109/ACCESS.2022.3163254.

[23] S. Bharany *et al.*, "Energy-efficient clustering scheme for flying ad-hoc networks using an optimized leach protocol," *Energies*, vol. 14, no. 19, 2021, doi: 10.3390/en14196016.

[24] M. Zivkovic, N. Bacanin, E. Tuba, I. Strumberger, T. Bezdan, and M. Tuba, "Wireless Sensor Networks Life Time Optimization Based on the Improved Firefly Algorithm," *2020 Int. Wirel. Commun. Mob. Comput. IWCMC 2020*, pp. 1176–1181, 2020, doi: 10.1109/IWCMC48107.2020.9148087.

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