International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2024/43 Volume 11, Issue 5, September – October (2024)

RESEARCH ARTICLE

Enhancing Energy Efficiency in Multi-Layer Wireless Sensor Networks Through Cluster Head Fuzzy Logic Type 2 and Multi-hop Node Strategies

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Received: 24 July 2024 / Revised: 24 September 2024 / Accepted: 01 October 2024 / Published: 30 October 2024

Abstract – Wireless Sensor Networks (WSNs) are composed of collaborative nodes that perform environmental monitoring and control tasks, but their functionality is constrained due to the limited energy of each node. The structural design of WSNs include the arrangements of nodes into clusters, the appointment of a Cluster Head (CH) for each cluster, and the optimization of energy usage. The process of selecting CHs is influenced by a variety of factors, including the node's remaining energy, the cost of communication, the density of nodes, mobility, and the size of the cluster. Inadequate CH selection can result in inefficient energy use. Furthermore, in the two-step communication process from nodes to the base station (BS), a significant amount of energy is expended. To mitigate this, a novel strategy that integrates various input parameters with a method based on distance thresholds has been developed to improve the selection of CHs and relay nodes. This strategy considers factors such as the Received Signal Strength Indicator (RSSI), the remaining energy of nodes, and their centrality. It employs fuzzy logic for the selection of CHs, and relay nodes are chosen based on their proximity to the BS. The determination of the optimal number of relay nodes is achieved through the K-Optimal and K-Means methods, ensuring that every CH is connected to at least one relay node for efficient data transmission. The proposed protocol, named Energy Efficient Cluster Heads and Relay Nodes (EECR), surpasses both the Multi-Layer Protocol (MAP) and Stable Election Protocol (SEP) in performance by extending the lifespan of the network by 43% and 33%, respectively.

Index Terms – Fuzzy Logic, Energy Efficient, Cluster Head, Network Optimization, Multi-hop Strategies, Wireless Sensor Network.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are defined by some of resource restrictions, including limitations in transmission range, computing power, and energy availability. Within these limitation, energy depletion and transmission range are prominent issues [1]. To overcome these constraints, Cluster Based Routing (CBR) were proposed for enhancing the efficiency of data routing in WSNs. The presence of multiple nodes concurrently transmitting data leads to interference, resulting in a weakened received signal strength. However, CBR addresses this issue by enabling sensor nodes to efficiently self-organize into several clusters. One Cluster Head (CH) will be formed by each cluster. These CHs collect information from nodes within their respective clusters and relay combined data to the base station, thus minimizing long-distance transmissions and conserving valuable energy. The clustering process itself involves two critical steps: CH selection and cluster formation. Furthermore, CBR facilitates communication within clusters (intra-cluster) and between the BS and the CHs (inter-cluster). In the realm of WSNs, transmission methods can typically be categorized as either single-hop or multiple-hop, with the choice depending on the specific application requirements. Previous CBR protocols employ single-hop transmission for communication within the cluster. The examples of CBR protocols that have gained popularity previously, such as CRSC, LEACH, and SEP. They all share the common goal of extending the operational lifespan of sensor nodes [2], [3], [4], [5]. These protocols have been designed to address the critical challenge of enhancing the network lifetime of sensor nodes. Besides, previous research has shown that in cases where the proportion of transmission loss is large, multiple-hop interaction between CHs and sensor nodes proves to be better than single-hop interaction in terms of energy efficiency. This holds particularly true when sensor nodes are deployed in densely populated areas, as multiple-hop communication effectively sent data to the BS without losing the signal. Energy consumption and its availability constitute critical

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concerns in WSNs [6]. The primary objective of nodes is to ensure sustained longevity of information collection, spanning from successor nodes to CHs and ultimately reaching the base station. However, the limitations imposed by restricted battery life and the low information rates of sensor nodes can pose challenges to achieving optimal performance, especially in demanding environments. To address these challenges, some researchers have explored the fuzzy logic application to reduce energy consumption.

Some of the approaches combine input parameter to efficiently select the CHs and conserve the sensor's battery consumption. Moreover, fuzzy logic type 2 approach is still infancy in selecting the CHs to increase the network's lifespan. The fuzzy logic type 2 is more robust as compared to fuzzy type 1 to select the CHs that can prolong the network lifetime [7]. This approach utilizes some input parameters to select the best CHs. Moreover, unoptimized path selection can cause an imbalance in the energy consumption of the network among the nodes. Therefore, it is crucial to employ intelligent approach to select the most suitable CHs and multi-hop communication. In this research, we have introduced an analysis of energy consumption in Multi-layer Wireless Sensor Networks, with a specific focus on achieving Energy Efficiency in Relay Node and Cluster Head (EECR) management. Our EECR model has been designed that includes remaining energy, centrality, and Received Signal Strength Indicator (RSSI) as crucial inputs for the process of choosing Cluster Heads (CHs) through the application of a fuzzy logic approach. The EECR model dynamically forms the clusters during iterative processes, thereby optimizing energy utilization in a 2-layer network. An essential feature of our work is the expansion of the energy model to accommodate and support multi-hop communication within EECR, effectively extending the operational lifespan of the network. The results highlight the increased effectiveness of our stated approach in compared to existing MAP and SEP protocols across various critical dimensions, including First Node Dies (FND), Last Node Dies (LND), and the energy balance. The proposed approach stands out by significantly reducing energy consumption for all sensor nodes, encompassing both relay nodes and CHs, when compared to other established protocols. This paper's contributions are outlined as follows:

1) EECR Model Advancement: We introduce the EECR model, which utilize three distinctive combinations of input variables, namely remaining energy and centrality (ResCen), remaining energy and RSSI (ResRSSI), and remaining energy, centrality, and RSSI (ResCenRSSI). This approach is designed to increase the network's lifetime. We employ a fuzzy logic type 2 method to identify the most suitable nodes to serve as CHs.

2) 2-Layer Network Design: We have designed a 2-layer network that establishes connections between relay nodes and the CHs for efficient data transmission. This architectural enhances the network's efficiency and performance.

3) Empirical Validation: Through a series of simulations, we demonstrate that the relay selection approach is not just theoretical but has practical implications. It significantly extends the network's lifespan while concurrently reducing energy usage among sensor nodes.

The remainder of the paper is structured as follows. Section 2 covered the relevant works. In Section 3, EECR protocol mechanism is presented. Then, the cluster formation is presented in Section 4. Next, we presented the performance evaluation in Section 5. Section 6 brought this paper to conclude.

2. RELATED WORK

The first protocol was presented by Heinzelman, known as LEACH (Low-Energy Adaptive Clustering Hierarchy) [8], utilizing straight communication from Cluster Heads (CHs) to the Base Station (BS). LEACH operates on the principle of remaining energy, distinguishing between two stages: the setup and the steady states [9]. During setup phase, the protocol undertakes the selection of CHs, whereas the steady-state phase occurs during transmission of data. Then, sensor nodes establish connections with CHs. Given that the selection of CHs is determined by a chance mechanism, the outcome might result in the selection of either a single CH or none. The decision threshold T(x) is calculated using equation (1):

$$T(x) = \begin{cases} \frac{z}{1-z\left(i \bmod \frac{1}{z}\right)} & \text{if } x \in F \\ 0 & \end{cases} \qquad (1)$$

Here z is the proportion of CHs in number from the total of nodes at any iteration i, the number of nodes is x, and F is the nodes set that is not chosen to be the CH (non-CH) in the first z rounds. Specifically, if the value of F is 0, no nodes will be selected as the CH. The non-CH nodes check the availability to become CH by comparing their random number (assigned for each node) ranging from 0 to 1 with the threshold value T(x). If the generated random number is less than the threshold value, the nodes get the chance to be selected as CHs. With this, the LEACH protocol balances the strain on the network because all the nodes get the chance to be CHs. However, there are several disadvantages with the probabilistic method in LEACH. Firstly, such method cannot guarantee the nodes with a random number less than the threshold value will be selected as CHs in each round. Secondly, the CHs that are selected might be close to one another, which could lead to overlapping of the clusters and hence deplete the energy in the network. Thirdly, the random number generation and the calculation of threshold value in a single iteration consume more CPU processing. The clustering method was used to enhance energy efficiency in WSNs. During this approach, the network is segmented through multiple clusters, every cluster led by a CH [10]. Each sensor node in a cluster sends data to the specified CH, which then aggregates and compresses this data prior to convey it all the way to Base Station (BS). Consequently, choosing right Cluster Head is vital due to the diverse tasks it must handle, including data aggregation and forwarding. Furthermore, the total count of CHs influences how many clusters will be established in the network. There are some related works that efficiently used energy through proposed clustering techniques. For instance, the works in [11] employed their technique to optimize the number of clusters. The finding in their work showed that too high and too low numbers of clusters consumed high energy consumption. Work in [12] proposed a Fuzzy Clustering Method (FCM) for partitioning nodes into clusters. The authors used Euclidean distance to figure out the ideal clusters number. While the clusters were evenly distributed across the network, achieving an optimal cluster count was not assured due to the inadequate categorization of the Euclidean distance weight values for varying node counts in the simulation. Another technique known as Self-Organizing Map (SOM) addresses the energy balancing problem with neural network-based clustering algorithm [13]. The experiment showed that the technique could reduce energy use and provide energy balancing between the sensor nodes. However, unsuitable selection of dataset in SOM could result in an inaccurate decision for the clustering process. The technique of multi-layer clustering divides the field network area into n-layers for execution. Such approach can reduce the routing overhead, which is a common issue in traditional multi-hop communication of WSNs. In addition, it offers scalability among sensor of node due to the number of nodes placed inside sensing region that may be numerous hundreds, thousands. The works that discussed multi-layer clustering were in [14]. Specifically, the technique utilized the routing protocol known as in a 2-layer network. Recent work on clustering has been discussed in [15] who suggested a routing protocol that is hierarchical and uses the k-d tree algorithm. The 2-d space is composed to organize nodes into a cluster. The approach allows creating divisions in the square area with the mean of the data of one of its dimensions. For example, a rectangle is divided into a smaller rectangle, and the process is repeated x times, to obtain successive smaller areas.

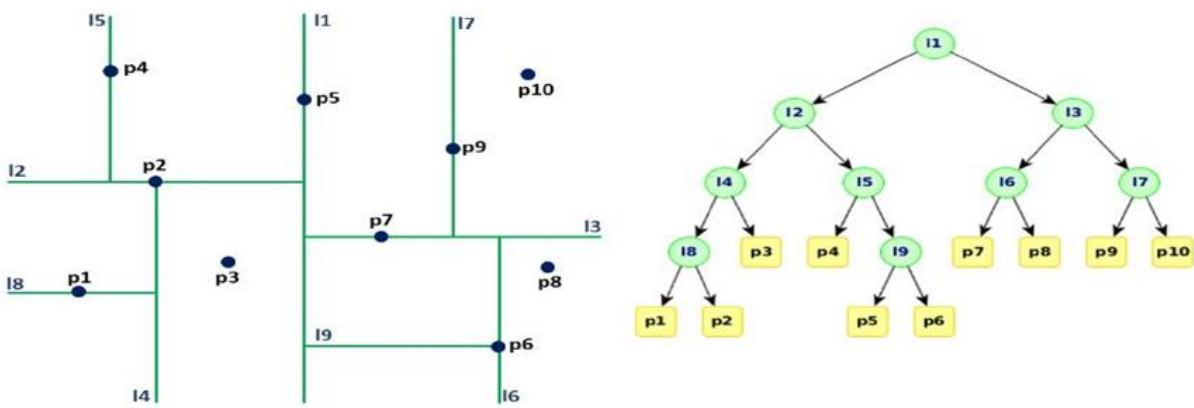

Figure 1 Visualization of the k-d Algorithm

The simulation results showed that the offered procedure, k-d tree enhances delay and jitter by 60% and 95% as compared to LEACH and LEACH-C, while keeping the same energy usage as LEACH [16]. Although the improvements have been made towards QoS in terms of throughput, delay, and jitter, the energy consumption is still considered high as it is unable to meet the real requirement of WSNs. Hence, there is a need for a better clustering technique to reduce energy consumption and scale well with many sensor nodes. The consumption of energy within nodes of WSNs is governed by three components: the sensing units, the communication transceivers, and the process of data transmission, with the latter being identified as the most substantial energy drain [17]. The mechanism of data transmission necessitates the source node to relay data packets towards the destined node, culminating in a notable depletion of battery life. Within this context, the CH, which is tasked with the aggregation of data from all constituent nodes within its cluster prior to forwarding this combined information to the Base Station (BS), emerges as a pivotal entity. Accordingly, the efficacy of CH selection mechanisms is directly correlative to the longevity and energy efficiency of the WSNs. The CH selection pose a significant challenge within the domain of WSN research. Several research in WSNs that discussed about CH selection can be found in the literature [18], [19]. The primary objective of these works is to lower the amount

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of energy used across sensor nodes. The integration of fuzzy logic input parameters facilitates the optimization of CH selection, thereby contributing to a reduction of sensor batteries usage. For instance, the modifications to the LEACH protocol in [9], which incorporate considerations of remaining energy, centrality, and the adjacency of neighboring nodes, prioritize the selection of CHs based on a high neighbor count and remaining energy. However, this methodology does not account for the proximity between sensor nodes and CHs, potentially accelerating the energy consumption rate. Moreover, the approach in [20], proposing a cluster-based dynamic routing, an energy-efficient adjustment for WSNs with mobile sinks, bases CH selection predominantly on remaining energy. This strategy involves the mobility of the sink around the coverage area's perimeter to collate data from CHs. Nonetheless, the exclusive reliance on remaining energy for CH selection in the presence of mobile sinks might permit the preservation of physical resources by the nodes, such as computational and battery power. Subsequent work will explore the existing scholarly contributions concerning CH selection, an important aspect of network lifespan and the diminution of energy consumption [21]. The strategic selection of input parameters, to be employed as fuzzy descriptors, has a crucial part in the identification of CHs towards energy efficiency. The methodologies for CH selection can be categorized into centralized and distributed frameworks. The centralized approach, which utilizes a global knowledge base of the network for CH selection, contrasts with the distributed approach that relies on local information for CH identification. Despite the centralized approach being generally preferred due to the computational intensity and memory requirements of fuzzy logic-based CH selection, the distributed strategy may entail increased expenditure in terms of energy and bandwidth, particularly when the communication is facilitated through the sensor nodes themselves. Besides, multi-hop communication that assisted with the relay nodes can lower the network energy use. A work in [7] investigated the total number of deployed relays by using Artificial Bee Colony (ABC). The authors discovered that the deployment cost could be minimized if a smaller number of relays was deployed. A novelty in this work was that it considered a heuristic method for searching the global optima to guarantee the network connectivity was maintained in short range communication. An ideal separation between the BS and relay nodes was considered. However, a smaller quantity of relay nodes could cause quick energy depletion of the relay nodes. In addition, a high number of relay nodes could not guarantee the life longevity of relay nodes. Similarly, a work in [22] proposed a Relay Node Cover Algorithm (RNCA) to generate all possible positions for relay nodes. Their aim was to find an acceptable balance between quantity of relay nodes, energy consumption, and distance of relay nodes and the BS for each node. Their findings suggested that multi-hop superior over single-hop in regarding energy efficiency. Furthermore, the results in their work showed that when the network became dense, the number of relay nodes could not be too large to achieve energy efficiency of the sensor nodes. However, this work only improved the pay-off of each sensor node. This could not guarantee the longevity of network lifetime and additionally, it could shorten the network lifetime. It is desirable for WSNs to prolong its network lifetime instead of the lifespan of a single sensor.

Most of the energy usage in WSNs are consumed during data transmission [23]. In a modern radio transceiver, the transmitting power is adjustable so that the signal can reach the destination either with single-hop and multiple-hop. To measure the multi-hop energy consumption, the signal loss between sender and receiver is calculated as in equation (2):

$$RP_r = RP_0 \times \left(\frac{d_0}{d}\right)^{\alpha} \qquad (2)$$

Where is RP_0 denotes as the received power at distance d_0 from a transmitter, a is the path loss exponent, and d represents the separation between the transmitter and the receiver. From the definition in equation (2), the received power of single-hop, double-hop, triple-hop, quad-hop, and until n-hop is given by in equation (3):

$$RP_1 = RP_2.2^{\alpha} = RP_3.3^{\alpha} = RP_4.4^{\alpha} = \cdots = RP_n.n^{\alpha} \qquad (3)$$

Therefore, the received power for single-hop (RP_{1H}), double-hop (RP_{2H}), triple-hop (RP_{3H}), quad-hop (RP_{4H}) and until *n*-hop (RP_{nH}) can be expressed as [24] by using equation (4), equation (5), equation (6), equation (7), and equation (8):

$$RP_{1H} = RP_1 \qquad (4)$$

$$RP_{2H} = RP_2 + RP_2 = 2.\frac{RP_1}{2^{\alpha}} \qquad (5)$$

$$RP_{3H} = RP_3 + RP_3 + RP_3 = 3.\frac{RP_1}{3^{\alpha}} \qquad (6)$$

$$RP_{4H} = RP_4 + RP_4 + RP_4 + RP_4 = 4.\frac{RP_1}{4^{\alpha}} \qquad (7)$$

$$RP_{nH} = n.\frac{RP_1}{n^{\alpha}} \qquad (8)$$

Based on the equation above, if the route loss exponent value is higher than 1, transmission over several hops will be more effective than transmission via one. Similarly, as the received power of the receiver (RP_r) is considered, the received power of single-hop until *n*-hop can be expressed as equation (9), equation (10), equation (11), equation (12), equation (13):

$$RP_{1H} = RP_1 + RP_r \qquad (9)$$

$$RP_{2H} = 2.(\frac{RP_1}{2^{\alpha}} + RP_r) \qquad (10)$$

$$RP_{3H} = 3.(\frac{RP_1}{3^{\alpha}} + RP_r) \qquad (11)$$

$$RP_{4H} = 4.(\frac{RP_1}{4^{\alpha}} + RP_r) \qquad (12)$$

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$$RP_{nH} = n.(\frac{RP_1}{n^{\alpha}} + RP_r) \quad (13)$$

The energy consumption of multi-hop communication can be further quantified to satisfy equation (13) by equation (14) showing below:

$$RP_r < \frac{n^{\alpha-1}-1}{(n-1).n^{\alpha-1}} \quad (14)$$

From equation (14), it can be noticed that multiple-hop transmission is more energy efficient due to the value of n that is never equal to zero. Furthermore, the receiver's power consumption must be smaller than the transmitter's energy consumption. By applying equation (14) with various numbers of α, the values of received power can be obtained as presented in Table 1.

Table 1 Modelling Table

Loss Exponent (α)	Double-Hop	Triple-Hop	Quad-Hop
2	$RP_r < \frac{1}{2}RP_1$	$RP_r < \frac{1}{3}RP_1$	$RP_r < \frac{1}{4}RP_1$
3	$RP_r < \frac{3}{4}RP_1$	$RP_r < \frac{4}{9}RP_1$	$RP_r < \frac{5}{16}RP_1$
4	$RP_r < \frac{7}{8}RP_1$	$RP_r < \frac{13}{27}RP_1$	$RP_r < \frac{21}{64}RP_1$
5	$RP_r < \frac{15}{16}RP_1$	$RP_r < \frac{40}{81}RP_1$	$RP_r < \frac{85}{256}RP_1$

For multi-hop transmission to be more energy efficient, it depends on several factors such as the distance of the relay nodes with BS and reception cost [25]. For example, if the separation between source and BS is 100 m, and the reception energy corresponding to the 50 m transmission range ($E_{RX} = E_{Tx}(50)$), then transmission with multiple-hop is much more efficient than transmission with a single-hop if the relay node is at around 15 m from the BS.

Therefore, such analytical analysis demonstrates that multiple hops use less energy when the reception power of the transceiver is lower than the maximum transmitting power. In general, most of the references are mainly interested in reducing energy consumption by using different kinds of variables.

3. THE EECR PROTOCOL MECHANISM

In this section, it is explained the network model, the process of fuzzy logic type-2 being used for cluster head selection, and cluster formation.

3.1. Network Architecture

The EECR architecture model employs a 2-layer network structure. In EECR, the BS is strategically positioned at the network center. The sensor nodes are set up equally in layer-1 and layer-2 of the network. The 2-layer network of EECR is shown in Figure 2.

The network's coverage area is set to 100m^2. It forms the coverage area in a form of circle based on the circle geometry calculation, πr^2. Thus, that give the diameter of Layer 1 and Layer 2 as 50m and 100m respectively. As shown in Figure 3, the circle is divided into two areas (i.e., Layer 1 and Layer 2). The big circle of A is calculated as $4\pi r^2$. To calculate the area of the smallest circle B, we use the formula πr^2, which allows us to derive the leftover space as $3\pi r^2$ by subtracting B from A, as indicated in the formula A – B.

In the diagram referred to, sensor nodes within a designated zone (namely, Layer 1 and Layer 2) were shown to be in communication with the BS. These nodes were evenly spread across a 100m by 100m (x, y) square region. Every node placed within this network was given a distinct identification code. The network itself was segmented into two levels, with the radii for Layer 1 and Layer 2 set at 25m and 50m, respectively. A series of nodes, labeled as $X_i, X_2, X_{3,\ldots}$ $X_n$were allocated within Layer 1 and Layer 2, following the circle area formula, πr^2. This bifurcation of the network into two layers is illustrated in Figure 3. Assuming A represents the total area encompassing both Layer 1 and Layer 2, it was determined by the formula $A = \pi(2r)^2$, equating to $4\pi r^2$ ... With B representing the surface area of the initial layer (i.e., Layer 1) calculated as πr^2, the resultant area of Layer 2 was then figured as A-B= $3\pi r^2$, tripling the size of Layer 1's area.

By dividing 100 sensor nodes into quarters, the result is 25 for each quarter. This division implies that Layer 2 is composed of 75 sensor nodes (calculated as 25 times 3), whereas Layer 1 contains 25 sensor nodes. This configuration indicates that there are thrice as many sensor nodes in Layer 2 compared to Layer 1. Moreover, the transmission of data was conducted through a multi-hop process. In Layer 1, the subordinate nodes within each cluster transmitted their data to their respective CHs. These CHs then gathered the consolidated data from their subordinate nodes for forwarding to the relay nodes. Subsequently, these relay nodes transmitted the data to the BS. Unlike Layer 1, in Layer 2, relay nodes transmitted information to the Layer 1 relay nodes prior to it reaching the BS. The EECR's multi-hop data transmission strategy was characterized by a triple-hop in Layer 1 and a quad-hop across Layers 1 and 2, as depicted in Figure 4 and Figure 5.

The nodes were static with no sleep mode to analyze the actual energy consumption. The BS was a node with a lot of computing capability to receive aggregated data from the CHs.

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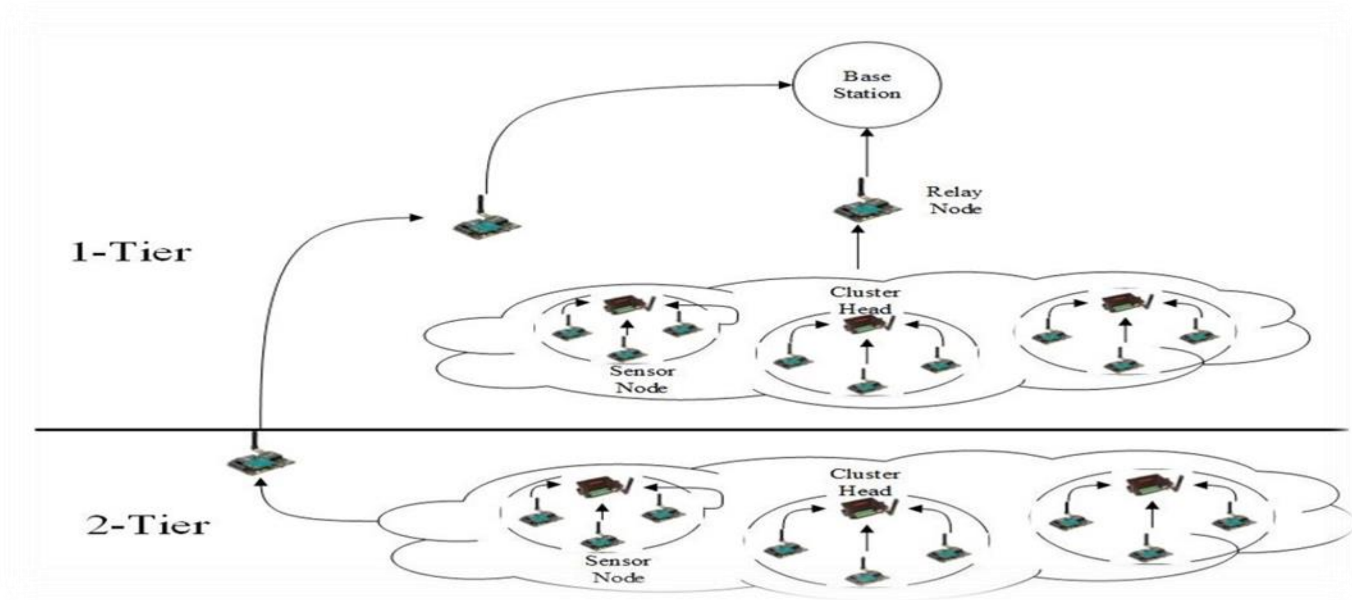

Figure 2 The 2 Layer Network Architecture

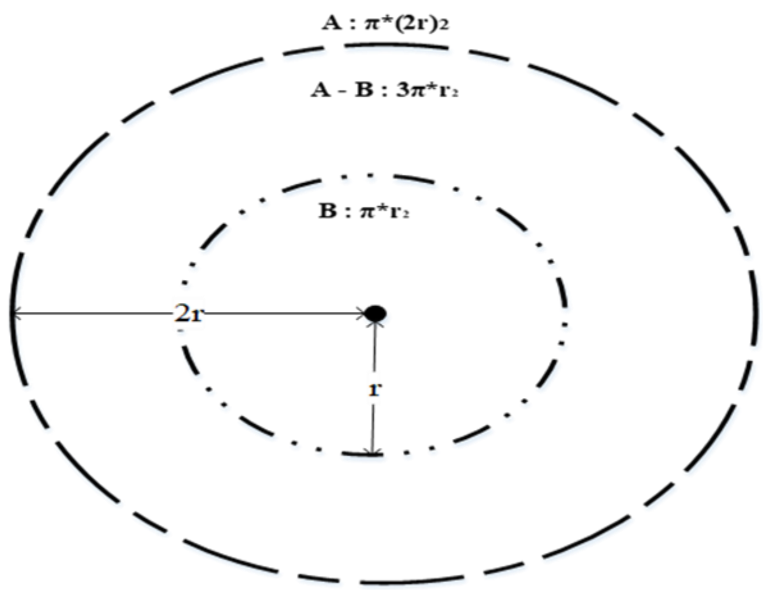

Figure 3 The Layer 2 Network Area Partition

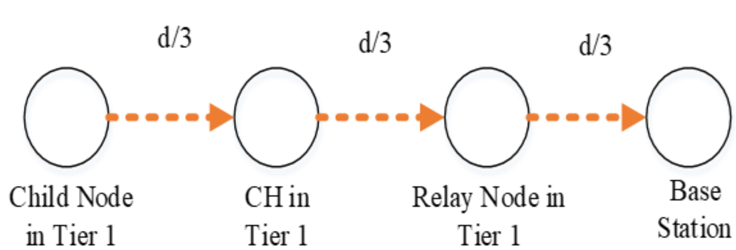

Figure 4 Triple-hop Communication in Layer 1

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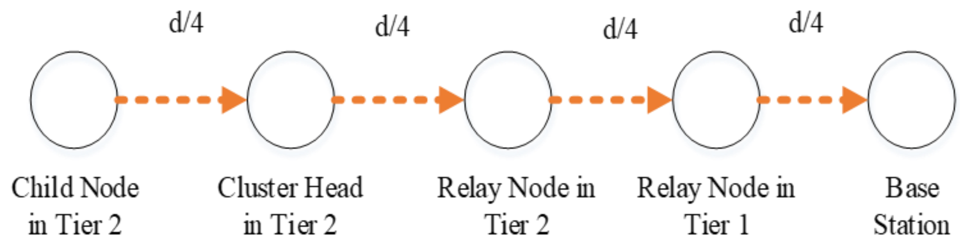

Figure 5 Quad-hop Communication in Layer 2

3.2. Fuzzy Logic Approach

Linguistic metrics including remaining energy, centrality, and RSSI serve as fuzzy descriptors for CH selection, owing to the adaptable crisp set of these linguistic input variables. The process of choosing CHs through fuzzy logic employs a centralized methodology. Fuzzy Type 2 Mamdani is utilized that consists of the Fuzzifier, Inference Engine, Rules and Output (Defuzzification and Type Reduction) as demonstrated in Figure 6. The interval of fuzzy logic type 2 is better than traditional fuzzy logic type 1 to handle the uncertainty in the wireless sensor network, Therefore, it further simplifies the calculation process of the interval fuzzy logic type 2 which more efficient in the WSNs environment.

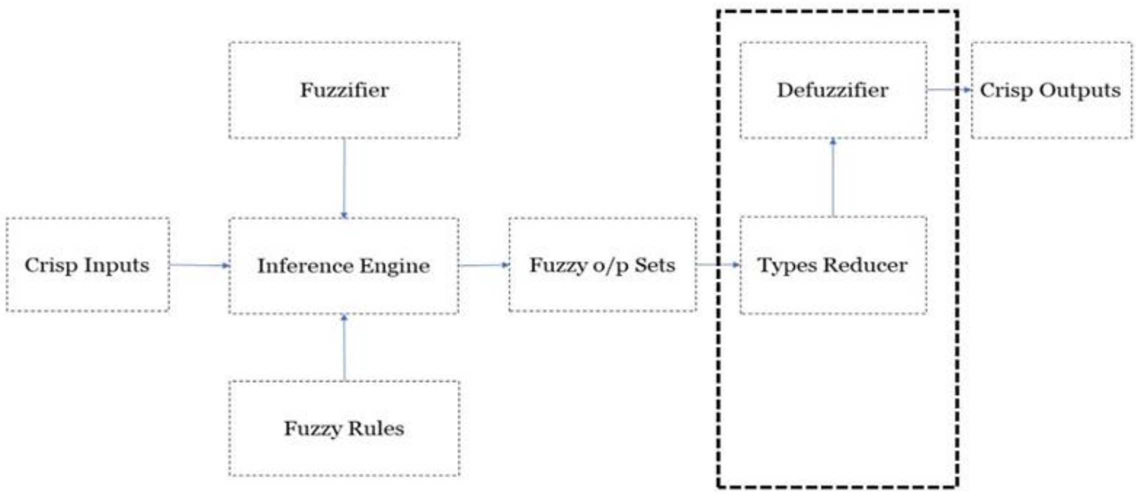

Figure 6 The Working Process of EECR Model

3.2.1. Fuzzification

The fuzzification process is to map individual crisp input value to a fuzzy set. In EECR, the fuzzifier component undertakes the task of mapping the crisp input vector $x^* = (x_1^*, \ldots., x_p^*)$ to the Type 2 fuzzy set A_x^*. To streamline the computation, a singleton fuzzification model is utilized. Specifically, for each *i = 1, ... p*, the membership function of the fuzzified input set X_i^* is delineated herein.

The membership function is defined as a fuzzy set *A* in *X* which denoted by $\mu_A(x)$. Hence, the element of X can be shown in the following form in equation (15):

$$X = \{x_1, x_2, \ldots \ldots . x_n\} \quad (15)$$

In the CH selection process of EECR, three linguistic variables (i.e., remaining energy, centrality, and RSSI) are specified for each membership function, all set within a uniform scale from [0, 1].

The term 'remaining energy' refers to the sensor nodes' remaining battery power. Nodes that have a higher level of remaining energy are capable of processing and sending a larger amount of data. These nodes, therefore, have an increased likelihood of being selected as CHs.

The membership function categorizing remaining energy into "low," "medium," and "high" segments these at intervals from 0 to 0.5, 0.2 to 0.8, and 0.5 to 1, respectively, as displayed in Figure 7.

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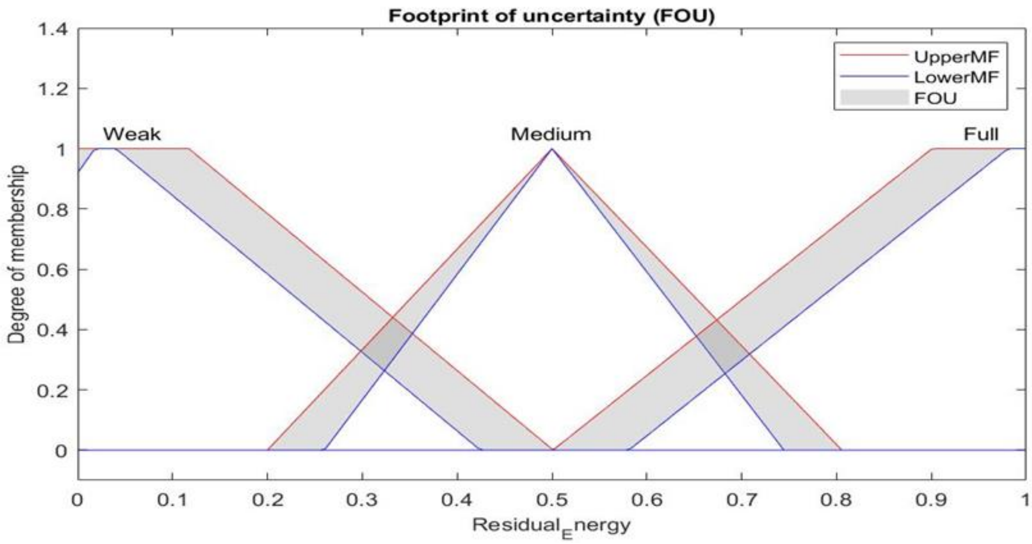

Figure 7 Membership Function of Remaining Energy

The centrality is measured with the sum distances between the nodes and its neighbor overall number of the nodes. In the EECR, the centrality measure is derived by first computing the separation between two nodes, node i and j, utilizing the Euclidean distance formula expressed in equation (16):

$$\mathrm{d}_{i,j} = \sqrt{((a_i - a_j)^2 + (b_i - b_j)^2)} \qquad (16)$$

Here, (a_i, b_i) and (a_j, b_j) represent the coordinates of nodes i and j, respectively, placed within the network. Utilizing equation (16), the centrality for a given node, C_n, is determined by equation (17):

$$\text{Centrality}(C_n) = \frac{(\sum_{a=1}^{k} d_{i,j})}{k} \qquad (17)$$

In this formula, k signifies the total nodes within the network and $d_{i,j}$ denotes the distance between nodes i and j, with $d_{i,j}$ being zero if the node acts as a CH. The membership function interval for centrality were divided into 0 to 0.4 for near, 0.1 to 0.9 for satisfactory, and 0.6 to 1 for far as shown in Figure 8.

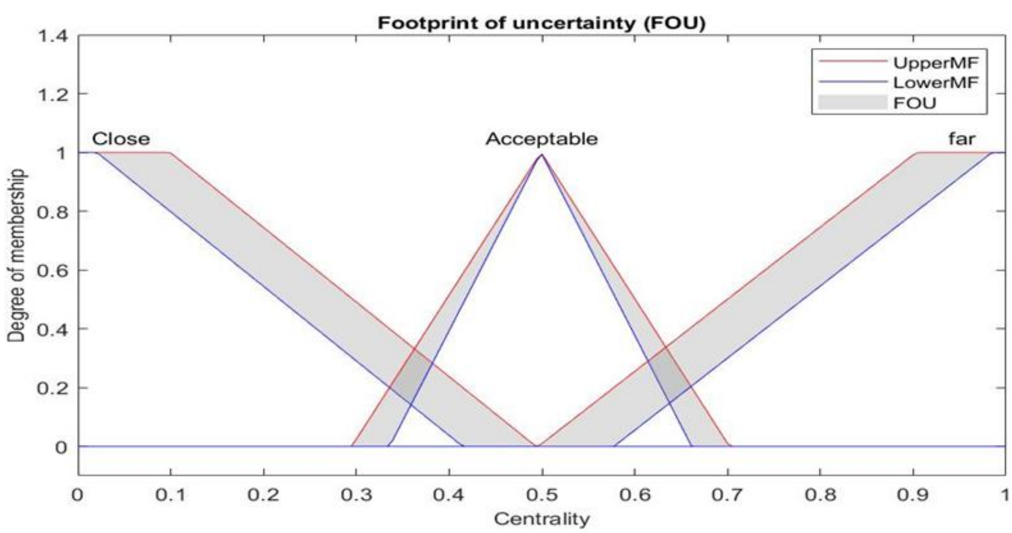

Figure 8 Membership Function of Centrality

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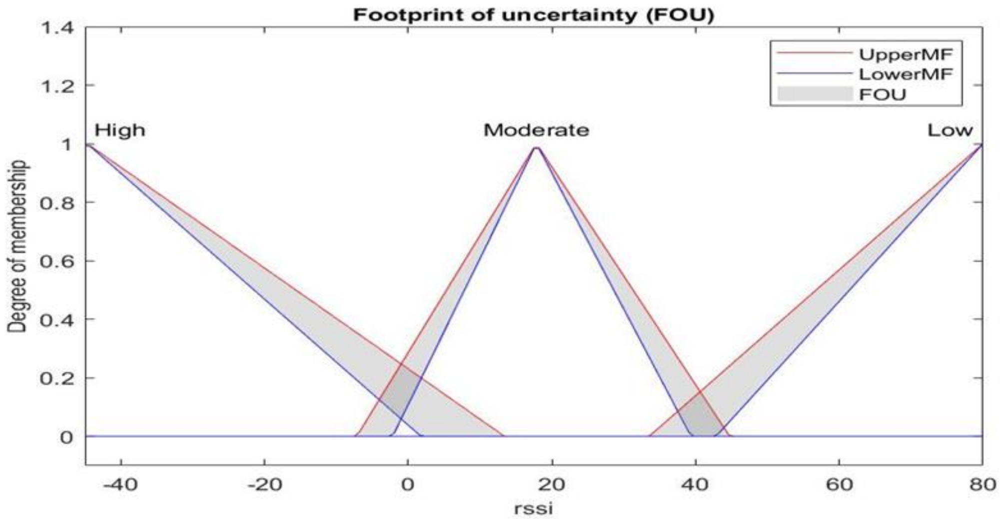

Figure 9 Membership Function of RSSI

The membership function for RSSI is divided into -45 to 10 for low, -10 to 45 for moderate, and 30 to 80 for high signal strength as shown in Figure 9.

3.2.2 Fuzzy Processing

The preceding stage's fuzzy processing results in an output determined by the Mamdani fuzzy inference rules. This method merges membership functions and control rules to generate a result for selecting CHs. The likelihood of selection varies with the levels present in the fuzzy variables.

The total count of rules, denoted as N, in the fuzzy logic controller is formulated as shown in equation (18):

$$N = \sum_{j=1}^{m}\left(\prod_{i=1}^{n} L_i\right) \quad (18)$$

In this context, m is the number of the collection of rules, L_i denotes count of membership functions, and n denotes the count of the given variables within a single rule set. Therefore, with m set to 1, L_i at 3, and n also at 3, the likelihood of selecting a CH was computed to be 3^3 = 27 is shown in Table 2.

Table 2 Rules of Parameter for ResCenRSSI

Rules	Remaining energy	Centrality	RSSI	Output
1	Full	Far	Weak	Moderate
2	Full	Close	Weak	Moderate
3	Full	Acceptable	Weak	Moderate
4	Full	Far	Acceptable	Moderate
5	Full	Close	Acceptable	Moderate
6	Full	Acceptable	Acceptable	High
7	Full	Far	Strong	Medium
8	Full	Close	Strong	High
9	Full	Acceptable	Strong	High
10	Medium	Far	Weak	Low
11	Medium	Close	Weak	Moderate
12	Medium	Acceptable	Weak	Moderate
13	Medium	Far	Acceptable	Moderate

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14	Medium	Close	Acceptable	Moderate
15	Medium	Acceptable	Acceptable	Moderate
16	Medium	Far	Strong	Moderate
17	Medium	Close	Strong	Moderate
18	Medium	Acceptable	Strong	High
19	Weak	Far	Weak	Low
20	Weak	Close	Weak	Low
21	Weak	Acceptable	Weak	Moderate
22	Weak	Far	Acceptable	Low
23	Weak	Close	Acceptable	Moderate
24	Weak	Acceptable	Acceptable	Moderate
25	Weak	Far	Strong	Moderate
26	Weak	Close	Strong	Moderate
27	Weak	Acceptable	Strong	Moderate

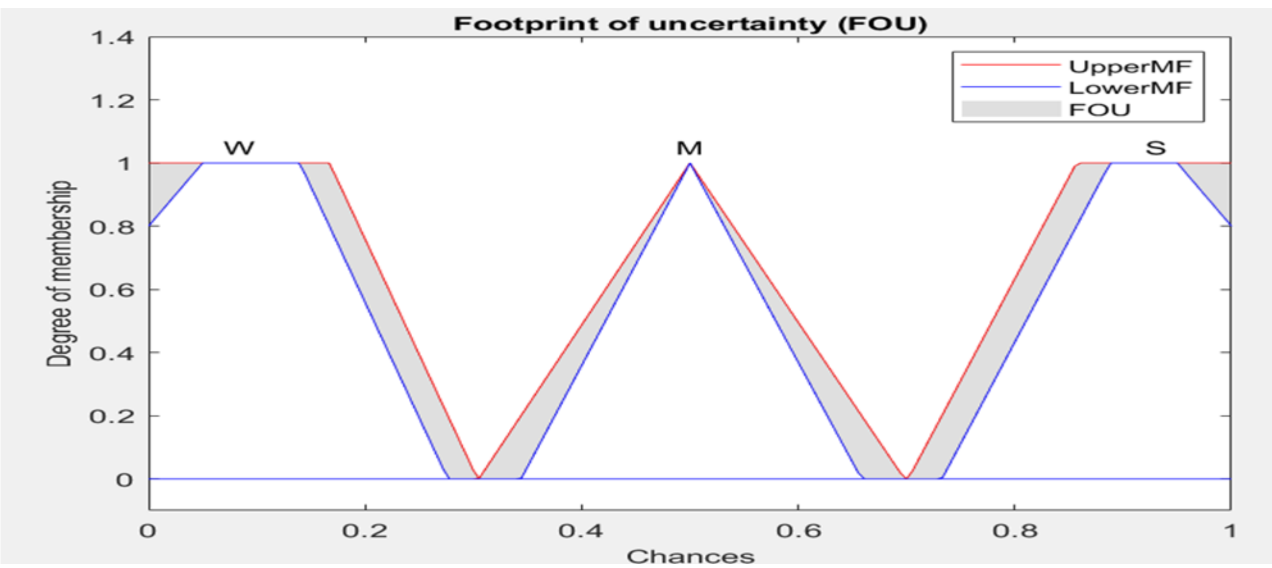

Figure 10 The Output Chances for CHs Selection

From each of the rules, the chances can be obtained from the fuzzy relations shown in equation (19):

$R^{t,s}$: $IF:\ x_1\ is\ A_1^{t,s}\ and\ x_2\ is\ A_2^{t,s}\ and\ x_p\ is\ A_p^{t,s}$

$THEN: y\ is\ C^{t,s}$ (19)

Where $C^{t,s}$ is the s^{th} consequent part associated with the s^{th} output context, $A_p^{t,s}$ is the s^{th} antecedent part associated with the p^{th} input variable, and $s = \{1,2,3, \dots, s^t\}$. In this case, three input variables, remaining energy, centrality and RSSI were used which produce 27 rules of fuzzy rules. For each of the rules, the fuzzy rules relations can be shown as equation (20):

$$R^{t,s} = A_1^{t,s} \cap A_2^{t,s} \cap A_3^{t,s} \rightarrow C^{t,s}\ ,\ \ s = 1,2,3, \dots\dots, s^t \quad (20)$$

Based on the Mamdani's implication rules, the results obtained below as equation (21):

$$\mu_{R^{t,s}} = \mu_{A_1^{t,s}}(x_1 *) \cap \mu_{A_2^{t,s}}(x_2 *) \cap \mu_{A_3^{t,s}}(x_3 *)\ ,$$

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$i = 1,2, \ldots\ldots, s^t$ (21)

The potential results of CH selection were categorized into three levels: weak (W), medium (M), and strong (S), as illustrated in Figure 10.

The criteria for categorizing the selection strength into weak, medium, and strong are defined by range values: weak from 0 to 0.3, medium from 0.3 to 0.7, and strong from 0.7 to 1. The established fuzzy rules are as follows:

CH_{strong} = {remaining energy = high, centrality = near, RSSI = good}

Hence, nodes that exhibit the highest levels of remaining energy, close centrality, and good RSSI are more likely to be chosen as CHs.

4. CLUSTER FORMATION

In cluster formation, sensor nodes positioned in both Layer 1 and Layer 2 link up with their respective CHs to enable data transmission. The method for establishing CHs is outlined in Algorithm 1.

1. Input: i = layer level, CH_i = Designated Cluster Head, CH_i= set of nodes
2. Begin
3. While (i <= 2) do
4. For each node in U_i:
5. If (node is CH i and operational) then
6. The CH establishes a cluster including the subordinate nodes
7. Else
8. Initiate re-clustering process
9. End If
10. End For
11. End While
12. End

Algorithm 1 Formation Process for CHs

The CHs would establish a cluster along with the successor nodes. The proximity of the successor nodes to their respective CHs was determined using the Euclidean distance to set up communication with the CH.

This connection process involved two main stages. Firstly, the overall count of accessible links at a node is determined. Then, the mean distance between the successor nodes and CH is calculated. This calculation is to identify the nodes with a high centrality value relative to the CHs.

5. PERFORMANCE EVALUATION

The efficiency of the EECR was assessed through computational modeling, focusing on its impact on the durability of networks and formation of clusters. Furthermore, the dependability of the EECR approach within the suggested framework was benchmarked against MAP protocols and the Stable Election Protocol (SEP). This assessment was anchored on three critical functionality indicators: the standard deviation of remaining energy (SDRE), the First Node Dead (FND), and the Last Node Dead (LND). The FND metric gauged the duration before the initial sensor node's failure in the network, whereas the LND metric recorded the time until the demise of the final node in the network.

5.1. Simulation Settings

In the simulations, sensor nodes were represented as stationary wireless scattered in 2-layer network environment. The experiments based on 3 scenarios that uses 100, 200, and 800 nodes The standard number of nodes is 100 as being used by another researcher. To assess scalability and compare energy consumption effectively, the experiment scaled up to include as many as 800 sensor nodes. The specific settings applied in these simulation trials are detailed in Table 3.

Table 3 Parameters for the Simulation Environment

Setting	Value
Sensor Nodes	100, 200 and 800
Connectivity Area	100meter x 100meter
Base Station Location	Center (50,50)
1st Layer Coverage	25 meters
2nd Layer Coverage	50 meters
Energy	1 Joule, 2 Joule
$Eelec$ (Energy per bit)	50 nJ/bit
εfs (Free space energy parameter)	10 pJ/bit/m^2
EDA (Energy for data aggregation)	5 nJ/bit/signal

5.2. Cluster Count

During this simulation, comparisons were drawn regarding the count of clusters and the tally of nodes still operational among EECR 1 (i.e., absent of optimal nodes and the K-Means method), SEP, and MAP.

These protocols differentiated in their approach to CH selection, based on varied input parameters.

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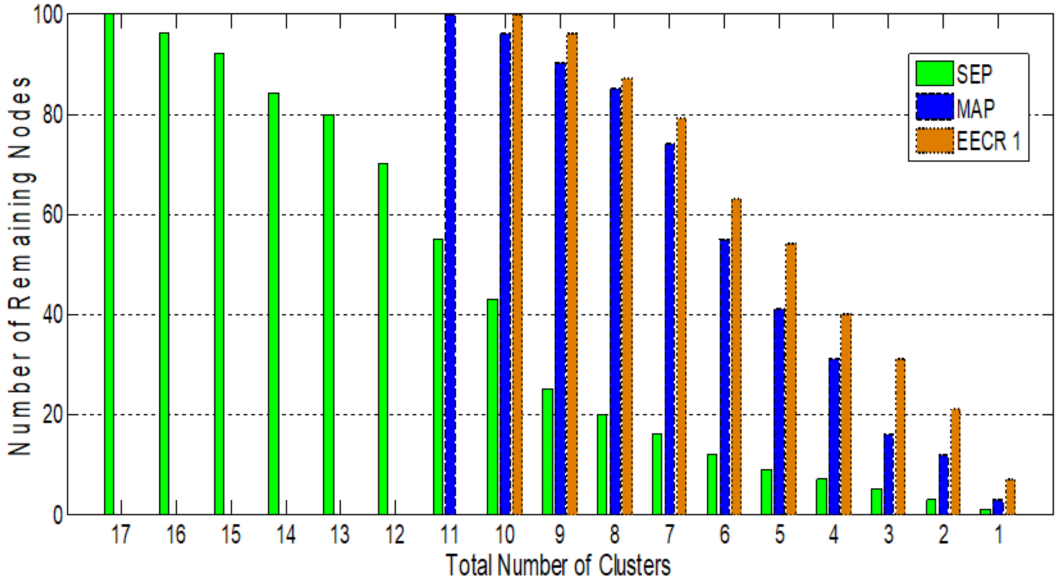

Figure 11 Count of Surviving Nodes Relative to the Total Cluster Count Regarding Scenario 1

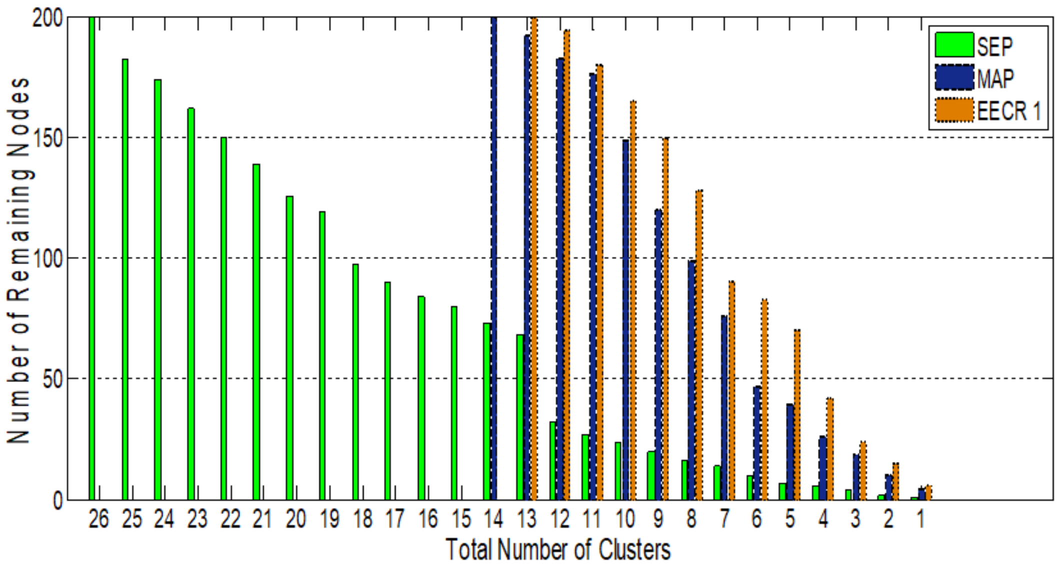

Figure 12 Active Nodes Relative to the All-Cluster Count Regarding Scenario 2

Figure 11, Figure 12, and Figure 13 illustrate the ratio of remaining nodes to the total number of cluster formations in each given scenario. In the first scenario, SEP created the most clusters, totaling 17, followed by MAP and EECR 1, which formed 11 and 10 clusters respectively. As depicted in Figure 11, MAP and EECR 1 exhibited similar patterns in the number of remaining nodes, attributed to their nearly identical total cluster counts. Consequently, the count of remaining nodes for both MAP and EECR 1 declined consistently as the number of clusters decreased. Conversely, SEP's remaining nodes diminished gradually, starting from a higher initial cluster count. In the second scenario, with an increased node count to 200, SEP, MAP, and EECR 1 were able to establish a greater number of clusters compared to the first scenario, forming 26, 14, and 13 clusters respectively. SEP displayed a more significant disparity in cluster numbers and remaining nodes than MAP and EECR 1, with a sharp decrease in remaining nodes at the 12th cluster. The remaining node counts for MAP and EECR 1 decreased uniformly until the formation of the last cluster. In the third scenario, SEP, MAP,

International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2024/43 Volume 11, Issue 5, September – October (2024)

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and EECR 1 produces fewer clusters, with counts of 16, 10, and 9 respectively. SEP's remaining nodes dropped sharply by the 8th cycle. The difference in the number of remaining nodes between MAP and EECR 1 widened, even though their trends were similarly downward, with EECR 1 preserving a higher count of surviving nodes per cluster than MAP.

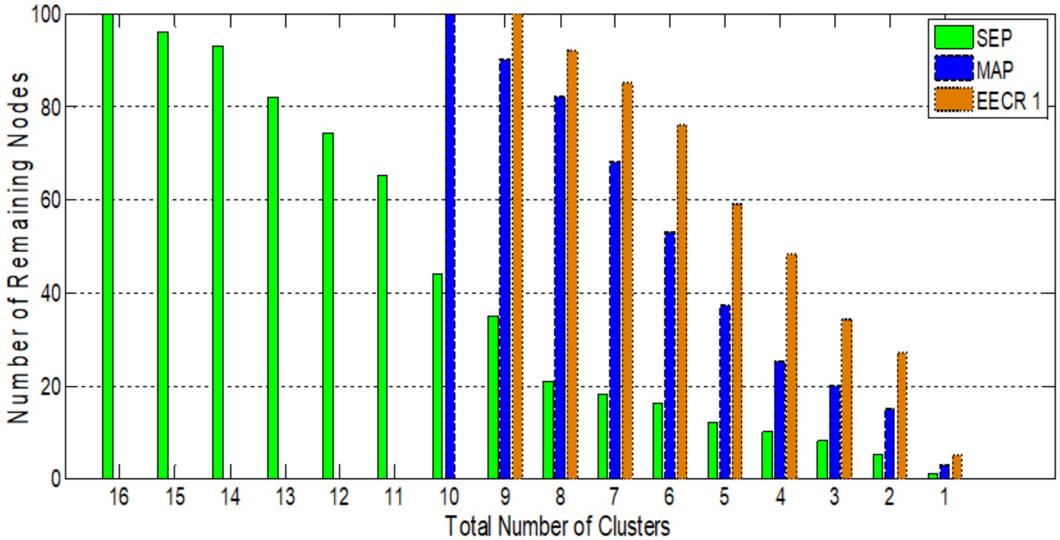

Figure 13 Active Nodes Relative to the All-Cluster Count Regarding Scenario 3

The results show that EECR 1 formed the fewest clusters, which proved the effectiveness in CH selection and cluster formation. EECR 1's selection criteria that utilize remaining energy, centrality, and RSSI, has significant role in its CH selection efficiency. It prioritized nodes with the maximum amount of energy still present, closest centrality, optimal RSSI to choose CH. These input parameters resulted in fewer but more suitable CH selections. In contrast, MAP produced a higher cluster count than EECR 1, as its selection criteria did not consider RSSI, instead used communication cost for selecting the nearest CHs to the Base Station (BS). While this method minimizes the separation between BS and the CHs, ignoring RSSI can affect energy consumption. SEP's performance was the worse. This is due to it disregard centrality, RSSI, and communication cost in its clustering process. Also, SEP relies on a probabilistic method that differentiates between normal and advanced nodes, leading to increased energy consumption due to the formation of more clusters. This analysis shows that EECR 1's approach for CH and cluster generation significantly enhances energy efficiency.

5.3. Energy Balance

In this experiment, the energy balance of ResCenRSSI, ResCen and ResRSSI were evaluated with different values of data aggregation. The model's situations are shown in Table 4.

Table 4 Simulation Situations for Energy Balance

Parameter	Scenario 1	Scenario 2
Node Count	100	200
Data Aggregation	5 nJ/bit/signal	10 nJ/bit/signal
Number of bits	4000	4000

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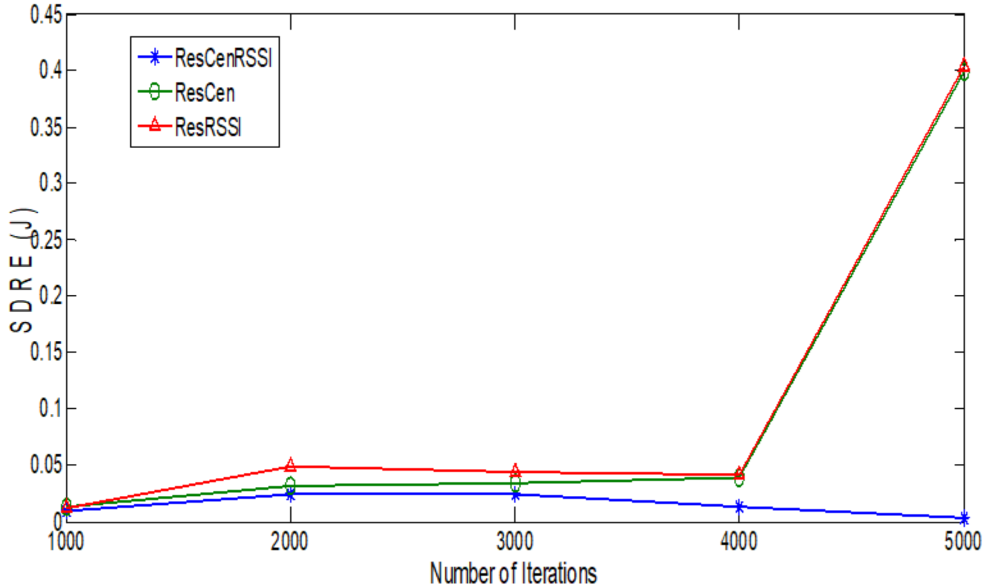

Figure 14 The SDRE for Scenario 1

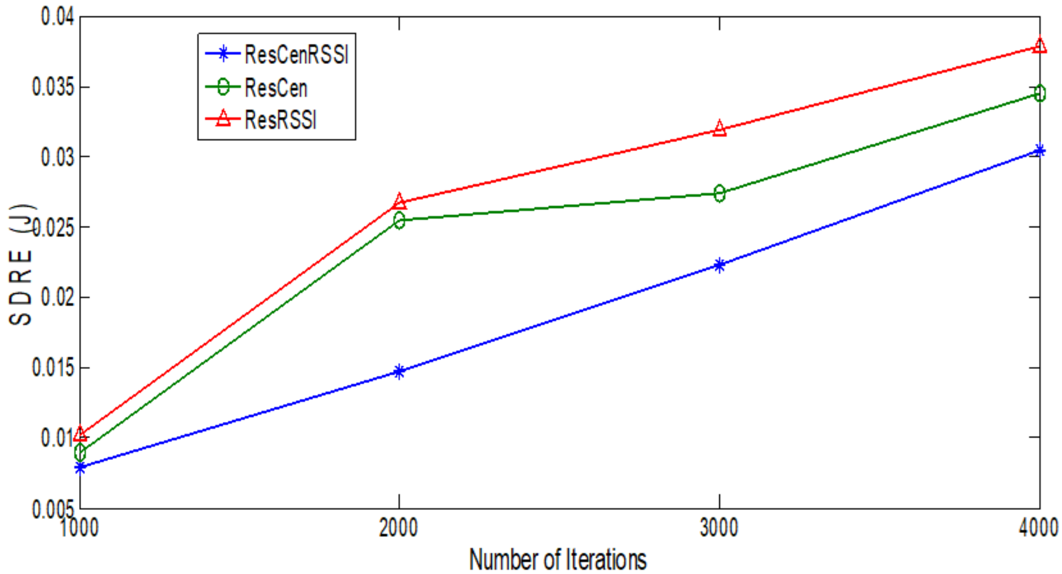

Figure 15 The SDRE for Scenario 2

These parameter values quantified the energy consumption of each combination of input variable with different values of cost transmit and data aggregation in CHs. Therefore, the scenarios were divided into: 1) Normal ratio of data aggregation and 2) High ratio of data aggregation. In the evaluated scenarios, the standard deviation of remaining energy (SDRE) is used as a measurement that indicates the energy equilibrium characteristics of the combination of input variable. The high standard deviation in the calculations of remaining energy indicates the uneven efficiency of energy between the nodes of sensor. Thus, the low value of SDRE is desirable for ResCenRSSI.

Figure 14 and Figure 15 shows the SDRE of ResCen, ResRSSI, and ResCenRSSI over iterations for Scenarios 1 and 2. There were different variations in SDRE for the different combinations of input variables. In Scenario 1, the SDRE of ResCenRSSI slope tends to flatten out. At about the 4000th iteration, there were sharp increases of SDRE for

ResCen and ResRSSI. ResCenRSSI showed a low SDRE value as compared to ResCen and ResRSSI. As the number of nodes increased to 200 in Scenario 2, the SDRE showed an upward trend. The SDRE of ResCenRSSI, ResCen and ResRSSI increased over iterations as compared to 100 nodes. It showed a similar trend with a close value of SDRE for ResCen and ResRSSI at the 2000th iteration. At the 3000th iteration, the ResCenRSSI obtained low SDRE as compared to ResCen and ResRSSI. ResCenRSSI outperformed ResCen and ResRSSI with a steady increase in SDRE.

The ResCenRSSI has the lowest value of SDRE for both scenarios. This is due to the inclusion of RSSI input variable in ResCenRSSI. RSSI considers the distance between sender and receiver when estimating received signal strength. Therefore, the nodes forward the data to the nearest CHs, which have a good received signal strength. When combining with other factors which are centrality and remaining energy of the nodes, it can provide balance among the nodes. Only the highest remaining energy, near centrality, and good received signal strength of nodes can be selected as CHs. On the other hand, ResCen selected high remaining energy and near centrality nodes. However, the nodes with bad RSSI might get selected as CHs which consume high energy. As a results, imbalance energy occurs among the nodes in the 2-layer network. Although ResRSSI selects the CHs with good received signal strength, exclusion of centrality can cause the nodes that are far from the successor nodes be selected as CHs. In fact, centrality is the most crucial input variable to maintain an equilibrium of energy between the sensor nodes. Centrality of the CHs offers balance energy distribution whereby data transmission operates in a centralized manner.

The increasing number of nodes to 200 give high variance for energy distribution in the network. This leads to an increase in SDRE value over iterations. However, ResCenRSSI managed to perform better than ResCen and ResCenRSSI in Scenario 2. Although the value of data aggregation was increased, the ResCenRSSI still outperform the others. Moreover, the SDRE of ResCenRSSI became more significant than ResCen and ResRSSI as compared to Scenario 1. This is because ResCenRSSI can select the most suitable CHs although several nodes were high. On the other hand, ResCen and ResRSSI selected unsuitable nodes, which resulted in higher energy consumption with 200 nodes. Thus, ResCenRSSI has shown the best performance of energy balance in both scenarios that contribute to longer network lifetime.

6. CONCLUSION

This paper presents the EECR strategy as a method to improve the energy efficiency of WSNs. A crucial aspect of this study is the use of a type-2 fuzzy logic approach to select CHs. The choice of CHs is based on three input parameters which are remaining energy, centrality and RSSI. Also, the 2-layer network architecture method provides scalability of the sensor nodes that can help balance the energy use when forming the clusters. The results from experiments show that EECR is better than previous methods like EECR 2, MAP, and SEP, in many ways. EECR stands out by reducing early and late node deaths, saving energy, and making the network last longer. The combination of fuzzy logic for CH picking and K-Means clustering makes EECR a leading solution for creating wireless networks that last longer and use energy more efficiently.

ACKNOWLEDGEMENTS

The authors express their gratitude to the ministry of higher education for providing financial support under Fundamental Research Scheme (FRGS): FRGS/1/2023/ICT08/UMP/02/2 (University Reference RDU23018). Furthermore, we would like to thank and acknowledge the Faculty of Computing, UMPSA for lab facilities and their support.

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How to cite this article:

Azamuddin Bin Ab Rahman, Sakib Iqram Hamim, "Enhancing Energy Efficiency in Multi-Layer Wireless Sensor Networks Through Cluster Head Fuzzy Logic Type 2 and Multi-hop Node Strategies", International Journal of Computer Networks and Applications (IJCNA), 11(5), PP: 690-705, 2024, DOI: 10.22247/ijcna/2024/43.