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CLUSTERING IN WIRELESS SENSOR NETWORK USING FUZZY LOGIC

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Abstract

In numerous research studies, fuzzy logic is employed to pick cluster heads in wireless sensor networks. The performance of clustering is discussed in this study as a function of the Fuzzification methods and membership functions used. The invention of a communication protocol based on fuzzy logic is the next contribution. The goal is to distribute load evenly over the network in order to save energy and extend the network's life. Because the suggested protocol minimizes the frequency of CH re-election, it has a lower message complexity, fewer operations, and hence lower energy usage.

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I. Introduction

Wireless Sensor Networks (WSNs) are made up of self-contained sensor nodes that are placed in the Region of Interest at random or by hand (RoI). The primary function of these sensor nodes is to sense/monitor the given RoI and send the data to the sink or Base Station (BS). WSNs are widely used in a wide range of applications, including intrusion detection, weather forecasting, military surveillance, environment monitoring, machine health monitoring, industrial process and control, medical diagnosis, and more. Monitoring systems derive information about physical or environmental conditions, and adjustments in the application technique occur based on the information detected. The nodes run on non-replaceable batteries and have limited battery life, energy, memory, processing power, and bandwidth.

During the sensing process, all sensing nodes execute three essential tasks: sensing, processing, and transfer. After sensing, the nodes interpret the input in a way that the BS can understand in the processing step. The detected data is then analysed and sent to the BS, bringing the sensing action to a close. However, the procedure is not as straightforward as it appears. With limited resources, and each node executing all three activities independently, the network's cost is increased due to the high energy consumed by the nodes. This results in a short network life.

WSN energy efficiency is a hot issue of research, owing to the large range of applications that these networks may support [1,2,3]. Data aggregation and selective node activation are two popular approaches for making these networks more energy efficient.

Data aggregation via cluster heads (CHs), which are specially appointed nodes, is thought to be a good approach. Because each CH is responsible for data aggregation inside its cluster and relaying the processed information to the base station, CH selection is more of a leader election challenge and is referred to as clustering in WSN. Apart from the CHs, the nodes' only function is to sense and communicate information to their

CH. As a result, enough energy is saved in the detecting nodes. Clustering also allows data to be compressed before being delivered to the CHs and then to the BS via local data fusion, reducing the amount of energy used.
Static clustering protocols choose CHs once and keep them for the rest of their lives. This could cause overloaded CHs to expire prematurely, resulting in network disconnectivity and under coverage. The LEACH algorithm [4] by Heinzelman et al. is the first dynamic clustering strategy that rotates the elected CHs at random to avoid draining the energy of a few nodes.
The concept of applying fuzzy logic for CH selection was presented by Gupta et al [5]. The chance of a node being elected as a CH is calculated using a simple set of IF-THEN rules applied to the fuzzified input variables. The probability must be defuzzified into crisp values in order to compare the probabilities of different nodes and elect the CH with the highest probabilities. The newly elected CHs then continue the cluster building and sensing process. Many scholars were inspired by the approach's simplicity and adaptability to numerous applications. The CHEF (Cluster Head Election mechanism using fuzzy logic in WSNs) [6], EAUCF (Energy Aware Unequal Clustering using Fuzzy logic) [7], NFEACS (Neuro Fuzzy Energy Aware Clustering Scheme) [8, and DUCF (Distributed Unequal Clustering using Fuzzy Logic) [9] are some popular fuzzy logic based clustering protocols.
Recent research has employed fuzzy logic to cluster WSNs with varying settings. [10, 11,12,13] are noteworthy, while [14] contains a full survey. Two fuzzy logic strategies for selecting CHs in WSNs are proposed in this research. With these CH selection approaches, a clustering strategy for WSNs is also proposed.

II. PROPOSED FUZZY INFERENCE SYSTEMS AND CLUSTERING PROTOCOL

A. Proposal A

The Sugeno approach [15] is used to fuzzify crisp input values into equivalent fuzzy linguistic variables in the Proposal A that we propose. Triangular membership is followed by these linguistic characteristics. The Product technique is utilised as the implication method, and the Sum method is used as the aggregator method.

B. Proposal B

Proposal B employs the Mamdani method [16] to fuzzify crisp input values into linguistic variables after Gaussian membership. The implication approach is called 'product,'
while the aggregator method is called 'Probabilistic Sum.' The Center of Area (COA) approach was used to defuzzify output linguistic variables after Gaussian membership and convert them to crisp values.

Fig. 1. Membership function for Residual Energy in Proposal B

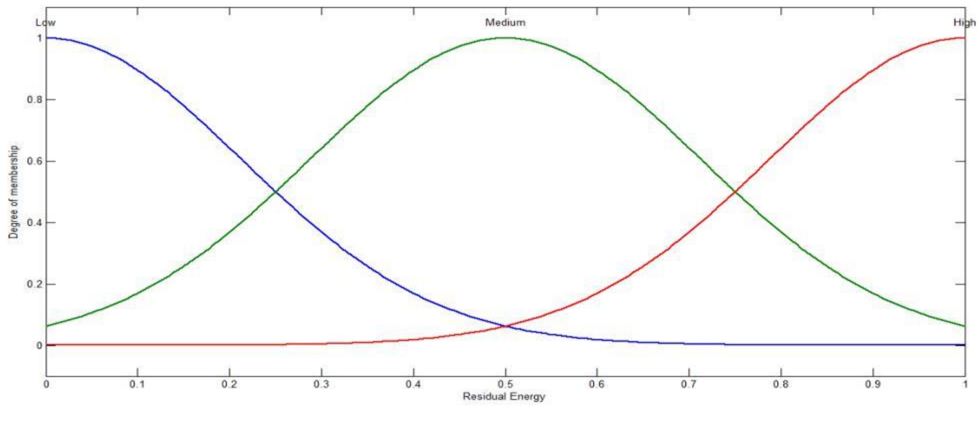

Fig. 2. Membership function for Node Degree in Proposal B

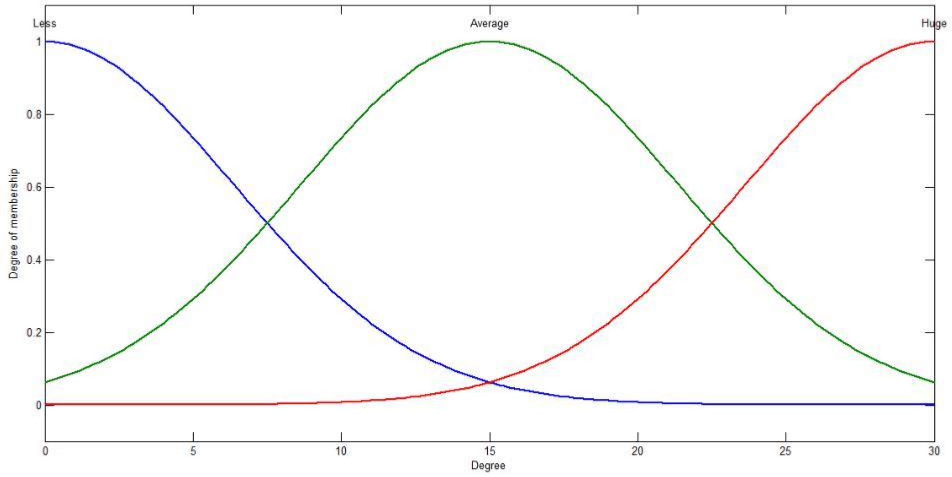

Fig. 3. Membership function for Distance to BS in Proposal B

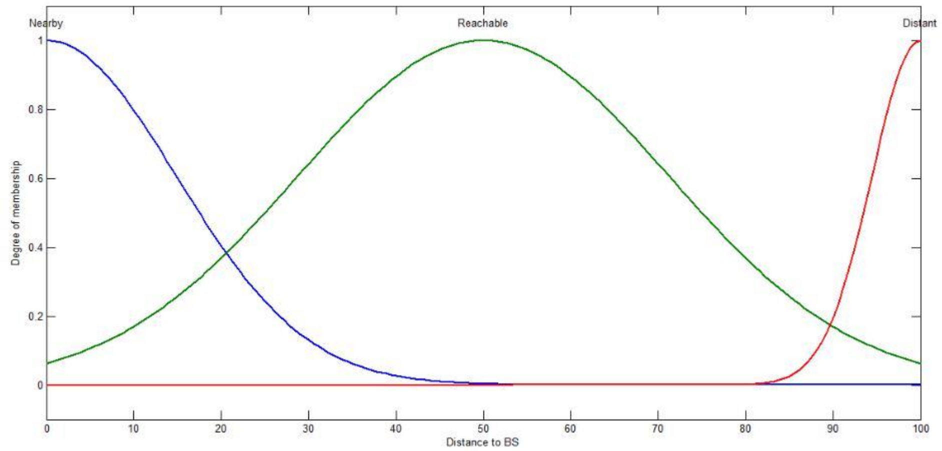

Fig. 4. Membership function for Chance in Proposal B

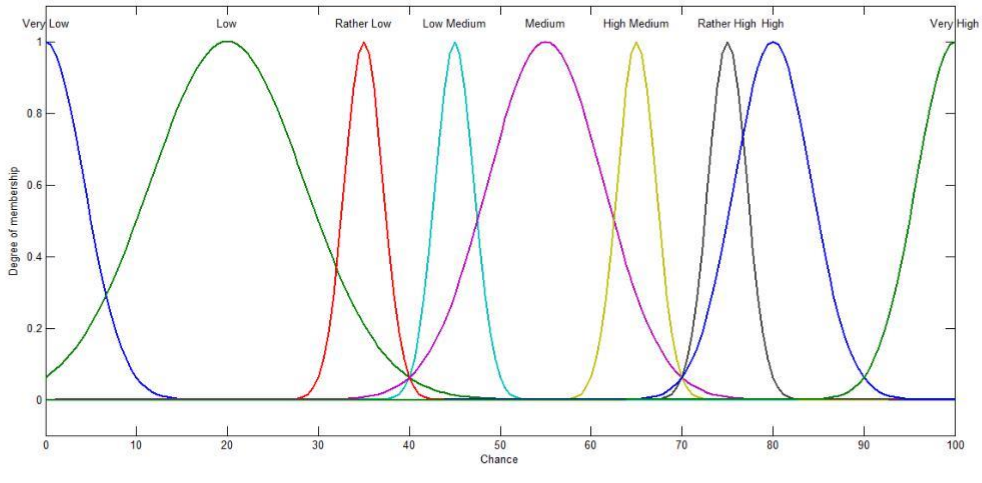

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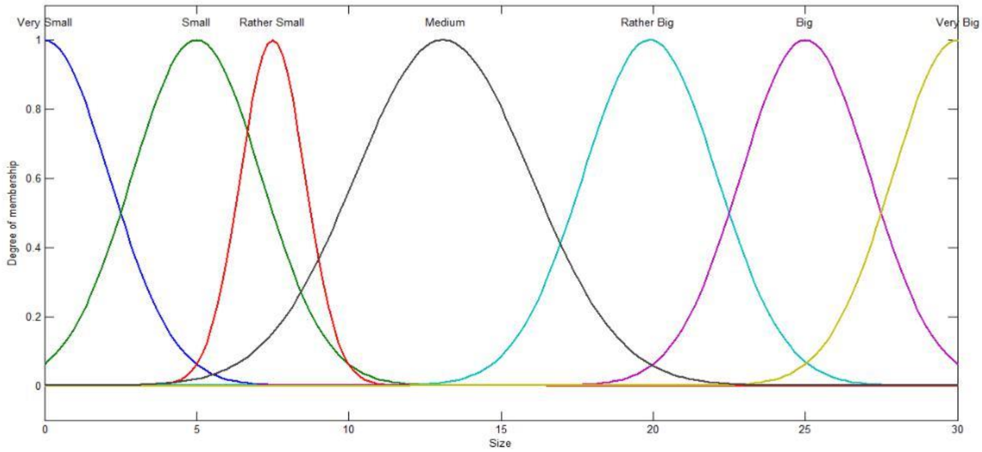
Fig. 5. Membership function for Size in Proposal B



C. Membership functions and Inference Rules

Three input and two output variables are used in the suggested fuzzy approach. Residual energy, node degree, and distance from BS are the input variables. The node can bear more load if its leftover energy is higher. The number of neighbours a node has is an estimate of the burden it will have to endure if it is elected as CH. The number of member nodes for a CH close to the BS should be lower to compensate for energy usage when relaying packets from distant CHs to the BS. The CHs that are far away from the BS should have more member nodes for multi-hop forwarding of aggregated data. Chance and size are the outcome variables. A node's chance is the likelihood of being elected as a CH. The size parameter specifies the maximum number of member nodes that a CH can have.

Each input variable has three language variables, resulting in 27 fuzzy inference rules (Table 1). The output fuzzy linguistic variables for 'Chance' and 'Size' are 9 and 7, respectively. Figures 1 to 5 for Proposal B demonstrate the membership functions for various linguistic variables, which are dependent on the suggested fuzzy inference methods applied. The membership functions for the FCWN-I fuzzy inference approach are not graphically represented.

D. Assumptions

The protocol takes into account a homogeneous sensor node network, a static deployment environment, and distance between nodes determined using the Received Signal Strength Indicator (RSSI). Every node has the same processing power, memory, transmission, and reception capabilities. The BS is familiar enough with the underlying network.

E. Protocol Description

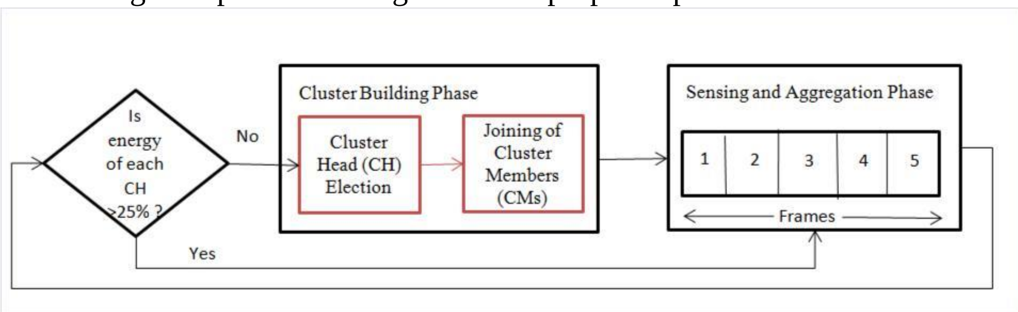
Cluster Building, Sensing, and Aggregation are the two steps of the proposed protocol. Electing CHs and connecting Cluster Members (CMs) to the nearest CH that accepts their membership are also part of the Cluster Building process. The suggested protocol's operations are depicted in Figure 6. In the operational diagram, the divisions in the sensing and aggregation phase indicate frames. In one cycle of data gathering, the frame lengths are all the same. A frame is the amount of time it takes for data to be transmitted from a member node to its associated CH. Every node calculates its chance and size throughout CH election using the current values of the fuzzy inference system's input. The Chance values are broadcast, and the node with the greatest Chance value among its neighbours is elected CH. CH informs his neighbours that he has won. By issuing a request, each non-CH node joins the CH closest to it. If the 'Size' of the CH enables it, the request is approved; otherwise, it is forwarded to the next closest CH. In the event that a non-CH is unable to join any CH, it announces itself to be one.

The CHs are re-elected only when the energy of any of the CHs falls below 25% of the beginning energy, not after each round of the procedure. Otherwise, the already-elected CHs will continue to be in charge of aggregation and transfer. This is done to decrease the number of messages sent during the protocol's CH election phase. Getting through the election procedure as quickly as possible.

TABLE I. FUZZY INFERENCE RULES OF PROPOSED SYSTEM

S. No	Input Variables			Output Variables	
	Residual energy	**Node degree**	**Distance to BS**	**Chance**	**Size**
1	High	Enormous	Nearby	Very high	Rather large
2	High	Enormous	Reachable	High	Large
3	High	Enormous	Distant	Rather high	Very large
4	High	Average	Nearby	Very high	Medium
5	High	Average	Reachable	High	Medium
6	High	Average	Distant	Rather high	Medium
7	High	Less	Nearby	Very high	Very small
8	High	Less	Reachable	High	Small
9	High	Less	Distant	Rather high	Rather small
10	Medium	Enormous	Nearby	High medium	Rather large
11	Medium	Enormous	Reachable	Medium	Large
12	Medium	Enormous	Distant	Low medium	Very large
13	Medium	Average	Nearby	High medium	Medium
14	Medium	Average	Reachable	Medium	Medium
15	Medium	Average	Distant	Low medium	Medium
16	Medium	Less	Nearby	High medium	Very small
17	Medium	Less	Reachable	Medium	Small
18	Medium	Less	Distant	Low medium	Rather small
19	Low	Enormous	Nearby	Rather Low	Rather large
20	Low	Enormous	Reachable	Low	Large
21	Low	Enormous	Distant	Very low	Very large
22	Low	Average	Nearby	Rather Low	Medium
23	Low	Average	Reachable	Low	Medium
24	Low	Average	Distant	Very low	Medium
25	Low	Less	Nearby	Rather Low	Very small
26	Low	Less	Reachable	Low	Small
27	Low	Less	Distant	Very low	Rather small

Fig. 6. Operational diagram of the proposed protocol



III. EXPERIMENTS AND RESULTS

A. Simulation Setup

Variations in fuzzy inference methods and membership functions of the input variables are used in both the DUCF and the proposed protocol. DUCF (Mamdani method and Triangular Membership functions), Proposal A (Sugeno method and Triangular Membership functions), and Proposal B (Sugeno method and Triangular Membership functions) are the three fuzzy inference methods utilised in the proposed and Baranidharan and Santhi's protocol (Mamdani method and Gaussian Membership functions). Because Baranidharan and Santhi's work was the first to employ this combination of fuzzy methods and membership functions, the initial technique is called DUCF. For the trials, three situations are considered: Scenario 1: Base Station situated randomly in the RoI; Scenario 2: Base Station located in the RoI's centre; and Scenario 3: Base Station located outside the RoI.

Each implemented protocol is tested for performance on all three scenarios in terms of the following measures

ξ **Rounds:** The total number of rounds a protocol takes to execute. This determines the network lifetime.

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ξ **First Node Die**: This factor determines the number of rounds a protocol runs before its first node dies.

ξ **Half Node Die**: This factor determines the number of rounds executed by the protocol before half of the population of the network dies. For practical purposes, the network is considered dead when 75% of the nodes of the network are dead. A list of simulation parameters used in the process is provided in Table II.

The energy consumption model of [1] is followed. The energy for transmission of *l* bits to a distance *d*, is given by

$$E_{tx} = l * E_{elec} + \varepsilon_{mp} * d^4, d > d_0 \qquad (1)$$

$$E_{tx} = l * E_{elec} + \varepsilon_{mp} * d^2, d < d_0 \qquad (2)$$

And energy consumed in receiving a packet of *l* bits is computed as

$$E_{rx} = l * E_{elec} \qquad (3)$$

TABLE II. SIMULATION PARAMETERS

Simulation Parameters	Description	Values
l	No. of transmitted bits	4000
E_{elec}	Energy consumed in transmission and reception	50 nJ/bit
ε_{fs}	Energy dissipated in free space propagation	10 pJ/bit/m^2
ε_{mp}	Energy dissipated in multipath propagation	0.0013pJ/bit/m^4
Data Packet Size	Size of a data packet	500 bytes
Control Packet Size	Size of a control packet	25 bytes
d_o	Threshold distance	87 m

B. Results and Interpretation

The measured values of in all three cases are shown in Figures 7 to 9, with fuzzy inference systems specified in the chart and the clustering methodology of [9] being applied. The values are recorded as shown in Figs 10 to 12 when the proposed clustering methodology is utilized with the three different fuzzy inference systems.

A large number of rounds indicate that the protocol runs for a longer period of time, implying that the network's lifetime has risen. A greater FND number indicates that it takes longer to drain the energy of a single node, implying that the load is dispersed evenly throughout the network. A greater HND score implies the same thing, however when the FND and HND values are combined, some intriguing conclusions can be derived. When comparing the findings of Scenario 3 in Figures 8 and 9, we can see that Proposal B has a greater FND than the others, but a lower HND. This means that while it took longer to exhaust the energy of a single node, the energy of numerous nodes eventually dropped at the same time. As a result, Proposal B is ineffective in Scenario 3.

Fig. 7. Comparison of total number of rounds executed by protocol [9] with indicated fuzzy systems

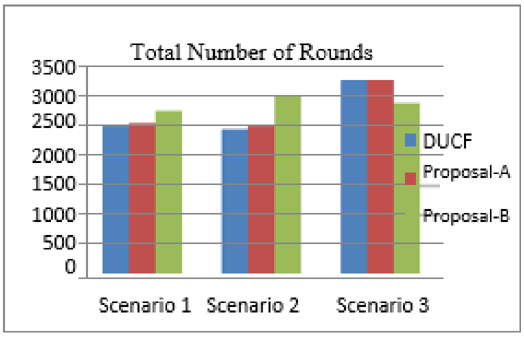

Fig. 8. Comparison of the First Node Die values, fuzzy methods as indicated, in the protocol of [9]

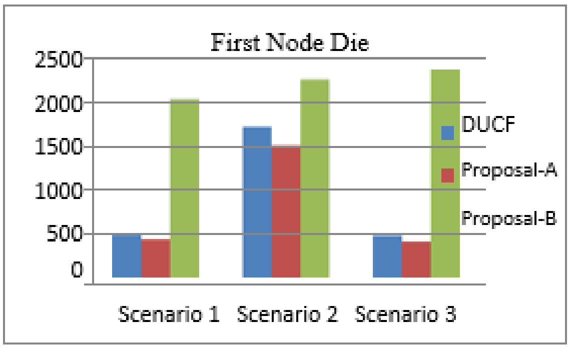

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Fig. 9. Comparison of the Half Node Die values, fuzzy methods as indicated, in the protocol of [9]

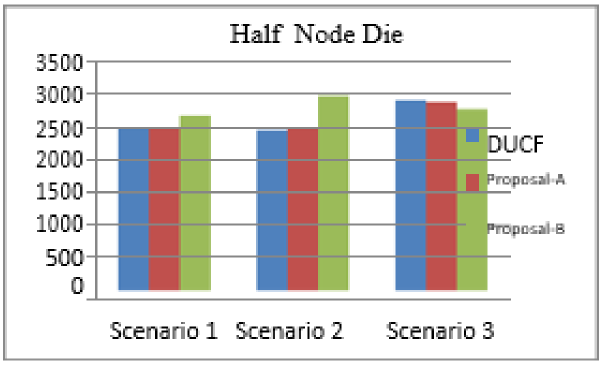


Fig. 10. Comparison of total number of rounds executed, fuzzy methods as indicated, in the proposed protocol

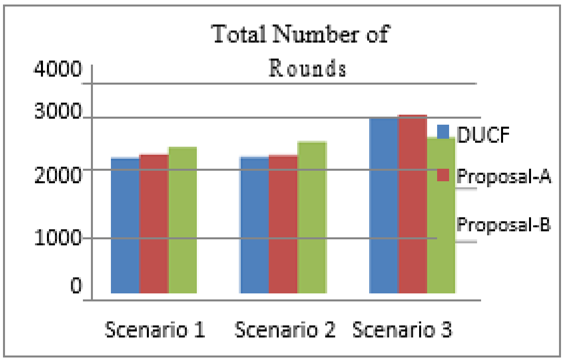


Fig. 11. Comparison of the First Node Die values, fuzzy methods as indicated, in the proposed protocol

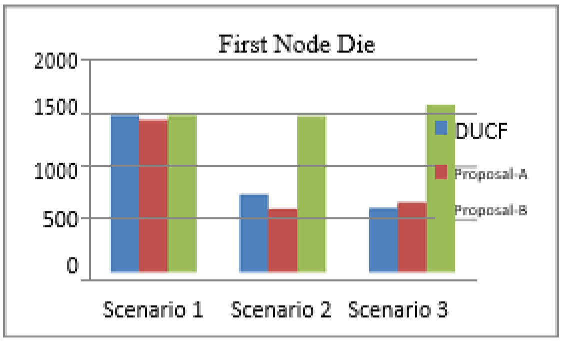
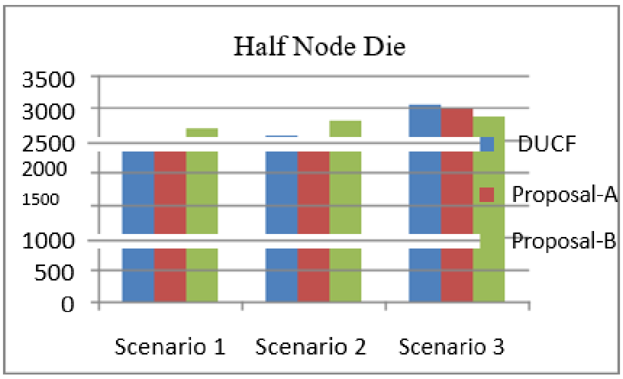


Fig. 12. Comparison of the Half Node Die values of the proposed protocol for all the three scenarios



IV. CONLUSION

When there are several uncertainties associated with a decision, fuzzy logic is a widely used decision-making approach. In many cases, such as cluster head election in Wireless Sensor Networks, traditional decision-making strategies based on a predefined criterion fail to produce the desired outcomes. The reason for this is that the efficiency of such findings is reliant on a number of overlapping criteria, and using a single metric to make a judgment can lead to bias. In the literature, there have been few attempts to use fuzzy rules to execute CH election in WSNs. The input variables examined, fuzzy inference output variables, and the fuzzy rule set are the main differences between them. This study presents two fuzzy inference algorithms that use the same input variables. Both of these systems provide two outputs. The outputs are used to choose CHs and determine how many people a CH will let to join it. The input variables are the three criteria for any sensor node's energy, distance, and neighborhood information. The protocol is quite similar to Baranidharan and Santhi's [9] work, but with less message complexity. The proposal's two fuzzy inference systems are completely different from any previous work.

Simulation tests are carried out for situations involving different base station locations. The number of rounds, First Node Die, and Half Node Die are used to quantify the effect of fuzzy inference systems and protocols on the energy characteristics of WSNs. The proposed fuzzy inference system type II has been found to be more successful than others in extending the network's lifetime. The suggested protocol has a lower message complexity, which saves nodes some energy indirectly. Overall, it is suggested a fuzzy CH election mechanism and a communication protocol that conserves energy by distributing load evenly across the network.

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