International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

DHCFL: Dual Head Clustering Based On Fuzzy Logic for Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSN) are constructed by interconnecting miniature sensor nodes for monitoring the environment uninterrupted. These miniature nodes are having the sensing, processing and communication capability in a smaller scale powered by a battery unit. Proper energy conservation is required for the entire system. Clustering mechanism in WSN advances the lifetime and stability in the network. It achieves data aggregation and reduces the number of data transmission to the Base station (BS). But the Cluster Head (CH) nodes are affected by rapid energy depletion problem due to overload. A CH node spends its energy for receiving data from its member nodes, aggregation and transmission to the BS. In CH election, multiple overlapping factors makes it difficult and inefficient which costs the lifetime of the network. In recent years, Fuzzy Logic is widely used for CH election mechanism for WSN. But the underlying problem of the CHs node continues. In this research work, a new clustering algorithm DHCFL is proposed which elects two CHs for a cluster which shares the load of a conventional CH node. Data reception and aggregation will be done by CH aggregator (CH-A) node and data transmission to the BS will be carried over by CH relay (CH-R) node. Both CH-A and CH-R nodes are elected through fuzzy logic which addresses the uncertainty in the network too. The proposed algorithm DHCFL is compared and tested in different network scenarios with existing clustering algorithms and it is observed that DHCFL outperforms other algorithms in all the network scenarios.

Keywords: Wireless Sensor Networks, Clustering, Fuzzy Logic, Energy conservation, Computational techniques

I. INTRODUCTION

The recent and rapid advancement in MEMS technology led to the mass manufacturing of miniature sensor nodes. These sensor nodes are capable of continuously monitoring the environment without any human interference. Since these nodes are spread and distributed over a large area it is better at predicting the surrounding environment with improved accuracy. Wireless Sensor Networks (WSN) are built of highly interconnected miniature sensor nodes [1]. The sensor nodes which are located nearby will generate redundant data. Transmitting the redundant data to the BS node will lead to energy wastage of the nodes and would not be much helpful in the monitoring task. Clustering technique is the best choice for solving this data redundant problem. It addresses the redundant data problem by aggregating the data from same region into a single data packet and transmit to the BS. In this clustering process [2], spatially nearby nodes will group together and form a cluster either through centralized or distributed approach. In the cluster, a node will be elected as Cluster Head (CH) which governs the clustering activities till next re-clustering process. The non-CH nodes in the cluster acts as Cluster Members (CM) and communicates the sensed information to their respective CH node in periodic interval. The CH nodes in turn will aggregate the data given by its CM into a single piece of information and forward the information to the Base Station (BS). CMs energy will be conserved since its radio unit is turned on only during its data transmission to the CH whereas a CHs radio unit should be turned on during the entire cycle and depletes its energy very faster than all other member nodes. This paper address the above problem with a new clustering algorithm for WSN which shares the workload of a conventional CH into two CHs named *CH Aggregator* (CH-A) and *CH Relay* (CH-R). The idea behind this new CH algorithm is a cluster in WSN will have dual CHs, CH-A node in a cluster will carry over data reception from CMs and aggregation activities whereas the data transmission to the distant BS node will be carried by CH-R node of the same cluster. Usually, computer based decision making system is based on binary logic. The binary logic has only two states: Yes or No. All the decision falls under these two categories only but in real time system it is difficult to accept something completely true (Yes) or completely false (No). In such cases, our decision making system needs multiple sets so that our decisions may fall under different sets with different membership values. Fuzzy Logic (FL) [3] is one approach where it supports multiple sets with different membership values in each sets. It is used wherever uncertainty is there.

Revised Manuscript Received on January 15, 2020
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II. RELATED WORKS

In LEACH [4**],** which is the prominent distributed clustering algorithm for WSN which uses probabilistic way of CH election. It ensures that CH role will be circulated among all the nodes in the network. Almost, all the clustering algorithms for WSN follows LEACH's experimental setup and energy model. LEACH–C [5] and LEACH-F [5] are the variants of LEACH.

The fuzzy logic based clustering was initiated by Gupta et al [6] for clustering in WSN. In their work, fuzzy logic was used to elect CHs based on residual energy, centrality and node degree. The output variable is the chance of the node to get elected as cluster head.

LEACH-FL [7] is an fuzzy approach based extension of LEACH. It is a centralized fuzzy based clustering protocol. Distance to BS, Node Degree and Residual energy are the input variables to EAUCF. The third input parameter 'distance to BS' is different from Gupta method and other methodologies are same like in Gupta's work. Like other centralized clustering algorithm, LEACH-FL has scalability problem.

FLECH [8] is designed for the nonuniform wireless sensor networks. It combines probabilistic and deterministic approach for electing CHs in the network. Initially, probationary CHs and then final CHs are elected from these probationary CHs based on the fuzzy approach. Thus, this mechanism ensures that all the nodes are elected as CH in even terms and balances the energy consumption.

EAUCF [9] elects CH nodes in the distributed fashion. At first, using random number generation tentative CHs are elected. The output of the FIS is the competition radius R_{Comp} for the Tentative-CH nodes. In turn, Tentative-CH will check whether any other Tentative-CHs with higher energy is existing within its R_{Comp}. If it found out any other higher energy Tentative-CH nodes, the current node will drop out from the Final-CH race. Intra-cluster communication cost is not considered for CH election in EAUCF. This is the major reason for low performance of EAUCF.

LEACH-SF [10], uses Sugeno [11] method for FIS and the fuzzy rules are updated using Artificial Bee Colony (ABC) algorithm which makes it unique apart from the other fuzzy approaches. Fuzzy C-means algorithm forms well balanced and distributed clusters. FIS follows Sugeno method whereas in most of the existing algorithms Mamdani [12] method is used. CHs are elected based on fuzzy rules as like in other fuzzy based algorithms. The fuzzy rules are updated periodically using ABC algorithm.

Adaptive MCFL [13] is a yet another clustering algorithm for WSN based on fuzzy approach. At first, the CH nodes are elected based on their number of neighbours and residual energy and it is termed as first clustering. In second clustering, since there would not be any major change in energy, the same CH is retained. In third clustering, now the chance of the nodes in being elected as CH in a cluster is computed based on Distance to current CH and residual energy. The node having higher chance value in a cluster is elected as new CH. The reduced chance of getting electing as CH if first clustering alone is repeated after second clustering is now addressed using third clustering in Adaptive MCFL. But again this may encourage the same nodes in being elected as CH will lead to earlier First Node Die (FND).

Gajjat et al, proposed FAMACROW [14], a fuzzy based algorithm. But when compared with other fuzzy based clustering algorithm, FAMACROW uses Link Quality Indicator (LQI) of the transmission channel of a node as an important factor for CH election. There are three phases in FAMACROW: (i) Network setup phase, where the BS transmits the control signal with its ID and location details, (ii) Neighbour finding phase, identifies the number of neighbour nodes for each node in the network and (iii) steady state phase, elects' CH based on the parameters like residual energy, number of neighbours and LQI of a node. ACO technique is used for route optimization between CH to BS.

The proposed algorithm, DHCFL solves the uneven energy consumption between CHs and CMs. In DHCFL, CH-A node collects the sensed information from all the CMs like other algorithms and aggregates it into a single packet. Then , the aggregated packet is sent to CH-R node which transmits it to the BS. The only responsibility of CH Relay is the data transmission to the BS.

III. DHCFL ALGORITHM

Like most of the clustering algorithms for WSN, DHCFL comprises of Creation and Operational phase. Again, the Creation phase comprises of CH-A election subphase and CH-R election subphase. Fig. 1. depicts the architecture of DHCFL.

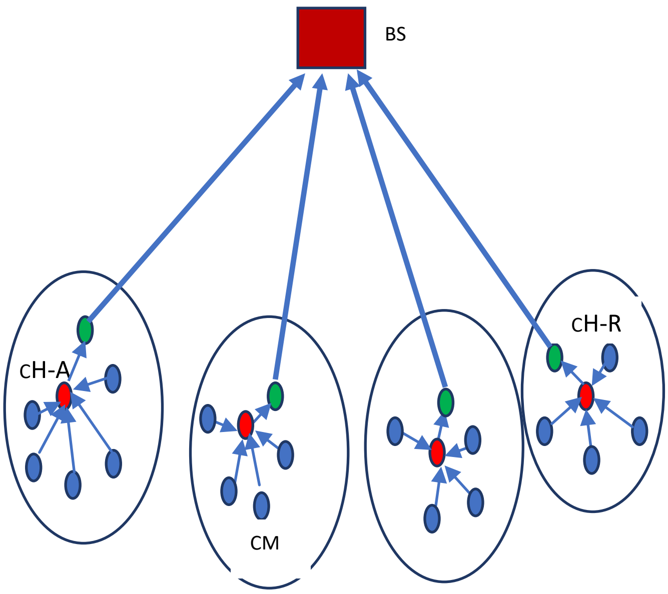


Fig. 1. Architecture of DHCFL

A. Creation phase:

As mentioned earlier, cluster formation phase has two sub-phases: (i) CH-A election subphase and (ii) CH-R election subphase. The responsibility of CH-A is generating TDMA schedule for the member nodes, collecting the data from them and aggregating the data into a single packet. The single packet of fused data is transmitted to the CH-R node and then the CH-R node will transmit the data to the BS node. So, the responsibilities differs the metrics used for electing CH-A and CH-R also differs. For electing CH-A, residual energy, node degree and node centrality are the main factors. Residual energy is the remaining energy of the node, node degree is the number of neighbour nodes and Node centrality is the measure of how the node is located centrally to its neighbours. For electing CH-R, residual energy, distance to BS and distance to CH-A are the main factors. For electing both CH-A and CH-R, two different Fuzzy Inference system are used.

Fig. 2,3 and 4 depicts the fuzzy membership forms for the input variables to FIS for electing CH-A. 'Low-Energy', 'Medium-Energy' and 'High-Energy' are the linguistic variables for residual energy (RE). 'Few', 'Moderate' and 'Many' are the linguistic variables for Node degree (ND). 'Nearest', 'Intermediate' and 'Far' are the linguistic variables for Node centrality (NC). The variables 'Few', 'Many', 'Nearest' and 'Far' follows trapezoidal form and the remaining linguistic variables follows triangular form.

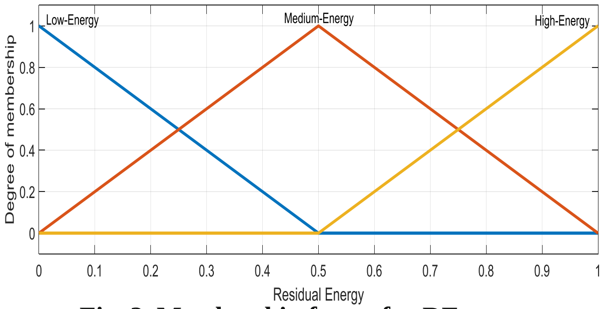


Fig. 2. Membership forms for RE

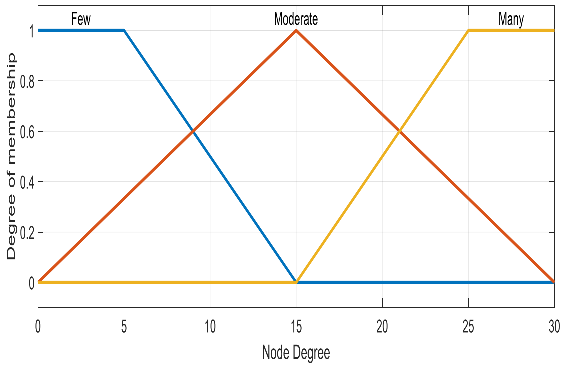


Fig. 3. Membership forms for ND

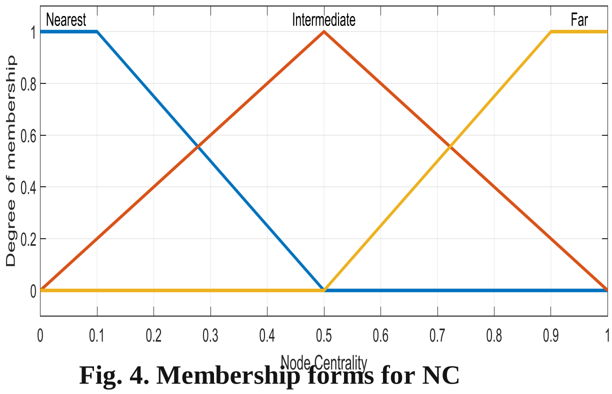


Fig. 4. Membership forms for NC

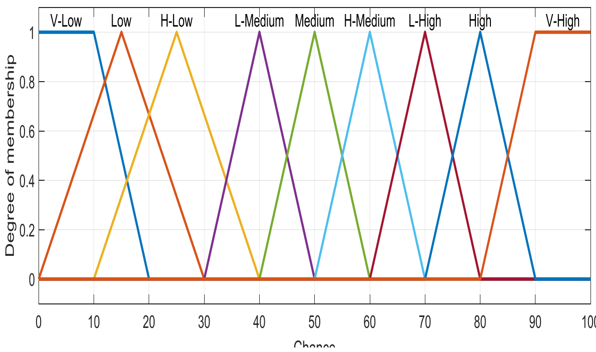


Fig. 5. Membership forms for Chance

Fig. 5. depicts the fuzzy membership functions for the output variable 'Chance'. The linguistic variables for 'Chance' are 'V-Low', 'Low', 'H-Low', 'L-Medium', 'Medium', 'H-Medium', 'L-High', 'High' and 'V-High'. In that, 'V-Low' and 'V-High' has trapezoidal form and other variables follows triangular form.

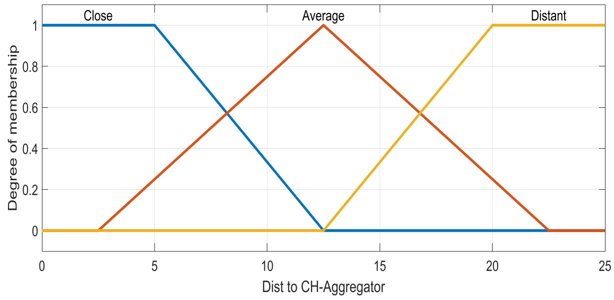


Fig. 6. Fuzzy Membership for Input variable *Dist to CH-Aggregator*

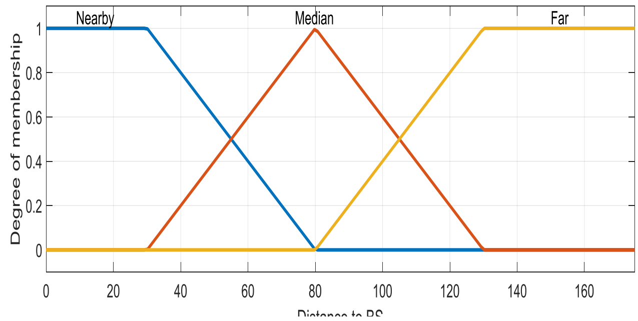


Fig. 7. Fuzzy Membership for Input variable *Distance to BS*

Fig. 6. and 7 depicts the fuzzy membership for the input variables 'Distance to CH Aggregator' and 'Distance to BS'. The linguistic variables for Residual energy used for CH-R is same as used for CH-A as such in Fig. 2. 'Close', 'Average' and 'Distant' are the fuzzy variables for *Distance to CH-Aggregator* whereas 'Nearby', 'Median' and 'Far' are the fuzzy variables for *Distance to BS*. 'Average' and 'Median' have triangular form and the remaining variables follows trapezoidal form. The output variable 'Chance' for CH-R election is also same as in Fig. 5. Table - I shows the fuzzy rules for electing CH-A node. Table - II shows the fuzzy rules for electing CH-R node.

Table – I: Fuzzy rules for CH-A

RE	ND	NC	Chance
Low-Energy	Few	Remote	V- Low
Low-Energy	Few	Intermediate	Low
Low-Energy	Few	Nearest	H-Low
Medium-Energy	Few	Remote	L-Medium
Medium-Energy	Few	Intermediate	Medium
Medium-Energy	Few	Nearest	H-Medium
High-Energy	Few	Remote	L-Medium
High-Energy	Few	Intermediate	Medium
High-Energy	Few	Nearest	H-Medium
Low-Energy	Moderate	Remote	Low
Low-Energy	Moderate	Intermediate	H-Low
Low-Energy	Moderate	Nearest	L-Medium
Medium-Energy	Moderate	Remote	L-Medium
Medium-Energy	Moderate	Intermediate	Medium
Medium-Energy	Moderate	Nearest	H-Medium
High-Energy	Moderate	Remote	L-High
High-Energy	Moderate	Intermediate	High
High-Energy	Moderate	Nearest	V-High
Low-Energy	Many	Remote	Low
Low-Energy	Many	Intermediate	H-Low
Low-Energy	Many	Nearest	L-Medium

Medium-Energy	Many	Remote	L-Medium
Medium-Energy	Many	Intermediate	Medium
Medium-Energy	Many	Nearest	H-Medium
High-Energy	Many	Remote	L-High
High-Energy	Many	Intermediate	High
High-Energy	Many	Nearest	V-High

Table – II: Fuzzy Rule for CH-R

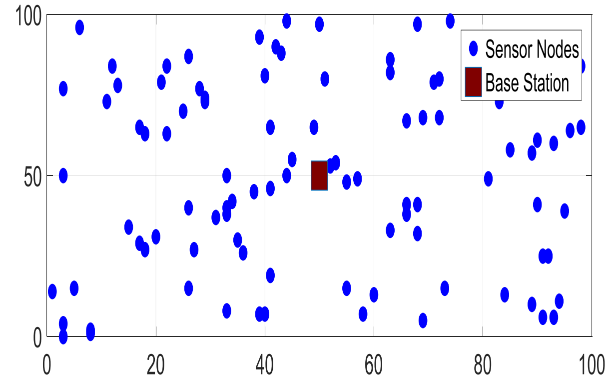
RE	Distance to CH-A	Distance to BS	Chance
Low-Energy	Close	Nearby	H- Low
Low-Energy	Close	Median	Low
Low-Energy	Close	Far	V-Low
Medium-Energy	Close	Nearby	H-Medium
Medium-Energy	Close	Median	Medium
Medium-Energy	Close	Far	L-Medium
High-Energy	Close	Nearby	V-High
High-Energy	Close	Median	High
High-Energy	Close	Far	L-High
Low-Energy	Average	Nearby	H-Low
Low-Energy	Average	Median	Low
Low-Energy	Average	Far	V-Low
Medium-Energy	Average	Nearby	H-Medium
Medium-Energy	Average	Median	Medium
Medium-Energy	Average	Far	L-Medium
High-Energy	Average	Nearby	V-High
High-Energy	Average	Median	High
High-Energy	Average	Far	L-High
Low-Energy	Distant	Nearby	H-Low
Low-Energy	Distant	Median	Low
Low-Energy	Distant	Far	V-Low
Medium-Energy	Distant	Nearby	H-Medium
Medium-Energy	Distant	Median	Medium
Medium-Energy	Distant	Far	L-Medium
High-Energy	Distant	Nearby	V-High
High-Energy	Distant	Median	High
High-Energy	Distant	Far	L-High

B. Operational phase:

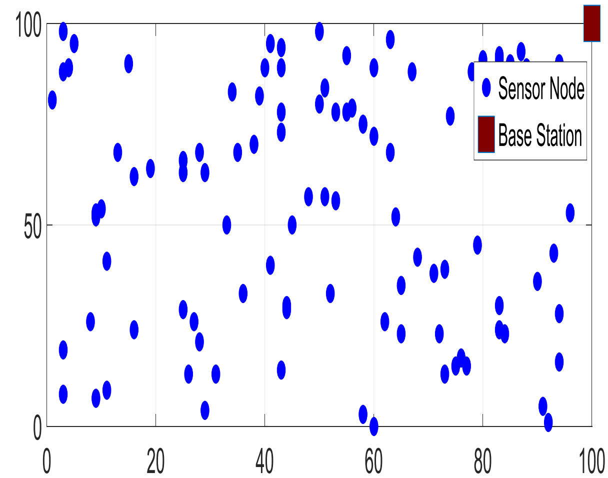
After the election of CH-A and CH-R nodes, TDMA schedule for CMs will be generated by the respective CH-A. All CMs in a cluster have to transmit their sensed information to CH-A on its assigned time slot. In other time slots, the radio of a CM would be put in sleep. Finally, CH-A combine the data from its CMs into a single packet of data. Then, the aggregated single packet of data is communicated to the CH-R and then from CH-R to the BS.

IV. EXPERIMENTAL SETUP AND RESULT ANALYSIS

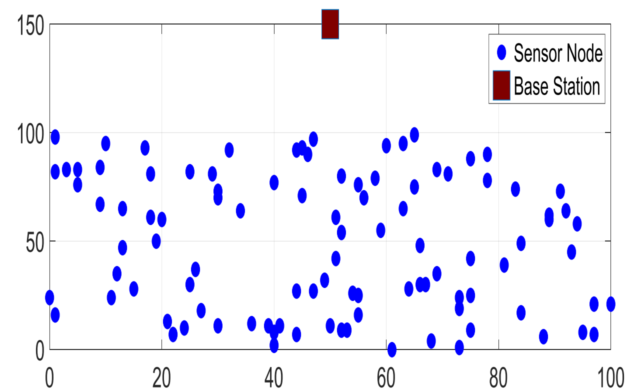
Transmission energy and reception energy model used for LEACH [4] is used for simulating the algorithms. DHCFL is compared with LEACH, EAUCF and FLECH based on overall energy consumption and network lifetime. Three different scenarios based on the placement of BS is taken foe experimental analysis. In scenario I, BS is located at the central point of the Sensing Region (SR), scenario II corresponds to location of BS at one corner of SR and in scenario III BS is placed away from the SR. The network deployment is depicted in Fig. 8. As a common case, in all the scenario 100 sensor nodes are used and the deployment is random in nature. The experimentations are done on 10 different topologies and the results are average of these.



(a) Base Station at the centre of ROI



(b) Base Station at the corner of ROI



(b) Base Station outside to the ROI

Fig. 8. Different Scenarios based on the location of Base Station

A. **Overall Average Energy Consumption:** The main purpose of clustering is to reduce and balance the energy consumption among the nodes. So, the overall energy consumption per round is compared and analysed. Fig. 9. shows the overall average consumption of the clustering algorithms. In all the three different scenarios, DHCFL fares better than others. In particular when BS moves out of ROI, the performance of DHCFL improves a lot. In other scenarios too, the proposed algorithms shows lesser energy consumption than existing algorithms.

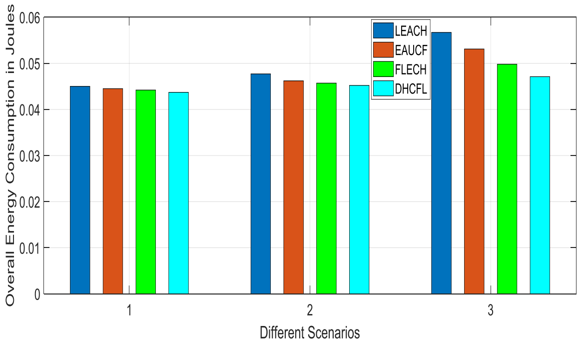


Fig. 9. Comparison of Overall Average Energy Consumption

B. **Network Lifetime:** In this metrics, number of completed communication rounds is compared against with the number of dead nodes over the period of time. Fig.10,11 and 12 depicts the lifetime of the WSN in Scenario I, II and III respectively. It is observed that DHCFL shows improved lifetime than LEACH, EAUCF and FLECH in all the scenarios.

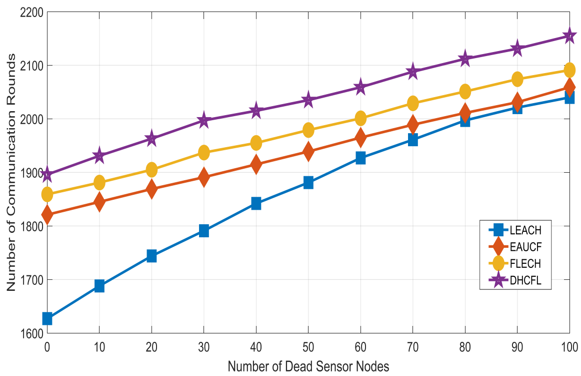


Fig. 10. Communication Rounds vs Dead Sensor Nodes in Scenario I

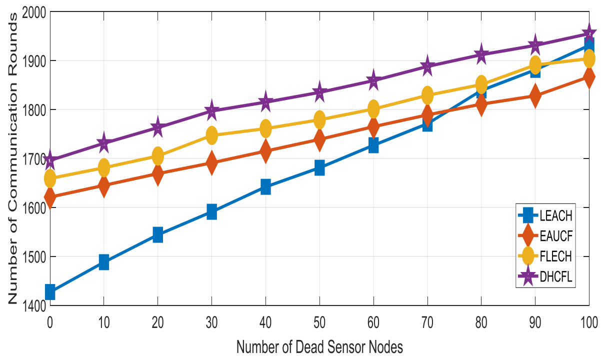


Fig. 11. Communication Rounds vs Dead Sensor Nodes in Scenario II

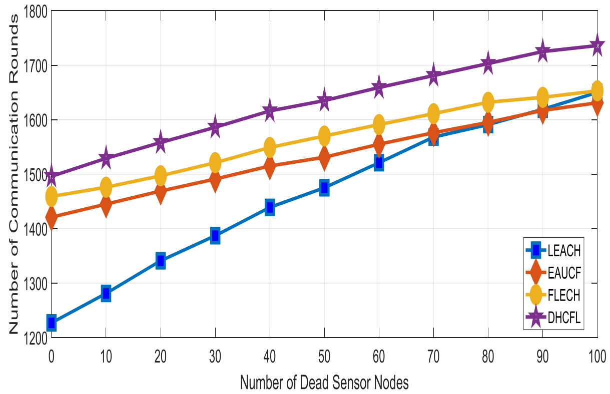


Fig. 12. Communication Rounds vs Dead Sensor Nodes in Scenario III

V. CONCLUSION AND FUTURE WORK

In this paper, DHCFL a fuzzy based distributed clustering algorithm is proposed with the idea of having two CHs for a cluster. The prime objective of the proposed algorithm is to minimize the energy consumption at CHs. So, unlike conventional clustering algorithms, in DHCFL two CHs are elected, one CH termed CH-Aggregator for data aggregation from member node and another CH termed CH-Relay for transmitting aggregated data to the BS. DHCFL is compared along with LEACH, EAUCF and FLECH based on their overall energy spending and their network lifetime (i.e) Number of communication rounds against number of dead sensor nodes. In increasing the network lifetime and reducing overall energy consumption DHCFL shows better improved results than others. In near future, DHCFL will be tested under different network deployments to further analysis the impact of dual CH in the network.

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