**International Journal of Computing and Digital Systems**
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 12, No.1 (Dec-2022)

https://dx.doi.org/10.12785/ijcds/1201107

# Elongate the Network Lifetime using Adaptive Network-Based Fuzzy Inference System in Wireless Sensor Networks

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*Received 20 Jul. 2021, Revised 7 Sep. 2022, Accepted 1 Dec. 2022, Published 8 Dec. 2022*

**Abstract:** The Wireless Sensor Networks is the collection of sensor nodes that can sense the environment and send it to the sink or access point for further processing based on the requirement. It works on the principle of "less effort and more comfort." These sensors collect the sensed data and transfer it to the access point. The Network framework is critical in selecting the optimum distance and degree of data-access point connectivity for effective communication between source, intermediate destinations, and the final destination. For this, Energy-efficient clustering is the ultimate mechanism for long-term energy efficiency in most Networks. To achieve long-term energy efficiency, we choose to enhance the LEACH protocol as it is a well-known protocol for energy efficiency and prolongs the network lifetime. Still, the cons of the LEACH protocol are it uses a random approach for cluster formation. It does not consider the node's residual energy for choosing the head node from each cluster. We enhanced the LEACH protocol by using an Adaptive network-based fuzzy inference system by overcoming the mentioned cons. We conducted a simulation to test the efficiency of our proposed routing protocol. It is better in terms of throughput, lifetime, energy dissipation, and the first node dies, quarter node dies, percent of node die, and several nodes alive after completion of rounds. Also, we compared our approach with two of the existing state of art approaches like LEACH using the Conventional approach, LEACH using the Fuzzy approach, and Multi-Criteria Cluster Head Delegation.

**Keywords:** Wireless Sensor Networks, ANFIS, Routing Protocol, Clustering, Head Node , Network Lifetime , Energy Efficiency

## 1. Introduction

Phenomenal technologic development, such as Very Large-Scale Integration(VLSI), Microelectromechanical systems (MEMs), and wireless communications, also lead to the broad usage of distributed sensor systems. As with many other innovations, the military was a guiding factor behind Wireless Sensor Networks (WSNs). [1], [2]. The Fig. 1 shows the layout of a Wireless Sensor Networks. WSN is a set of sensory nodes for environmental sensing and knowledge collecting and is transferred to the entry point or base station to be processed further. Wireless Sensor Networks specialize in providing the potential for a wide variety of applications whereby minimal human interference and integral in rendering the future smarter [3]. It uses spatially dispersed self-governing nodes, which can use sensors for monitoring either independently of physical or environmental circumstances [4].Wireless sensor networks are the most powerful way to track and control human output. The application's ease of execution, the ability to function in unstable conditions, and high results are many explanations of why the application is famous. In this mechanism, by balancing glide, node capacity is the primary difficulty in which sources are scarce, to say a way to minimize energy intake and extend network lifetime for the layout of wireless sensor networks utilizing current routing protocols [5]. In terms of overall network efficiency, routing protocols play an influential role. Overall, Routing is the most challenging method in a WSN. It is essential to look for the shortest route from the source node to the destination node. This approach is mathematics used by human ideas. The key aim of every network is to transfer information from source to destination effectively. Routing is the best approach to providing an effective and best route for contact in wireless sensor networks. In terms of overall network efficiency, routing protocols play a central role. In the Routing portion, we used Cluster selection to choose the best path for intra-clustering and inter-clustering. The classification of routing protocols depends on two main elements: the configuration of the network and the protocol's application. The chore of finding and maintaining routes in WSNs is not minor as energy constraints and abrupt shifts in a node, which involve failures in node intent typical and unexpected topological adjustments. Their primary advantage is its potential to be utilized in all fields and any environment, unlike other innovations that need lengthy conditions for their usage. In the initial, there has been an abundance of competition in WSN, and it is still receiving

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popularity. There is a broad range of applications for the latter category, particularly pipeline surveillance, human activity tracking, transportation, goal tracking, underground mining, structural health monitoring, and environmental monitoring [6]–[13].

The term "Low energy adaptive clustering hierarchy (LEACH)" refers to an adaptive clustering hierarchy with a low energy usage. This is the first protocol for hierarchical routing (HRP). The majority of HRPs are synthesized from LEACH. It is a self-organizing, adaptive clustering system that makes use of randomness to equally divide the energy load throughout the network's sensors. The nodes organize themselves into local cluster heads in this case. LEACH operates on a round-based system. It is divided into two phases during each round. The initial step is the construction phase, during which each node randomly selects a value between 0 and 1. If the selected value is smaller than the threshold value T(n), the node is designated as the cluster head. The Lateral phase is when data is transmitted according to a Time Division Multiple Access schedule and data aggregation or fusion is performed by the cluster heads. The prolongation of network lifetime plays an important part, and LEACH is the hierarchical energy adopted protocol that extends network lifetime. However, it is challenging to achieve energy quality and energy balance during the routing process. It is challenging to evaluate mainly using the standard. We would optimally align both the energy conservation and the energy balance. On the other side, Fuzzy Logic(FL) needs less computational power than conventional non-FL approaches and can manage uncertainties [14]–[18]. It considers the difference between the head node and the node member in this method and the head node's energy level, the distance between the sink node and the head node, the residual energy of the nodes, etc.

Based on the forgoing analysis, we have made the following observations.

1. LEACH is the first HRP which still has the scope of improvement than existing improvements. 2. The integration of Fuzzy Logic in LEACH has the scope for less computation power than conventional non-FL approaches and can manage uncertainties. 3. This FL makes it easier to integrate and accurately analyze different criteria accurately. Many existing FL-based LEACH work exists, but few of the authors used only local distance as a primary parameter for choosing network efficiency. Still, it is not suitable for various ranges of network sizes. Few of them have considered only two parameters, i.e., residual energy and distance to Sink for choosing the node as a head node by ignoring node degree, which is the crucial parameter for selecting the head node. Few authors have used three parameters: residual energy, node degree, and distance to Sink, for choosing an efficient head node. Still, at times lagged the optimal number of head nodes and maintained stability, improving the network lifetime. A new approach is proposed to address the problems mentioned above, i.e., integrated a neuro-fuzzy approach for prolonging the network lifetime and energy balancing of the entire network to maintain stability.

Therefore, the contributions of our work in this paper can be summarized as follows.

- Our approach is for extending the life of a network by choosing the correct head node based on residual energy, the distance between ordinary nodes, head nodes, and access points in each cluster.
- Our proposed protocol's simulation results were carried out and contrasted with the three states of art protocols, i.e., LEACH [19], LEACH using the Fuzzy method [20] and Multi-Criteria Cluster Head Delegation based on Fuzzy Logic (MUCH) [21]. The performance is better in terms of First Node Die(FND), Quarter Node Die(QND), Ten Percent Node Die(PND), the number of nodes that survived.

The rest of the paper is organized as follows. In Section 2, we review the related works and Section 3 introduces the proposed method. Section 4 provides the performance study of proposed method and compared with one of the improved method. Finally, Section 5 concludes the paper.

## 2. Related Work

In general, Neural Network,Fuzzy systems and genetic algorithms are distinct soft computing techniques evolved from the biological computational strategies and natures way to solve problems. Clustering algorithms and routing strategies for WSN have been proposed in recent years. Throughout this portion, we briefly examine the important current contributions to LEACH, with the significant developments in ANFIS approaches.

A Fuzzy Multi-hop clustering protocol (FMSFLA) has proposed in [22]. To achieve optimum application-based efficiency, the FMSFLA considers successful parameters, including energy, distance from the base station (BS), the number of neighboring nodes, actual node distance from the BS. It involves selecting parents, cluster forming, and the constant state during each round of the phases of the choice of CH. The selection process of parents started with the decision of network CHs in our protocol. At the end of this step, each CH parent is calculated based on the largest fluid production. The clusters are created based on the determined CHs in the cluster forming process. Finally, in the stable state process, the information obtained by CHs is submitted to BS via the parents. In addition to their acceptable propagation speeds and other network existence and protocol scalability parameters, the FMSFLA will be against the LEACH, LEACH-EP, LEACH-FL, ASLPR, SIF ERA protocols utilizing three application-oriented scenario models. In both cases, the FMSFLA performed much stronger about targets and device functionality than the other protocols, according to the simulation performance.

The Multi-point Relay (MPR) selection process, the downside of Optimized Link State Routing Protocol (OLSR)

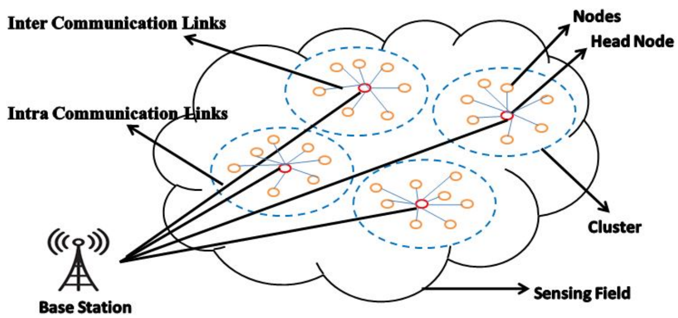


Figure 1. Wireless Sensor Network Layout

which does not consider node energy, is discussed. The suggested enhancement is on the OLSR routing protocol called A-OLSR protocol utilizing node energy during its MPR process [23]. The enhancement is focused on the adaptive neuro-fuzzy inference method (ANFIS). The packet distribution ratio (PDR) and end-to-end latency metrics are used to determine the proposed A-OLSR protocol's efficiency. The findings of the simulation show the supremacy of the suggested procedure in PDR terminology.

In [24] unequal sensor loads quickly deplete their power, which can interrupt the activity of the network. Moreover, a single artificial intelligence approach is not enough to solve load balancing and minimize energy usage because of the convergence of ubiquitous smart-sensor-enabled IoT. They suggested an adaptive neuro-fuzzy clustering algorithm (ANFCA) to match the load between sensors evenly. We synthesized fuzzy logic and a neural network to counterbalance the optimal number of cluster heads and load distribution among the sensors. We defined fuzzy rules, sets, and membership functions of an adaptive neuro-fuzzy inference technique to decide if a sensor could play the role of a cluster head based on the parameters of residual energy, node distance to the base station, and node density. The proposed ANFCA outperformed the state-of-the-art algorithms in terms of node death rate ratio, remaining active nodes, overall energy consumption, and residual energy standard deviation.

The proposed algorithm improves network efficiency in [25]. The longevity of a WSN may be estimated using various general parameters, such as when the first node dies and other program-specific parameters. Substantial evidence supports cluster head selection as one of the most crucial moves in maintaining the WSNs long-term viability. The downside of clustering protocols depends on the distribution probabilities of the cluster. Two cluster heads are chosen for two different clusters, and these cluster heads are on the edge of the cluster. This method of head shape selection reduces the computer's efficiency. To simplify the suggested cluster heads' lives, we have implemented a fuzzy logic-based set of cluster heads and cluster creation. For selecting the head of the cluster and the formation of the cluster, the decision was made to use a cluster rather than a distributed approach. To pick a vice cluster chief, we have adopted a hierarchical system utilizing fuzzy logic, which is also a decentralized solution. The proposed algorithm has been found to maximize the WSN's performance by balancing each node's energy load.

Furthermore, in IoT-based sensor networks, the energy available for communication is a big barrier in preventing massive packet loss or drop, quick bandwidth depletion, and network-wide unfairness, which results in node performance declines and packet transmission delay raises. As a result, there is an urgent need to monitor node energy consumption in order to optimize overall network performance by utilizing sophisticated machine learning algorithms to enable optimal routing decisions. In order to accomplish effective routing, a contemporary Neuro-Fuzzy Rule Dependent Cluster Development and Routing Protocol is employed in IoT-based WSNs. The investigations conducted in this paper [26] utilizing the proposed model revealed that the proposed routing algorithm provided higher network performance in terms of metrics such as energy utilization, packet propagation ratio, latency, and network lifetime.

For wireless sensor networks, indoor positioning is an easy operation [27]. The article addresses a modern WSN system. The recommended approach relies on a system of adaptive fuzzy localization. The first recommendation is to interpret rooms as a fuzzy collection of adjacent areas marked by a fuzzy indicator of location (FLI). FLI provides a hazy image of the system so that we can properly interpret it. The FLI collects DNA from distinct images Received Signal Strength Indicator (RSSI). A fuzzy inference method of Sugeno type-0 is proposed and submitted to a supervised learning procedure. Simulation and analysis at Synapses have demonstrated that an effective learning process leads to a high success rate.

To quickly and flexibly schedule the clustering task to alleviate the re-clustering overhead, this paper [28] suggests a fuzzy-based hyper round strategy (FHRP). Clustering is performed instead of a round in FHRP at the start of a Hyper Round (HR), which is made up of many circles. During the network lifetime, the period of an HR is not fixed and is determined using a fuzzy system of inference. The node's remaining energy and its distance from the sink are used as this fuzzy device's inputs, and the HR duration is its output. Thus, the situation of the nodes is taken into account to determine the re-clustering time. The simulation results demonstrate the effectiveness of FHRP in reducing

overhead clustering power, extending network existence, and sustaining network node energy.
Lifetime improvement is an important concern because much of the wireless sensor networks run in unattended areas and people cannot be present. Clustering is one of the most effective ways to group up nodes in a cluster to enable greater scalability, power efficiency, and much longer network lifespan. To solve this problem, several researchers have proposed various many clustering algorithms. However, several suggested algorithms overburden the cluster head during cluster creation. In order to solve this issue, several researchers have come up with the concept of fuzzy logic (FL). These algorithms enable for CH to be adopted, scalable, and intelligent enough to spread the load among the sensor nodes. Unfortunately, several algorithms use type-1 FL (T1FL) model. A Type-2 Interval-Type FL Model is suggested [29] for the determination of interval level judgment.
Therefore, a modern Neuro-Fuzzy Rule Dependent Cluster Development and Routing Protocol proposed in [30] which is used to achieve successful routing in IoT-based WSNs. The experiments carried out in this research study using the proposed model indicate that in terms of metrics, the proposed routing algorithm provided better network performance, including energy use, packet delivery ratio, network latency and lifespan. The following table I represents the abbreviations used in this paper.

## 3. SYSTEM MODEL

In this section, we present typical WSN system model that include Network Model in section 3-A, certain Assumptions in section 3-B and Energy Model in section 3-C.

### A. *Network Model*

Undoubtedly the first and most significant architecture problem for a WSN is energy conservation, and This condition must be recognized in the whole process of constructing a network. The node distribution and formation of wireless sensor networks, and the mote is in the center of the nodes is shown in Fig. 2 . These nodes form into clusters for each cluster's head node. These head nodes are liable for propagating the individual mote data in a single hop without redundancy. In this network model, the connectivity between nodes and head nodes of each cluster is based on clustering communication levels and between head nodes of each group to the mote.

### B. *Preliminaries*

The goal of our proposed approach is to resolve energy usage problems, reliability in terms of the time taken to the first node to deplete its whole energy and network existence in the WSN. We found the following assumptions applicable to the network before continuing with the suggested approach for the simulated wireless sensor network scenario:

- Initially, all sensor nodes are stationary and deployed with equivalent resources.
- With the exception of the mote, all nodes are uniform and have the same energy limits.
- Only header nodes in each cluster are allowed to mote data with a single hop.
- Nodes have positioning details that they submit to the base station with their respective energy levels during the process of implementation of the set up phase.

### C. *Energy Model*

The following table II represents the symbols and notations used in this paper. The energy model Fig. 3 for transmitting and receiving q bits and the communication distance $\beta$ , the energy utilized from transmission to receiving are in the following Eq 1

$$P_\alpha(s,\beta) = \begin{cases} s*\gamma*p + s*\kappa*p*\beta^2 \\ \text{for } \beta < \beta_0 \\ s*\gamma*p + s*\omega*p*\beta^4 \\ \text{for } \ \beta \geq \beta_0 \end{cases} \tag{1}$$

Note that $(P_\alpha)$ is the energy consumption per bit for running transmitter or receiver circuit,$s$ is the number of bits, The distance $(\beta)$ of the transmitter and receiver is taken and compared with the threshold $(\beta_0)$. If distance is less than $(\beta_0)$ then the free space with $(\beta^2)$ loss is considered else multipath model $(\beta^4)$ loss is choosen.
Here $\beta_0$ is computed based on the ratio of $\kappa$and $\omega$

$$where \beta_0 = \sqrt{\frac{\kappa}{\omega}}$$

$\kappa$ and $\omega$ are propositional constant for the transmit amplifier with free space and for multi-path.
The head node energy is calculated by $E_\beta$ in the following equation Eq 2

$$E_\rho = a\Re E - Cp * E_\rho * \ell * \left(\frac{a_i}{\upsilon}\right) \tag{2}$$

where $a$ is the number of nodes,$\Re E$ is the residual energy,Cp is the current packet length,$E_\rho$ is the cluster head probability, $\ell$ is the round number,$a_i$ node number,$\upsilon$ is the number of clusters formed

## 4. PROPOSED SCHEME

An Adaptive Neuro-Fuzzy Inference System(ANFIS) or an Adaptive Network-Based Fuzzy Inference System(ANBFIS) approach to cluster-head elections is proposed based on three descriptors-energy, cost, and distance.These three inputs play a crucial role in choosing the head node in each cluster. The energy refers to the residual energy of the node during each iteration of rounds, the nodes which have maximum energy will be chosen as head nodes apart from we considered node minimum distance in between neighbor nodes, and cost refers to the minimum length of cluster head to access point or sink. By considering maximum node energy as energy, minimum

TABLE I. Abbrevations used in this paper

| S.No | Symbol | description |
|---|---|---|
| 1 | VLSI | Very Large Scale Integration |
| 2 | MEMs | Microelectromechanical Systems |
| 3 | WSN | Wireless Sensor Networks |
| 4 | LEACH | Low Energy Adaptive Clustering Hierarchy |
| 5 | HRP | Hierarchical Routing Protocol |
| 6 | FL | Fuzzy Logic |
| 7 | FND | First Node Die |
| 8 | QND | Quarter Node Die |
| 9 | PND | Ten Percent Node Die |
| 10 | SFLA | Shuffled Frog Leaping Algorithm |
| 11 | FMSFLA | Fuzzy Multi-hop clustering protocol Shuffled Frog Leaping Algorithm |
| 12 | LEACH-EP | LEACH-Energy-based protocol |
| 13 | ASLPR | Application Specific Low Power Routing protocol |
| 14 | SIF | Swarm Intelligence based Fuzzy routing protocol |
| 15 | ERA | Energy-aware Routing Algorithm |
| 16 | OLSR | Optimized Link State Routing Protocol |
| 17 | ANFIS | adaptive neuro-fuzzy inference system |
| 18 | A-OLSR | ANFIS based OLSR to select multi-point relay |
| 19 | MPR | Multi-point Relay |
| 20 | ANFCA | adaptive neuro-fuzzy clustering algorithm |
| 21 | RSSI | Received Signal Strength Indicator |
| 22 | FLI | fuzzy indicator of location |
| 23 | FHRP | fuzzy-based hyper round |
| 24 | HR | hyper round |
| 25 | IoT | Internet of Things |
| 26 | PDR | packet distribution ratio |
| 27 | CH | Cluster Head |
| 28 | T1FL | Type-1 Fuzzy Logic |
| 29 | HN | Head Node |

TABLE II. Symbols used in this paper

| Symbol | description |
|---|---|
| a | Number of nodes |
| B | Area of the Network |
| $S_{p,q}$ | Position of sink |
| (p,q) | Represents coordinate positions of the node in the network |
| W | width of the network |
| L | length of the network |
| $\beta_{1tob}$ | Initial energy of each node (joules) |
| $\vartheta_{HN}$ | Packet size for cluster head per round (bits) |
| $\Upsilon_{HN}$ | desired percentage of cluster heads |
| $\mho_{C}$ | Range for cluster |
| $Œ_{Pr}$ | Lowest possible of a node being cluster head i.e. cluster head probability |
| $\ell$ | Max Number of simulated rounds |
| $\partial_p$ | Packet size for normal node per round (bits) |
| $\hbar$ | average Time in seconds taken in setup phase |
| $\wp$ | average Time in seconds taken in steady state phase |
| $\zeta_T$ | Energy for transmitting one bit |
| $\eta_R$ | Energy for receiving one bit |
| $\gamma$ | Data aggregation energy for each node |
| $\kappa$ | Energy of free space model amplifier |
| $\chi_{DA}$ | Total Energy for Data Aggregation |
| $\varrho$ | Distance between sender and the base station or recipient |
| $\mu_{Th}$ | Threshold |
| $\omega$ | Energy dissipation of amplifier during multi-path amplifier. |
| $\beta$ | Distance |
| $\Omega_{Hn}$ | Cluster head |
| $\Re E$ | Residual Energy |
| ß | Cluster Head Probability |
| $p$ | Packet length |
| $Cp$ | Current Packet Length |
| $\lambda$ | Energy Transmission and Energy for data aggregation |

node distance as distance in inter clustering, and minimum distance as cost in intra clustering as parameters to choose an efficient head node. The simulation results show that by our approach and depending on the configuration of the network, a significant increase in network life can be achieved compared to the probabilistic selection of nodes as cluster heads using only local information. In the case of a cluster, the node chosen by the base station is the node that has the maximum chance of becoming a cluster-head using three fuzzy descriptors.

## *A. ANFIS Parameters and Rules*

In this, we propose a better approach than existing in choosing the Head Node using a adaptive neuro fuzzy logic approach. In our approach, we considered three inputs and one output. The three inputs viz. Residual Energy, Minimum Distance, and Cost table III the output is the chance of choosing a head node *wi* table IV.

The first input variable Residual Energy that is the nodes remaining energy, the node which has the high power among other nodes is chosen first among different nodes, the fuzzy linguistic Residual Energy variable that describes

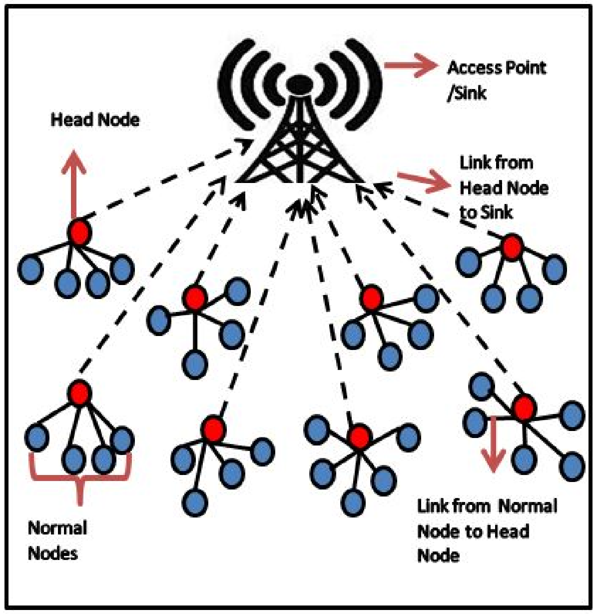


Figure 3. Network model for Wireless Sensor Network.

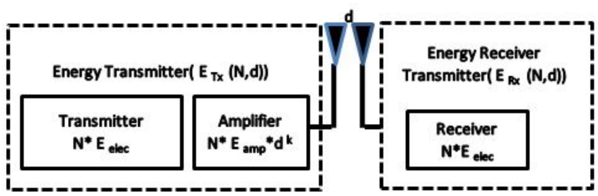


Figure 4. Energy model for LEACH protocol.

TABLE III. Input Membership Function

| Input | Membership | | |
|---|---|---|---|
| Residual Energy | High | Medium | Low |
| Distance | High | Medium | Low |
| Cost | High | Medium | Low |

TABLE IV. Output Membership Function

| Output | Membership | | | | |
|---|---|---|---|---|---|
| Chance | High | Very High | Medium | Low | Very Low |

the parameters are Medium(M), High(H), Low(L). The second input variable Minimum Distance which means the minimum distance between a node and a sink or base station is chosen as a head node, the fuzzy linguistic Minimum Count variable that describe the parameters are Medium(M), High(H), Low(L). The third input variable Count represents the number of time the node previously chosen as a head node, the fuzzy linguistic Count variable that describes the parameters are Medium(M), High(H), Low(L). The fuzzy output variable is represented in terms of chance as $Wi$. The Linguistic Chance variable that describes the parameters are Very Large(VL), Large(L), Medium(M), High(H), Very High(VH). A Z-shape Membership Function is chosen for all types of input and output linguistic variables. The Fuzzy If-then Rules are developed based on the Mamdani method and used to map the input linguistic variables to appropriate fuzzy output linguistic variables. We have presented a total of 27 Fuzzy If-then rules depicted in the table V. Finally, the default Centroid method is chosen to obtain the crisp output values.

## B. Proposed Algorithm

The main steps of our proposed an adaptive neuro-fuzzy based Leach(ANFIS-LEACH)approach are explained in

TABLE V. FUZZY IF THEN RULES

| Rule No | Residual Energy | Distance | Cost | Chance |
|---|---|---|---|---|
| 1 | High | High | Low | High |
| 2 | High | Medium | Medium | Very High |
| 3 | High | Low | High | Medium |
| 4 | High | High | Low | Medium |
| 5 | High | Medium | Medium | Very High |
| 6 | High | Low | High | Medium |
| 7 | High | High | Low | Medium |
| 8 | High | Medium | Medium | Very High |
| 9 | High | Low | High | Medium |
| 10 | Medium | High | Low | High |
| 11 | Medium | Medium | Medium | Medium |
| 12 | Medium | Low | High | High |
| 13 | Medium | High | Low | High |
| 14 | Medium | Medium | Medium | Medium |
| 15 | Medium | Low | High | High |
| 16 | Medium | High | Low | High |
| 17 | Medium | Medium | Medium | Medium |
| 18 | Medium | Low | High | High |
| 19 | Low | High | Low | Low |
| 20 | Low | Medium | Medium | Medium |
| 21 | Low | Low | High | Very Low |
| 22 | Low | High | Low | Very Low |
| 23 | Low | Medium | Medium | Medium |
| 24 | Low | Low | High | Very Low |
| 25 | Low | High | Low | Very Low |
| 26 | Low | Medium | Medium | High |
| 27 | Low | Low | High | Very Low |

the algorithm In Proposed Algorithm, Like the LEACH protocol, our proposed approach also operates in terms of Rounds. In every round, each sensor node chooses a random number between 0 and 1. If the chosen number is less than a threshold Th, the chosen node is selected as a Current Head Node. The current heads of nodes calculate their $wi$ value using the fuzzy method and broadcast the current HN message to all nodes coming under the communication range. The current HN message, which has high residual energy, is selected as an HN. At times if the elected HN has received a current HN message with high $wi$ than its own, the initial elected HN becomes a node member.

$$dBS = min(\sqrt{(S_p - sa_i)^2 + (S_q - sa_j)^2}) \tag{3}$$

The member nodes choose the nearest HN and join it to form clusters, respectively using Eq. (3).
where $S_p$,$S_q$ are the length and width of the area of the network respectively and $sa_i$,$sa_j$ are the sink coordinates.
Let us consider three inputs as $I_{RE}$, $I_{Cost}$, $I_{Distance}$ and one output $O_{Chance}$, the Zero Order Takagi Sugemo if then rules can be defined as follows:

If $I_{RE}$ is $I_1$ and $I_{Cost}$ is $J_1$ and $I_{Distance}$ is $K_1$ then $V_1 = a_1 * I_{RE} + b_1 * I_{Cost} + c_1 * I_{Distance} + d_1$

If $I_{RE}$ is $I_2$ and $I_{Cost}$ is $J_2$ and $I_{Distance}$ is $K_2$ then $V_2 = a_2 * I_{RE} + b_2 * I_{Cost} + c_2 * I_{Distance} + d_2$

The method of choosing a head node the use of neuro-fuzzy procedure is done in 4 layers:. The structural representation of Neuro -Fuzzy approach is shown in Fig. 4 The function of each layer is discussed as below

Input and fuzzification:

In this layer, crisp input is given to the node $a_i$ which is related to $I_i$ or $K_{i-3}$ or $J_{i-3}$ linguistic label. Thus the membership function calculates the different level of membership for the given inputs viz. Residual energy (High,Medium,Low), cost (High,Medium,Low), distance (High,Medium,Low). The output of this layer can be calculated using Eq 4

$$Q_{1,i} = \begin{cases} \mu_{A_1}(I_{RE}) \text{for} i = 1,2,3 \text{ OR} \\ Q_{1,i} = \mu_{B_{i-2}}(I_{Cost}) \\ \text{ for } i = 4,5,6 \text{ OR} \\ Q_{1,i} = \mu_{C_{i-3}}(I_{Distance}) \\ \text{ for } i = 7,8,9 \end{cases} \tag{4}$$

$\mu_{A_i}(Y_1)$,$\mu_{B-i}(Y_2)$ and $\mu_{C-i}(Y_3)$ is the Gaussian membership function while $Q_{1,i}$ specifies the degree to which the given input satisfy the quantifier $A$.

Fuzzy inferences:

Each node $a_i$ in this layer calculates the firing strength. The output of this is computed by product of all incoming membership values in Eq 5.

$$O_{2,i} = \mu_{A_i}(I_{RE}) * \mu_{B_i}(I_{RE}) * \mu_{C_i}(I_{RE}) \text{for } i = 1,2,3 \tag{5}$$

Aggregation:

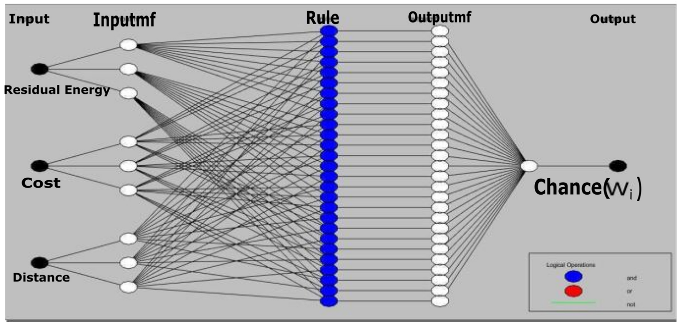


Figure 5. Proposed ANFIS structure.

Computation of normalized firing strength is as follows in Eq 6.

$$O_{3,i} = \bar{f_i} = \frac{f_i}{\sum_{i=1}^{27} f_i} \tag{6}$$

Output Layer:

Adaptive node $a_i$ with a node function is as shown in Eq 7

$$O_{4,i} = \bar{f_i}U_i = \bar{f_i}(a_iY_1 + b_iY_1 + c_iY_1 + d_i) \tag{7}$$

Where, $a_i$,$b_i$ ,$c_i$,$d_i$ are consequent parameters which are equal to zero. This layer is called defuzzification layer in which single output is computed with the summation of all the incoming signal in Eq 8.

$$y = \sum_{i=1}^{27} \bar{f_i} * d_i \tag{8}$$

Deciding the parameters of fuzzy membership function is the major concern for the modeling of fuzzy based system because parameters of membership function are decides manually by the user with their experience or/and trail and error method, and this may cause the man-made error.

The Pseudo-code for the Proposed algorithm is as followsFig: 6

## C. Simulation Environment

All the following results in this paper are executed using MATLAB R2018a with the system configuration is Intel i5 processor (2.7 GHz) with 16GB memory running on Windows 10 Operating System. Our efficiency assessments are simulating any number of wireless sensor nodes that form a wireless sensor network across a flat rectangle. All network nodes start the simulation by specific initial energy in Joules. Also, the power of the destination node is considered unlimited. During the simulation process of data transmission between nodes from the source, through intermediate nodes and to the final destination nodes, each node uses its limited power, causing the depletion. Any node which has reached a specific limit value of user choice is considered dead.The simulation parameters for performing our experiment is shown in the table **??**.

## D. Simulation Results and Analysis

Here we compared three protocols LEACH,FUZZY LEACH, MUCH and the proposed ANFIS-LEACH. Simulation was done in MATLAB simulator and initially a total of 100 nodes are randomly scattered in a 100m by 100m square area. depicts the number of sensor nodes alive in the network. From the Fig. 10 it is observed that in initial fuzzy LEACH and one of the improved Fuzzy Leach termed MUCH 99% of nodes will die after completing of 5000 rounds but in our proposed ANFIS-Leach only 81% of nodes die this results better energy efficiency of the nodes as well as improved network lifetime. Similarly we tested for various number of nodes like 200,500 and 1000 nodes the comparative analysis in terms of First Node Die(FND), Quarter Node Die(HND), Ten Percent Node Die(PND) and Number of Nodes Alive after completion of max rounds i.e., 5000 rounds is shown in the following subsubsections.

### 1) First Node Die

The Fig. 5 shows at which round the first node dies(FND). In this table we considered the two state of art existing approaches along with the proposed method for comparative analysis of FND. From the analysis we can analyze that the existing methods the FND at the earliest rounds when compared with our proposed method. As we considered a modified distance metric and neuro fuzzy approach in the process of communication.

### 2) Quarter Node Die

The Fig. 6shows at which round the Quarter of the nodes dies(QND). In this statistical analysis we considered the two existing approaches along with the proposed method for comparative analysis of QND. From the analysis we can analyze that the existing methods QNDs at the earliest rounds when compared with our proposed method. As we considered a modified distance metric and neuro fuzzy approach in the process of communication.

### 3) Percent Node Die

The Fig. 7 shows at which round the Percent nodes dies(HND).In this table we considered the two existing

**Algorithm 1:** The Pseudo code for the Proposed algorithm

**Input:**
Total number of nodes($A$),
the desired percentage of Concurrent NH($p_r$),
current round($r$),
sensor node($a$)

**for** *all alive nodes in the network* **do**
    $rand_{number} = rand(0, 1)$
    **if** $rand_{number} < Th$ **then**
        $b = ConcurrentHN$
        $ResidualEnergy$ = remaining energy of b
        $Count$ = Neighbors alive of b
        $MinimumDistance$ = Distance from b to BS
        $\overline{f}_i$ = NeuroFuzzyLogic (Minimum Distance, Residual Energy, Count)
    **else**
        $b = member$
    **end**
    **for** $E = 1$ *to* $E_{max}$ **do**
        Input the .FIS file into the Zero-order modeling of the
        Mamdani fuzzy inference engine using equation Eq. (4)
        Membership function $\mu_{ma}(M)$ tuned using equation Eq. (5).
        Normalize the firing strength of each node $a_i$ using equation Eq. (6) in normalized layer.
        Defuuzification using equation Eq. (7)
        Aggregated output is produced for each node$a_i$ using equation Eq. (8) in the last layer.
        **for** *allaliveclustermembers* **do**
            $JointheclosestHN$
        **end**
    **end**
**end**
**Output:** Head Node

Figure 6. The proposed Algorithm to Elongate the Network Lifetime

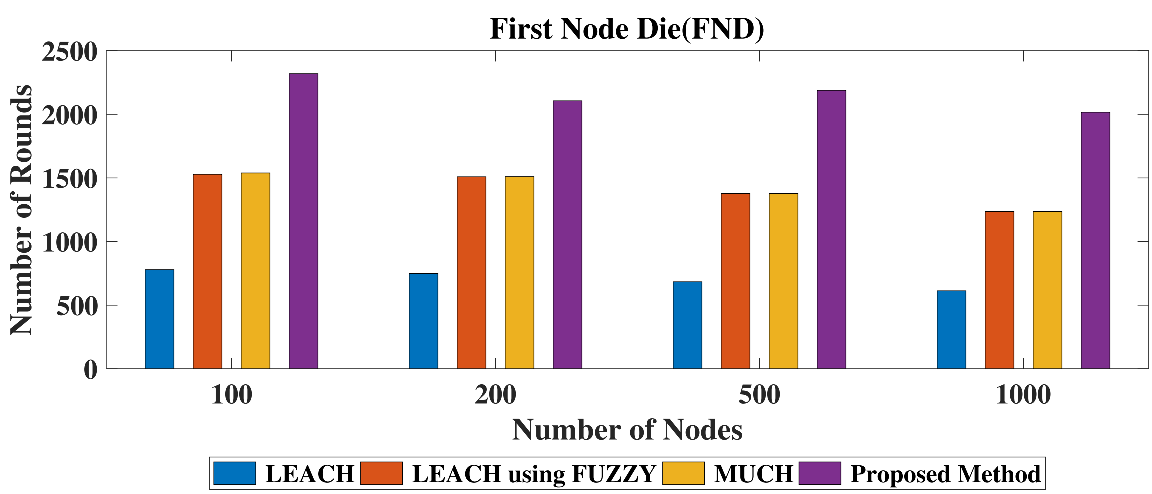


Figure 7. First Node Die.

approaches along with the proposed method for comparative analysis of PND. From the analysis we can analyze that the existing methods PNDs at the earliest rounds when compared with our proposed method. As we considered a modified distance metric and neuro fuzzy approach in the process of communication.

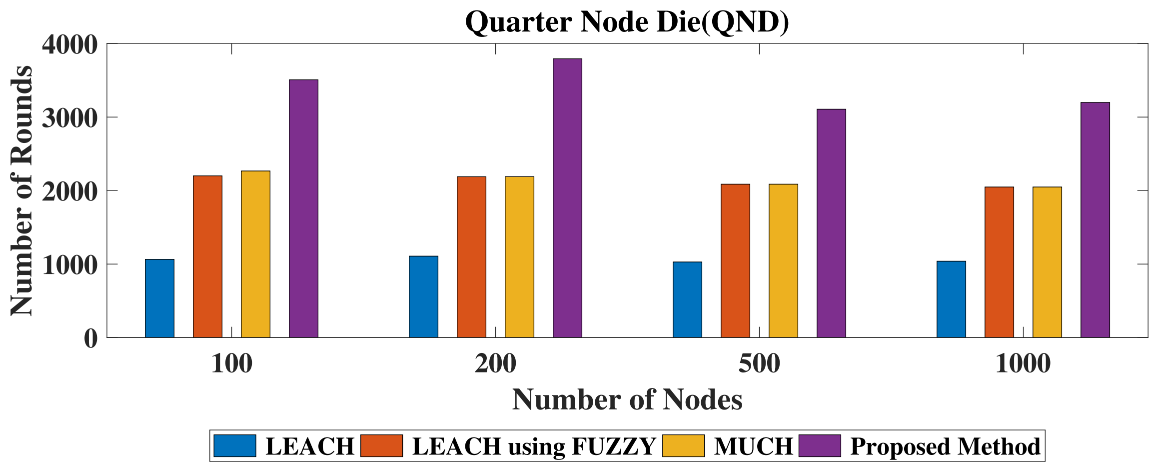


Figure 8. Quarter Node Die.

#### 4) *Number of Nodes Survived*

The following tableFig. 8 shows the total number of nodes alive after completion of the certain number of simulation rounds. Here we considered 5000 rounds to stop the simulation. In this table we considered the two existing approaches along with the proposed method for comparative analysis of available number of nodes. From the analysis we can analyze that the existing methods have less number of nodes alive earliest rounds when compared with our proposed method. As we considered a modified distance metric and neuro fuzzy approach in the process of communication.

The comparison is made based on Residual Energy, Lifetime of Sensor nodes and Throughput these three parameters are used as comparison parameters with the traditional LEACH,Fuzzy LEACH, one of the previous Improved Leach method termed as MUCH and our proposed method in LEACH termed as Proposed Fuzzy LEACH. The following graphs Figures 9,10,11 shows the comparative analysis in the following subsections respectively.

#### 5) *The amount of data transmission*

The quantity of packets received with the useful resource of the sink is known as universal performance or throughput. The overall performance is based upon the huge shape of nodes in a community that is alive or lively. The quantity of packets sent to the sink corresponds without delay to the amount of energetic or alive nodes. It's miles critical and important, particularly in WSN data. Therefore, the lack of a packet is significantly reduced, and the throughput maximized. As shown in Fig. 9, our proposed protocol has more throughput as compared to LEACH, Fuzzy LEACH,MUCH and PROPOSED METHOD.

#### 6) *Lifetime of sensor nodes during the maximum simulation rounds*

The average network lifetime of the Wireless Network has been calculated using three mentioned routing protocols. Here, the forwarder node is regarded in each round to be the node with most considerable rest energy. As the Fig. 10 shows. The average network life will be extended when the information is transferred from nodes to sinks through our suggested protocol routing. In other words, in terms of average network life, our proposed plan outperformed existing schemes.

#### 7) *Residual Energy of the nodes initially dissipated*

In this experiment, we have considered the average residual energy of all the nodes as a measure of performance and compared our protocol to three others. Higher residual energy is essential to extend the network life. From Fig. 11, we can see. This residual average power is above four mentioned protocols.

From the Figs 5-11, it can be deduced that the proposed routing algorithm gives a better network lifetime than LEACH and other two existing works due to the forming period. Head nodes form our proposed work consider residual energy, distance, and cost. Increasing the pause in the death of the first node, reduces the error of the others. From simulation data, we can conclude that the method is gaining positive results relative to the number of live nodes.

## 5. CONCLUSION AND FUTURE WORK

In wireless sensor networks, the sensor's energy supply relies on the node's power ability. WSN clustering can also minimize energy usage since the transmission energy is proportional to the gap between the sender

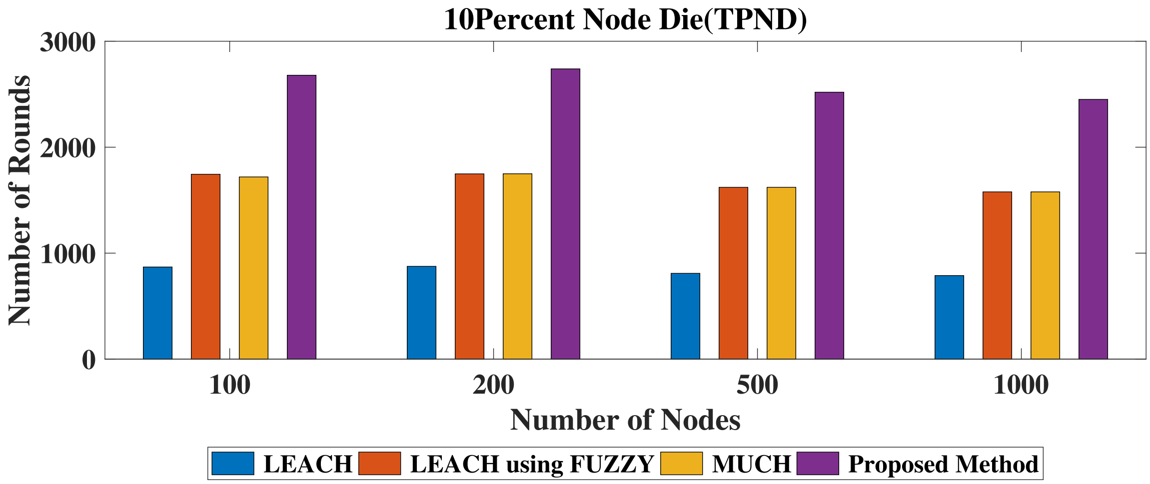


Figure 9. Percent Node Die.

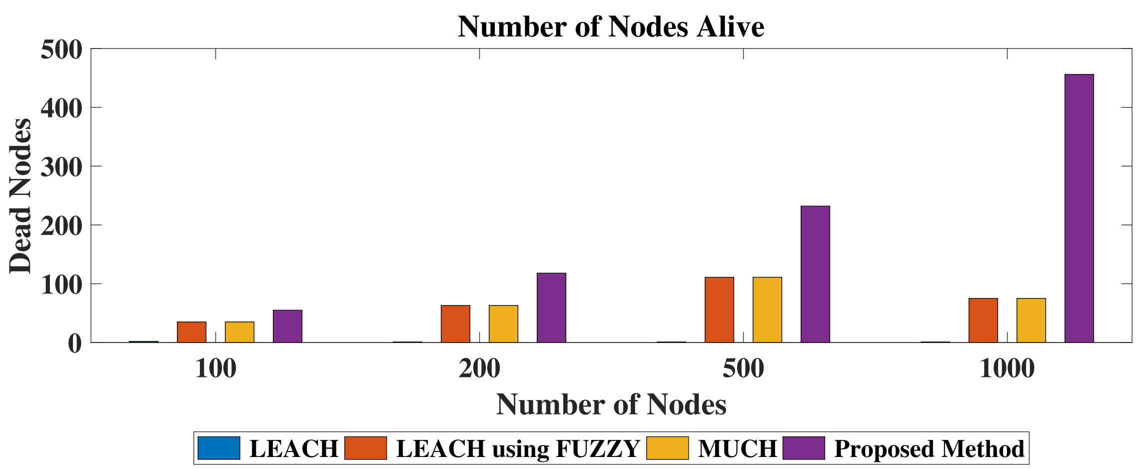


Figure 10. Nodes Alive after completion of 5000 rounds.

and the recipient. Using Adaptive Neuro-Fuzzy approach, WSN can escape complex mathematical models and have tremendous versatility to cope with confusion and perception throughout the network's existence.Though WSN plays a prominent role in almost every emergent technology, One of the obstacles is reducing energy consumption and maximizing network life, for which routing can be a solution. In this paper, for experiment purposes, we considered the LEACH protocol as it is the first adaptive clustering protocol with the self-organizing capability and appears to be a suitable protocol. Some reliable improvement areas make the LEACH protocol more attractive and widespread. The most notable point is almost, the existing and advanced protocol used in networking takes the roots from the LEACH protocol. This proposed technique is a revision of LEACH's choice of selecting an optimum number of cluster head selection. The simulation results reveal that, as the network's scale increases, our proposed approach produces better outcomes than other current three state-of-the-art algorithms and proves to be salable and FND, QND, PND, and count of nodes alive after completion of 5000 rounds. The proposed method can be extended by giving a future scope using Hierarchical Fuzzy Logic approaches, Machine learning,

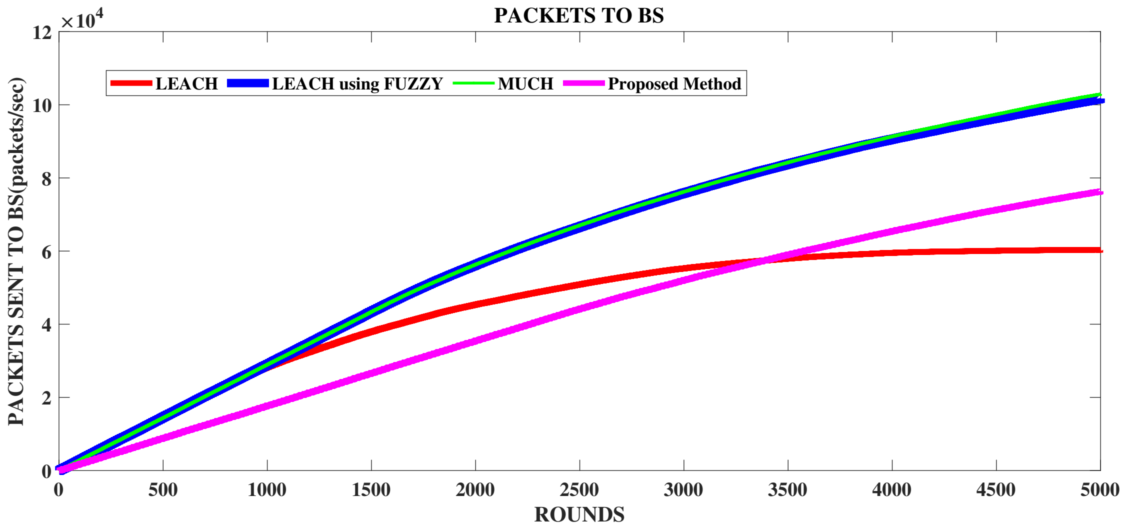


Figure 11. Performance of the node based on data transmission among nodes to mote.

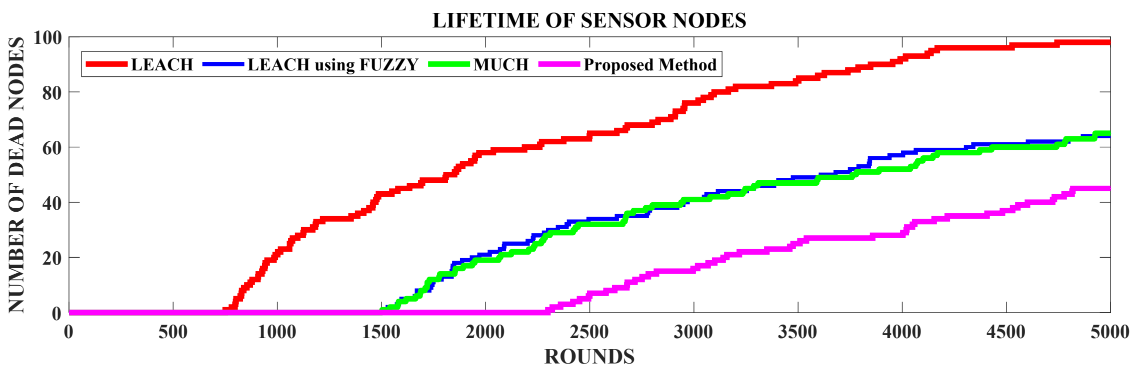


Figure 12. Lifetime of the Sensor Nodes in the Network.

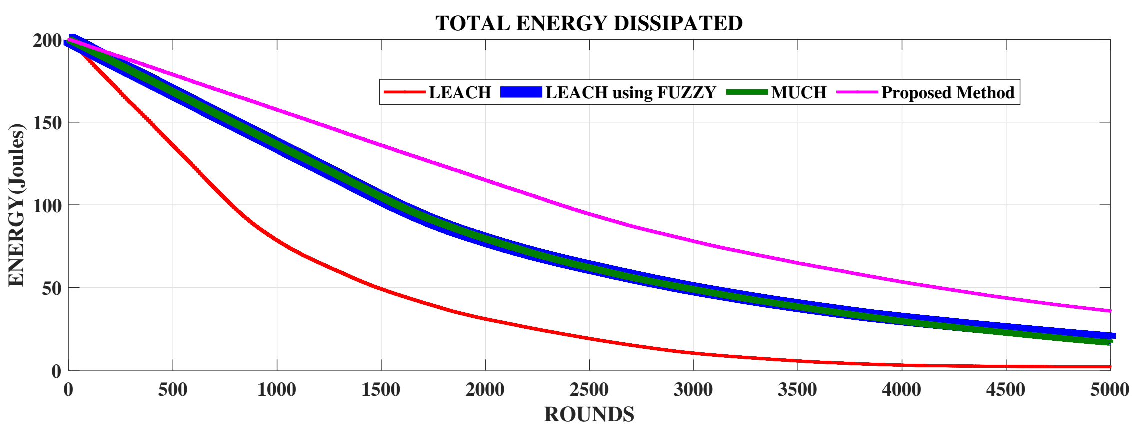


Figure 13. Total Energy Dissipated among the nodes during each round.

Deep Learning, Energy Harvesting approaches.

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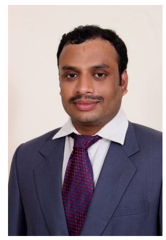

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