Type 2 Fuzzy Logic based Unequal Clustering algorithm for multi-hop wireless sensor networks

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Abstract
Wireless sensor network (WSN) is an integral part of IoT and Maximizing the network lifetime is a challenging task. Clustering is the most popular energy efficient technique which leads to increased lifetime stability and reduced energy consumption. Though clustering offers several advantages, it eventually raise the burden of CHs located in proximity to the Base Station (BS) in multi-hop data transmission which makes the CHs near BS die earlier than other CHs. This issue is termed as hot spot problem and unequal clustering protocols were introduced to handle it. Presently, some of the clustering protocols are developed using Type-2 Fuzzy Logic (T2FL) but none of them addresses hot spot problem. This paper presents a Type-2 Fuzzy Logic based Unequal Clustering Algorithm (T2FLUCA) for the elimination of hot spot problem and also for lifetime maximization of WSN. The proposed algorithm uses residual energy, distance to BS and node degree as input to T2FL to determine the probability of becoming CHs (PCH) and cluster size. For experimentation, T2FLUCA is tested on three different scenarios and the obtained results are compared with LEACH, TEEN, DEEC and EAUCF in terms of network lifetime, throughput and average energy consumption. The experimental results ensure that T2FLUCA outperforms state of art methods in a significant way.

Keywords: Decision making; Fuzzy logic; Hot spot problem; Unequal clustering; IoT; Energy efficient communication.

1. Introduction

Integration of smart objects into *IoT* is the reason for the major evolution of Wireless Sensor Networks (WSN). It is still being an active research area because of its applications in various fields like military surveillance, environmental monitoring; home automation, smart buildings, healthcare, industrial control, etc. [1], [2]. The applications of WSN in diverse fields become practical due to the versatile nature and characteristics of smart sensor nodes. WSN comprises of a massive number of autonomous sensor nodes undergo random deployment in the sensing field. It is commonly used for data gathering or target tracking applications where human involvement is very difficult. Since the sensor nodes are smaller in size and are connected in a wireless medium, it is limited by energy, bandwidth, memory and processing capabilities. Practically, sensor nodes are deployed with limited power supply interms of inbuilt battery, it should sustain for a longer time period based on the application at a stretch without any intervention. For example, a WSN is deployed by a team of engineers on a small island ten miles off the coast of Maine to explore the nesting behavior of petrels. Now, the biologists can monitor the petrels from their labs; browse information from sensors connected by the satellite. The entire operation is planned upto nine months and the sensor nodes should be active only with its inbuilt battery. It is not possible to recharge or replace the sensor nodes in harsh environments and the nodes should exploit the available energy efficiently to extend its lifetime [3]. In WSN, energy is spent for three operations such as sensing, processing and data transmission. Some studies reported that higher amount of energy is spent for data transmission and the energy spent for sensing and processing is highly negligible [4].

Clustering is an energy efficient technique aims to minimize the energy utilization and stretches the lifetime of WSN [5]. The optimization of clustering problem can be considered as a real time optimization system. Network lifetime can be termed as the active lifetime of a network after node deployment or it can be defined as the total time period between deployment and network failure. The basic idea behind clustering is the process of grouping nearby nodes to

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clusters and a cluster head (CH) is chosen from the nodes whereas rest of the nodes are considered as cluster members. The cluster member simply senses the physical parameters and transmits the sensed data to CHs. The CHs are responsible for the following duties [6]: receiving data from its cluster members, performing data aggregation, relaying aggregated data to BS and forwarding data from the lower level CHs. Clustering offers some benefits like energy efficiency, low bandwidth requirement, less overhead, high stability, less delay and uniform load distribution. When multi-hop data transmission is involved, due to the clustering process, the CHs near to BS are loaded with large amount of data when compared to CHs located farthest from the BS. It results in the earlier death of CHs and disturbs the network connectivity and reduces network lifetime. This issue is called as hot spot problem and unequal clustering protocols are introduced to eliminate it [7]. Unequal clustering technique constructs clusters of smaller sizes near BS and clusters of larger size father from BS. A simple model of unequal clustering is shown in Fig. 1. Various unequal clustering protocols are developed and found in the literature [8].

Since nodes are inter-dependent on each other with inter-related metrics, cluster construction by the use of fixed rules is not preferable. Recently, fuzzy logic becomes more popular to solve the clustering problem in WSN. The fuzzy logic possesses several advantages like flexibility, fault tolerance and low complexity. In the recent days, numerous fuzzy logic based clustering techniques have been proposed. Moreover, type 2 fuzzy logic (T2FL) has the capability to manage uncertainty precisely than Type 1 Fuzzy Logic (T1FL) due to the fact that the membership degrees of T2FL are itself fuzzy sets. Generally, random uncertainties are interrelated to the theory of probability and linguistic randomness is linked to fuzzy sets. The nature of fuzzy sets modifies with variant types of fuzzy models like type-1 to type-n, as they are planned to deal with different levels of uncertainty. This paper employs T2FL model with an aim of maximizing the network lifetime by effectively selecting the CHs and cluster size. The motivation for using a T2FL are [9]: (i) it is easy to design fuzzy rules from expert knowledge and from natural language due to the fact that the membership grade of a IT2 is an interval rather than a crisp number, which maximizes the robustness of the system, and (ii) IT2 fuzzy logic controller are highly adaptable than T1FL because of the complex relationships between their input and output, which is of vital significance in systems with higher levels of uncertainty like WSNs.

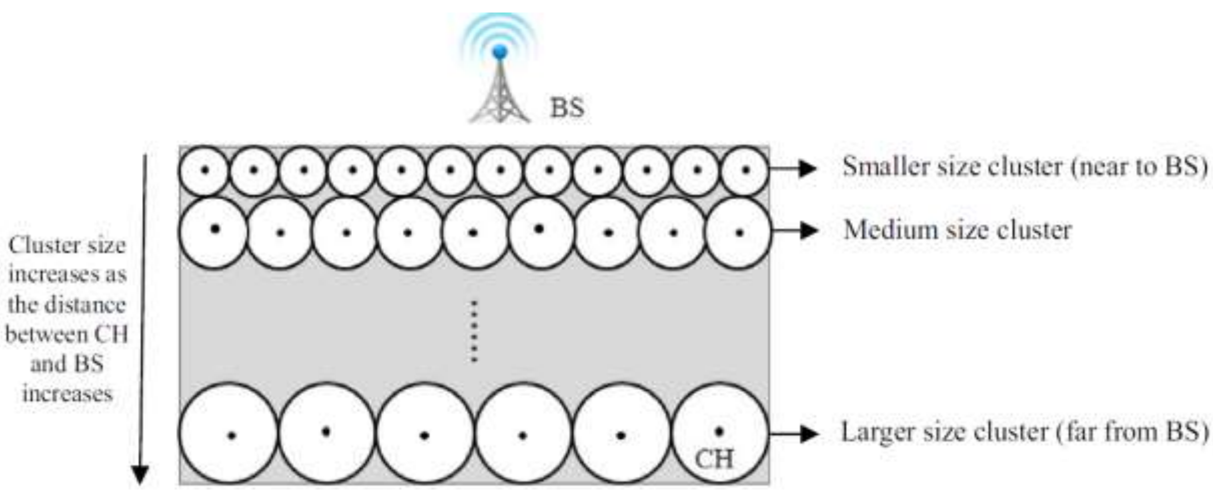

Figure1: Architecture of unequal clustering [8]

This paper addresses the hot spot problem using unequal clustering to enhance the network lifetime significantly. This paper presents a Type-2 Fuzzy Logic based Unequal Clustering Algorithm (T2FLUCA) for appropriate election of CHs and cluster size. T2FL is employed for CH and cluster size selection by the use of three input parameters namely residual energy, distance to BS and node degree. The inclusion of three fuzzy input parameters in unequal clustering leads to uniform load distribution which eventually eliminates hot spot issue and increases network lifetime. Furthermore, first order radio energy model is used with three scenarios of node deployments. To validate, T2FLUCA is experimented on different deployment scenarios based on the location of BS. A performance comparison is also made with LEACH, TEEN, DEEC and EAUCF interms of network lifetime, throughput and average energy consumption.

The succeeding part of the paper is formulated as follows. A short review of fuzzy based clustering techniques is provided in Section 2. The system model is provided in Section 3. Section 4 describes the T2FLUCA in detail. The

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outcome of the experimentation is analyzed in Section 5. Finally, the highlights of the paper are given with conclusion in Section 6.

2. Related work

Recently, a number of researchers employed fuzzy logic to resolve clustering problem in WSN. Molay et al. [10] employed fuzzy logic with energy, node concentration and centrality as input to compute the chance of becoming CHs. This process operates same as LEACH except that it selects CHs using fuzzy logic rather than the randomized selection. An extended version of LEACH with fuzzy logic (LEACH-FL) is proposed [11] using residual energy, distance to BS and node density as input parameters. Next, a distributed fuzzy logic based clustering technique called CHEF [12] is developed which make use of local information of the network to produce clusters. It maximizes the lifetime of WSN using energy level and neighboring distance as input parameters. These techniques performs CH selection using fuzzy logic and it fails to resolve hot spot issue which results in reduced network lifetime. Some of the fuzzy based unequal clustering techniques were developed to determine proper cluster sizes along with CH selection. Energy Aware Fuzzy Unequal Clustering Algorithm (EAUCF) is presented to increase the stable periods as well as lifetime of WSN in a distributed manner [13]. For CH and cluster size determination, remaining energy level and distance to BS are employed as input parameters. Likewise, Improved Fuzzy Unequal Clustering Algorithm (IFUC) [14] is also developed to solve hot spot issue by constructing unequal size clusters using three input parameters like residual energy, distance to BS and node density. However, ACO algorithm is also used for effective inter cluster communication. CHs select the relay node using communication cost as well energy utilization. Since EAUCF employs probabilistic method for tentative CH selection and uses only two input parameters for closeting process, FBUC [15] is proposed to overcome these issues by utilizing residual energy and node degree are utilized to select final CHs from tentative CHs. Another distributed clustering approach called DUCF presented in [16] which takes residual energy, node degree and distance to BS as input parameters. It also achieves uniforms load distribution using multi-hop inter-cluster communication. FAMACROW [17] uses fuzzy logic for clustering and ACO algorithm for routing problem. ACO algorithm determines the relay node using some parameters like residual energy, distance to BS, queue length and delivery likelihood.

CRT2FLACO is a T2FL based clustering protocol with ACO based inter-cluster routing. It uses the same three fuzzy input parameters as DUCF. Another T2FL based clustering technique is developed [18]which partitions the entire WSN to a number of levels and at every level, a CH will be selected using T2FL Model. The three fuzzy parameters namely residual energy, distance to BS and node concentration are used to select the CHs. The simulation results reported that the proposed method attains better stability and lifetime when compared to T1FL, single hop and multi-hop LEACH. A Cluster Head Enhanced Election Type-2 fuzzy AlgoritHm (CHEETAH) is presented [19] to select CHs in a dynamic manner by the use of T2FL with four input variables namely remaining energy, relative distance to BS, historical contribution and efficiency. Though few of the clustering techniques use T2FL for node clustering, none of the methods addressed the hot spot problem.

3. System Model

3.1. Network model

A sensor network is assumed with N number of sensor nodes undergo random deployment in the field to be monitored and some assumptions are made [20].

- Sensor nodes and BS are not mobile
- Initially, all the nodes have equal amount of energy after node deployment
- All nodes are homogeneous
- The distance between the nodes and BS can be determined by Received Signal Strength Indicator (RSSI)
- Node death is due to exhaustion of energy
- Sensor nodes can change the transmission power by the use of power control based on its the distance to the receiving node

3.2. Energy model

A simplified first order radio model is used as the energy model of the network [18]. The energy spent for the transmission and reception of *l* bit packet over distance *d* is given in Eq. (1) and Eq. (2).

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

$$E_{RX}(l) = l \times E_{elec} \quad (2)$$

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where E_{elec} is the dissipated energy in transmitter or receiver circuit, d_0 is the threshold distance which is calculated by $A = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$. Based on the transmission distance d, free space (ε_{fs}) or multipath fading (ε_{mp}) is used in the transmitter amplifier.

4. Type-2 Fuzzy Logic based Unequal Clustering Algorithm (T2FLUCA)

The proposed T2FLUCA involves two phases: CH selection phase and cluster construction phase. In the former phase, BS executes the proposed algorithm to elect proper CHs and appropriate cluster size for uniform load distribution. In the latter phase, the elected CHs will form clusters with nearby nodes. For CH and cluster size selection, fuzzy logic with three input parameters such as namely Residual Energy (RE), Distance to Base Station (DBS) and Node Degree (ND) are used. The output parameters are Probability of becoming CH (PCH) and cluster size. The first input RE represents the total amount of energy reside in a sensor node. The second parameter DBS indicates the total distance between the sensor node and BS. The third parameter ND denotes the total number of neighboring nodes present in its competition radius. The output parameter PCH provides a value which indicates the chance of becoming CH. A node with higher value of PCH has a greater chance of selecting as CH whereas the node with lower value of PCH has only a lesser chance of electing as CH. The output parameter, cluster size gives the competition radius of every node.

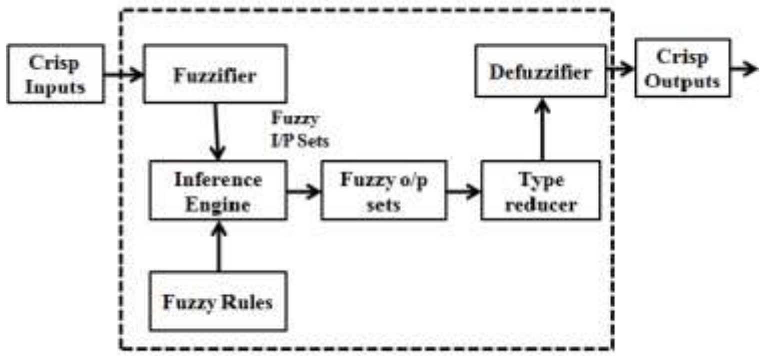

Figure 2: T2FL model

T2FL consists of four steps as shown in Fig. 2 which is listed below:

Fuzzifier

It converts the crisp input to fuzzified values. The input parameters with its linguistic variables to elect CH and cluster size are tabulated in Table 1. The linguistic parameters of the first input RE are low, average and high. The linguistic parameters of the first input DBS is near, far, farthest. The linguistic parameters of the first input ND is low, medium, high.

Table 1: Parameters and linguistic variables

Parameters	**Linguistic Variables**
RE	Low, Average, High
DBS	Near, Far, Farthest
ND	Low, Medium, High
PCH	Very Poor, Poor, Below Average, Average, Above Average, Strong, Very Strong
Cluster size	Very small, Small, Below Average, Average, Above Average, Large, Very Large

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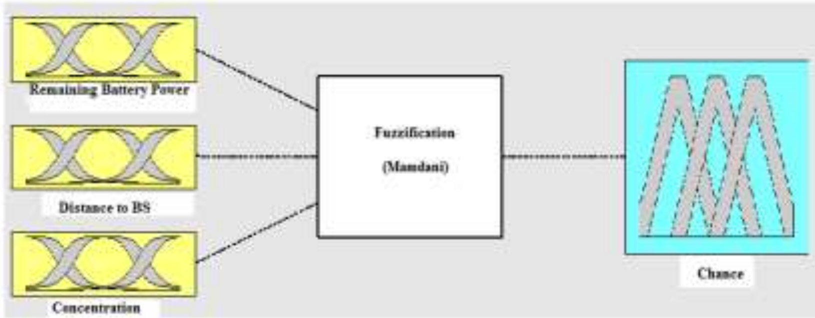

Figure 3: T2FL for the proposed model

Fuzzy rules/Inference engine

The structure of T1FL and T2FL is same. In this work, a set of 27 rules are used. The collection of fuzzy rules for CHs and cluster size determination is given in Table 2. A rule can be expressed in (3).

$$Rule\ (i) IF\ x1\ is\ A_1(i)\ AND\ x2\ is\ A_2(i)\ AND\ x3\ is\ A_3(i) THEN\ y1\ is\ B_1(i) AND\ y2\ is\ B_2(i) \tag{3}$$

where i is the i^{th} rule in the fuzzy rule, A_1, A_2 and A_3 is the corresponding fuzzy set of x_1, x_2 and x_3. The rule base inference engine contains 27 rules and is generated based on a Mamdani Inference system. The set of fuzzy rules are tabulated in Table 2. In the type-2 FLS, the inference engine integrates the rules and maps the input type-2 fuzzy sets to output type-2 fuzzy sets. It is essential to calculate unions and intersection.

Membership functions:

The membership functions of the input and output variables are shown in Figs. 4, 5, 6, 7 and 8. T2FL is represented by a superior membership function and an inferior membership function. These two functions can be denoted (each one) by a T1FL membership function. The interval between these two functions indicates the footprint of uncertainty (FOU) which is used to describe a T2FL set. Let the FOU is expressed as *f*. If $f \in [0, 1]$, and $f \rightarrow 0$, then Member Function is considered as T1FL. If $f \rightarrow 0$ to 1, then T2FL have a wide range of FOU between 0 to1. But, the formation of rules in T2FL logic is similar to T1FL and can be defined as:

$$Type\ 2\ FL = Principal\ MF\ (Type\ 1\ FL) + FOU \tag{4}$$

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Table 2: Fuzzy rule set

Input parameters			Output parameters	
RE	**DBS**	**ND**	**PCH**	**Cluster size**
Less	Near	Low	Very poor	Very small
Less	Near	Medium	Poor	Small
Less	Near	High	Below Average	Below Average
Less	Far	Low	Poor	Small
Less	Far	Medium	Below Average	Below Average
Less	Far	High	Average	Average
Less	Farthest	Low	Below Average	Below Average
Less	Farthest	Medium	Average	Average
Less	Farthest	High	Above Average	Above Average
Average	Near	Low	Poor	Small
Average	Near	Medium	Below Average	Below Average
Average	Near	High	Average	Average
Average	Far	Low	Below Average	Below Average
Average	Far	Medium	Average	Average
Average	Far	High	Above Average	Above Average
Average	Farthest	Low	Average	Average
Average	Farthest	Medium	Above Average	Above Average
Average	Farthest	High	Average	Average
High	Near	Low	Above Average	Above Average
High	Near	Medium	Strong	Large
High	Near	High	Below Average	Below Average
High	Far	Low	Average	Average
High	Far	Medium	Above Average	Above Average
High	Far	High	Average	Average
High	Farthest	Low	Above Average	Above Average
High	Farthest	Medium	Strong	Large
High	Farthest	High	Very Strong	Very Large

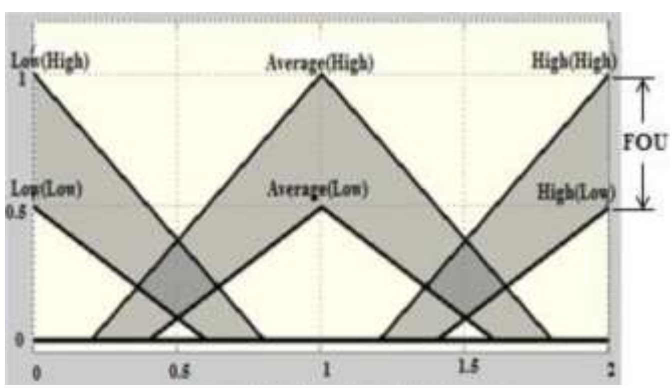

Figure 4: Membership function of RE

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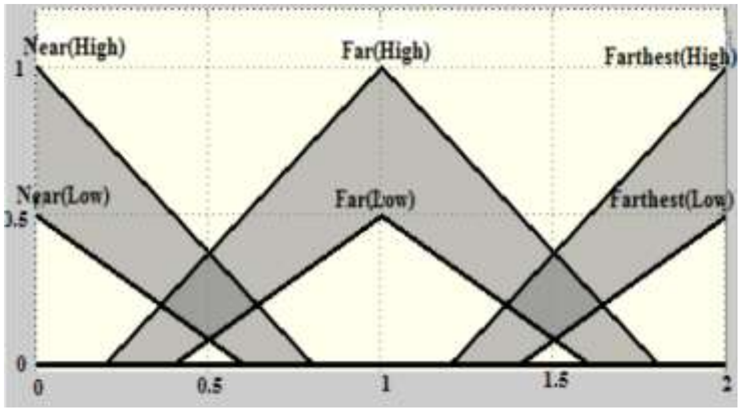

Figure 5: Membership function of DBS

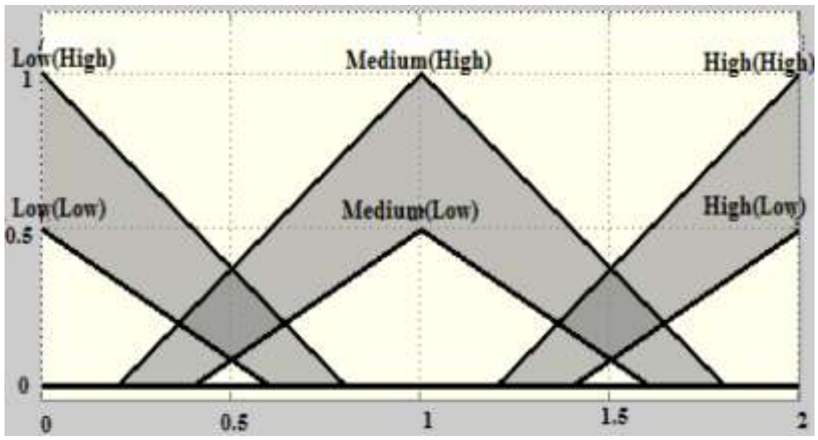

Figure 6: Membership function of ND

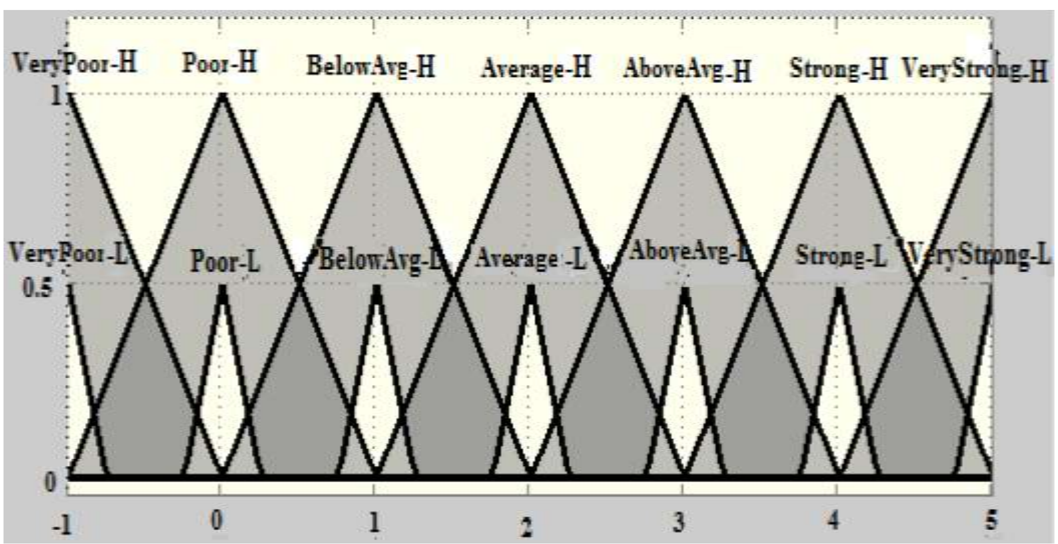

Figure 7: Membership function of PCH

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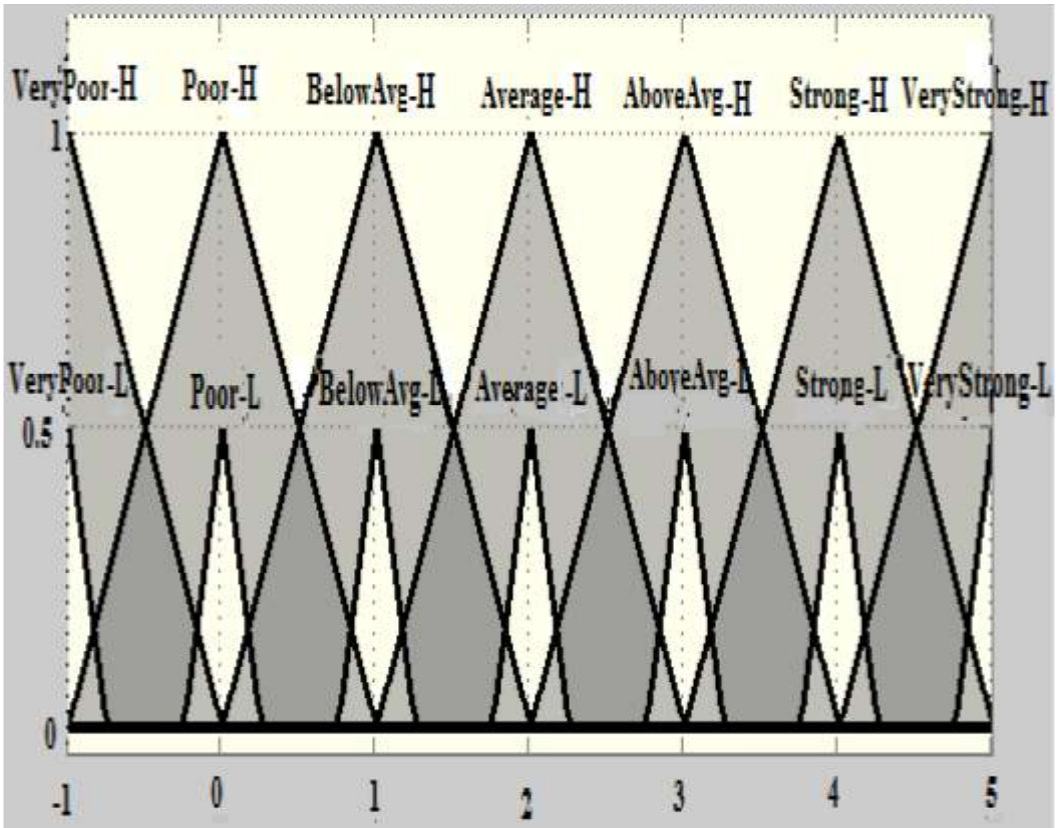

Figure 8: Membership function of cluster size

Type reducer/ Defuzzifier

The type-reducer produce a T1FL output, which is then transformed to a numeric output after the execution of defuzzifier.

Once every node receives its PCH and cluster size, it broadcast an advertisement message to its neighboring nodes. The message encloses the node ID and value of PCH. The nodes with higher probability are chosen itself as CH and send CH_WON to the nearby nodes. A node may get many CH_WON from its nearby nodes. In such cases, it transmits CH_JOIN message and joins to the closer CH. On receiving CH_JOIN message, the nearest CH verifies the available cluster size in prior to accepting new members. As the total number of present cluster members is not higher than the calculated cluster size, it accepts the new CM by replying CM_ACCEPT message, otherwise, it will send CH_REJECT message.

When a node receives a CM_REJECT message, it retransmits a CM_JOIN message to the next nearer CH not including the previously rejected CH and this process repeats until a new CH is found. In some situations, when a node fails to join to any other CH inside its coverage region ‘R’, it selects itself as CH. As a result, every node belongs to a cluster and no nodes are isolated in WSN. After several rounds, to prevent the earlier death of CHs, the CHs rotation process will takes place. When the residual energy of the CH crosses the threshold value (15% of initial value), CH rotation will be done. Once the residual energy of a CH crosses a threshold value, new CH will be selected using PCH. This process eliminates the early death of CH and also leads to high network lifetime.

5. Experimental results and discussion

To highlight the effectiveness of the T2FLUCA, a series of experiments are done under different testing scenarios. A number of performance measures is used, to validate the effectiveness of the proposed method are listed below:

- *Average energy consumption*- It measures the total amount of energy, on average, spent by all the sensor nodes in every round.
- *First Node Die (FND)* - It indicates the round number in which the first node in WSN depletes its total energy. It is useful to determine the amount of time period that the network is completely operative.

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- *Half Node Die (FND)* - It represents the round number in which the half of the total nodes in WSN depletes its total energy.
- *First Node Die (FND)* - It denotes the round number in which the 100% of the sensor nodes in WSN depletes its total energy. It is helpful to determine the actual round number that the network becomes completely inoperative.

For validating the consistency of the proposed method, it is rested in three different scenarios based on the location of BS which are represented by S1, S2 and S3 respectively.

- S1- BS is placed at the centre of the target area
- S2- BS is placed at the corner of the target area
- S3- BS is placed far away from the target area

The proposed method is implemented using MATLAB R2014a. For simulation, 300 nodes are deployed randomly in the target area of 100x100m. Moreover, the first order radio energy model is used with the following parameters: Eelec =50nJ/bit, Efs =10pJ/bit/m2, Emp =0.001310pJ/bit/m4 and EDA =5nJ/bit/signal. The simulation setup is tabulates in Table 3. A set of five clustering techniques are used for comparison purposes and they are

- LEACH: A highly cited and traditional clustering protocol selects CHs in a random manner to achieve energy efficiency.
- TEEN: A popular reactive protocol reduces energy consumption by transmitting data only upon the occurrence of an event.
- DEEC: A hybrid clustering protocol which integrates the TEEN characteristics with deterministic approaches.
- EAUCF: A fuzzy based unequal clustering protocol commonly used for comparison purposes.

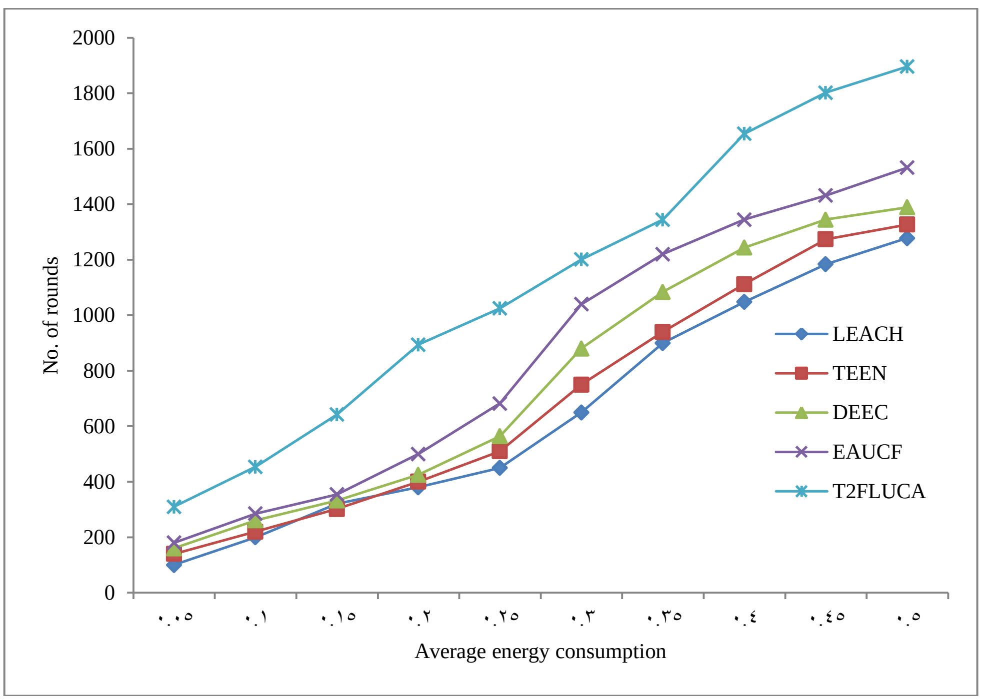

Figure 9: Average energy consumption: Scenario 1

To ensure the effective performance these protocols, the average energy consumption of S1, S2 and S3 are computed and are shown in Figs. 9-11. The energy consumption is determined by computing the total amount of energy utilized by every sensor node, on average in every round. The proposed method seems to be highly energy efficient than the compared algorithms. This is due to the fact of effective CH and cluster size selection using type 2 fuzzy logic. It assures that the node with higher RE, lesser DBS and lower ND will be elected as CHs. It eventually reduces the amount of energy spent for data transmission between CHs. LEACH shows worst performance than other methods

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because of the following features: random selection of CHs makes it possible for any node to become CH more than once or a node with lowest RE can also become a CH. It also does not consider any parameters like RE, DBS and ND which are essential in the CH selection process. Furthermore, the absence of multi hop data transmission leads to higher amount of energy consumption. The reactive nature of the TEEN protocol results in lower energy consumption than LEACH and at the same time the random selection of CHs makes it to fail when compared to DEEC, EAUCF and proposed algorithm. Though EAUCF uses fuzzy logic for CH selection, probability based tentative CHs selection and the use of T1FL degrades the overall performance.

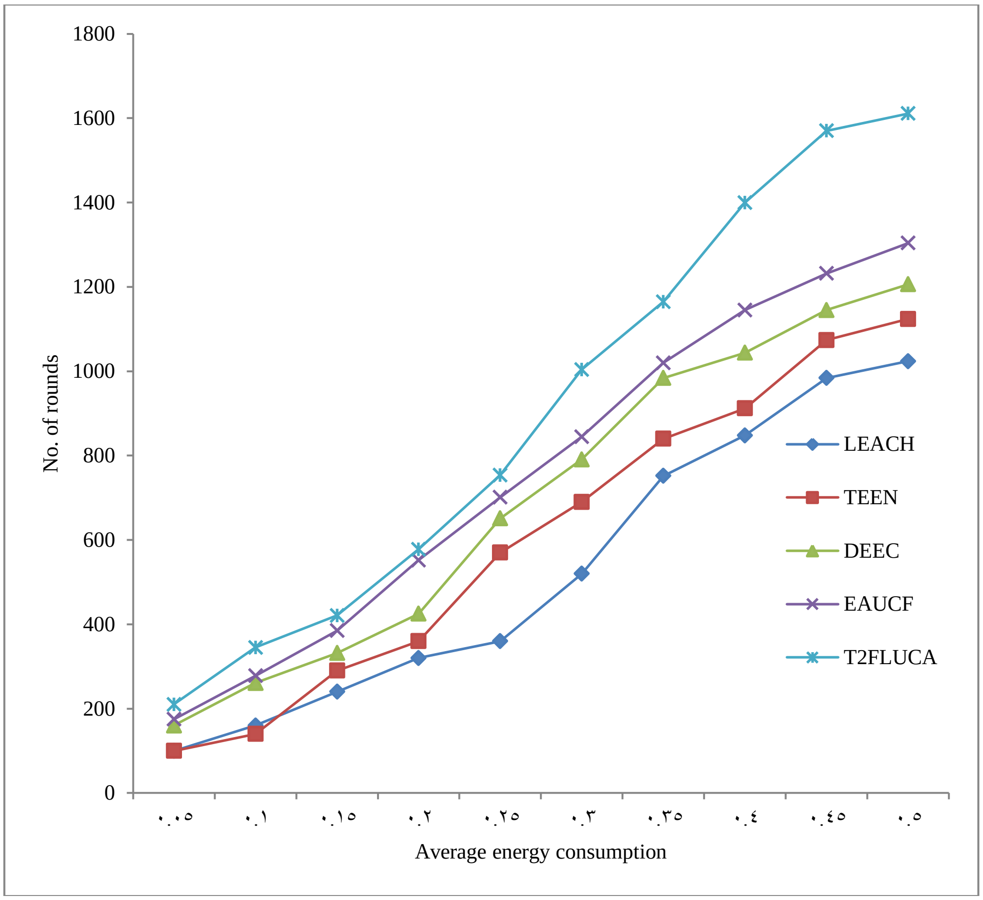

Figure 10: Average energy consumption: Scenario 2

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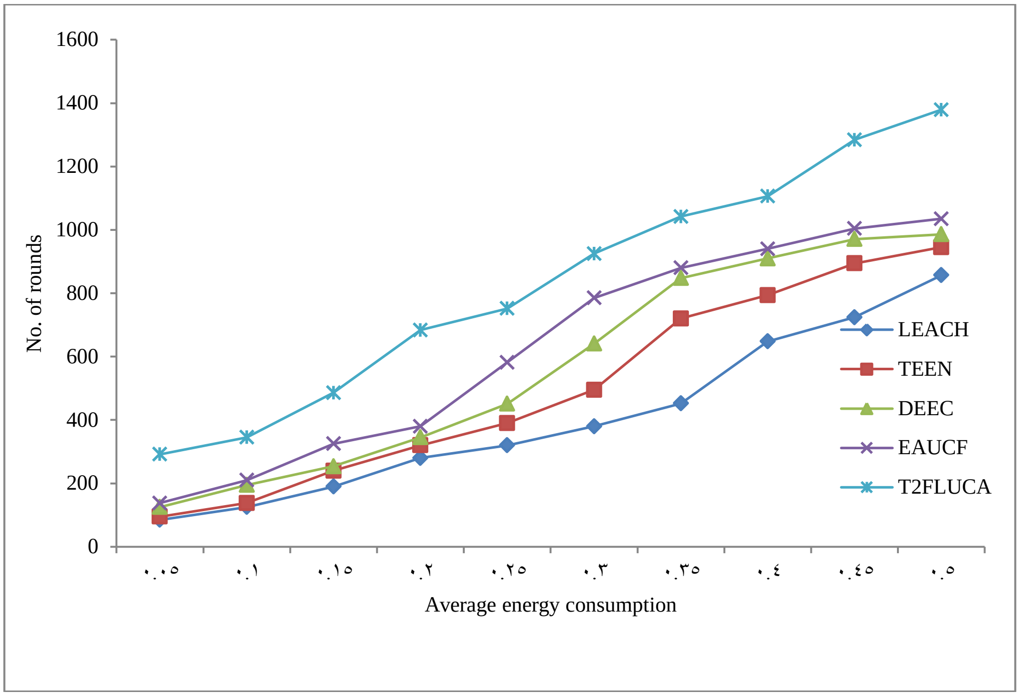

Figure 11: Average energy consumption: Scenario 3

Next, network lifetime is also an important metric to measure the performance of the clustering algorithm in WSN. Network lifetime is termed as the total number of rounds completed until all nodes in the WSN exhaust its energy. Since the neighboring nodes in WSN may send the same data, the FND does not have impact of the overall functioning of the network. But, at the same time, the quality of the sensing data begins to degrade. When the LND reaches, the whole WSN becomes inactive. The obtained FND, HND and LND of the proposed method on three scenarios are given in Table 3. The results of the number of dead nodes in three scenarios are illustrated in Figs. 12-14 respectively. From the Table 3, it is apparent that the FND of the proposed algorithm does not occur earlier than the compared algorithms.

Table 3: Comparison of various algorithms interms of FND, HND and LND

Algorithm	**Scenario 1**			**Scenario 2**			**Scenario 3**		
	FND	**HND**	**LND**	**FND**	**HND**	**LND**	**FND**	**HND**	**LND**
LEACH	802	1126	1278	542	849	1024	452	614	857
TTEN	1024	1089	1327	768	889	1124	389	602	945
DEEC	1088	1102	1386	948	1041	1206	894	948	986
EAUCF	1342	1496	1532	1196	1274	1304	941	988	1035
T2FLCA	1501	1689	1896	1278	1436	1611	1064	1195	1379

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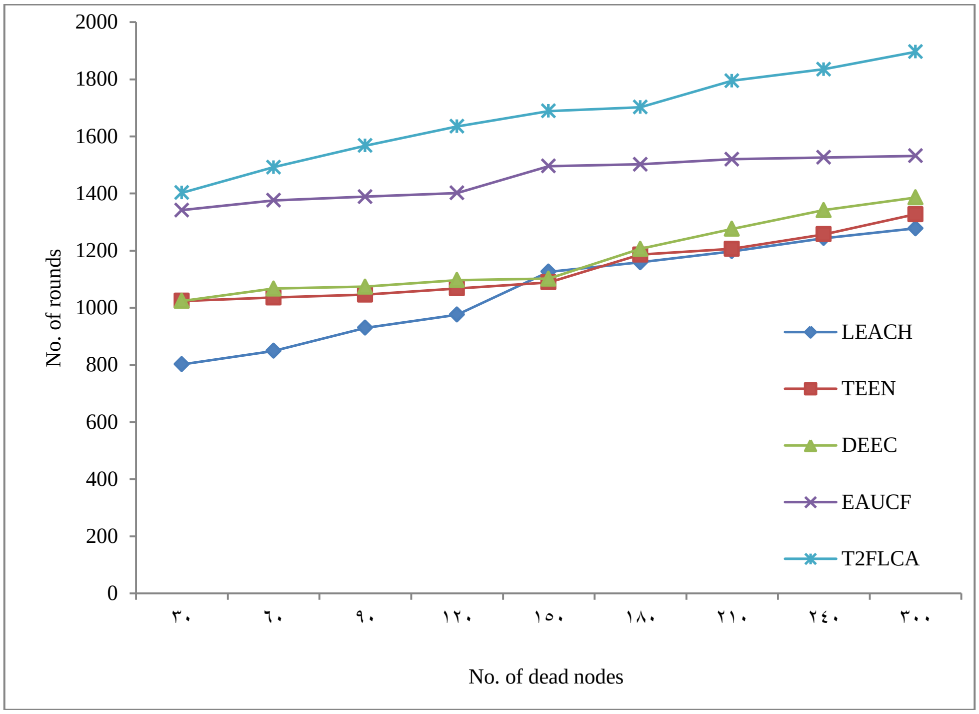

Figure 12: No. of dead nodes for several rounds: Scenario 1

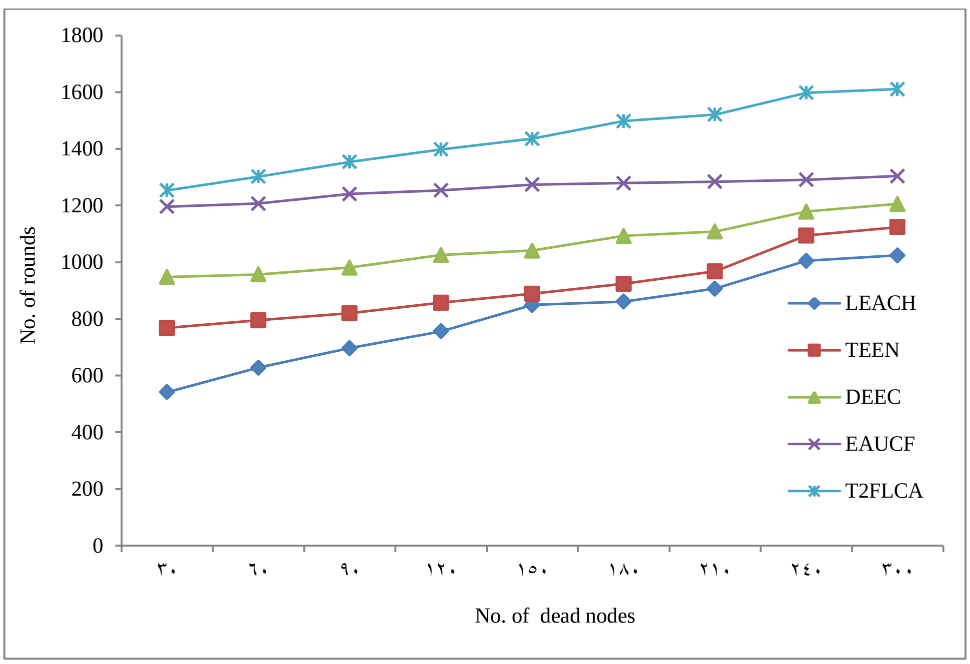

Figure 13: No. of dead nodes for several rounds: Scenario 2

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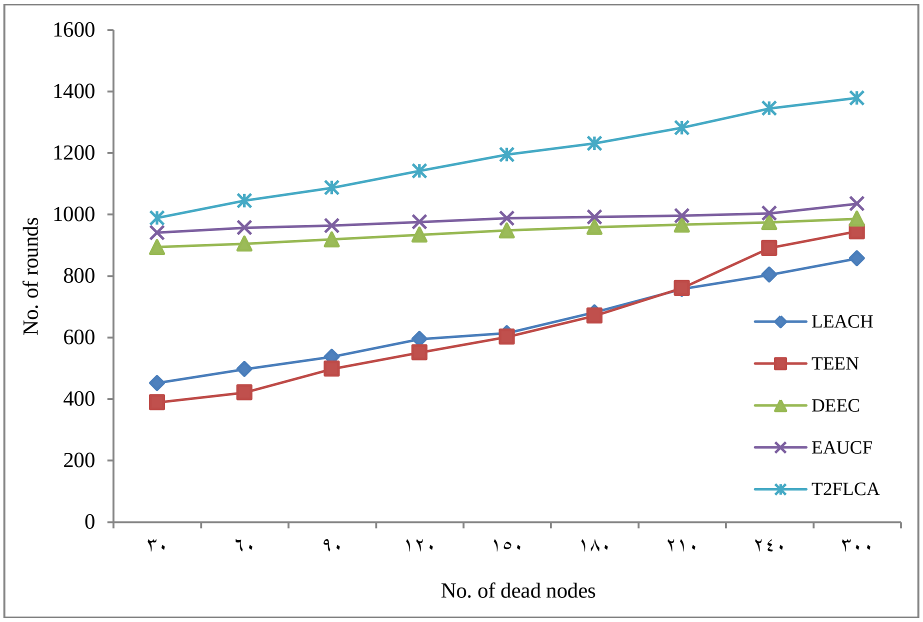

Figure 14: No. of dead nodes for several rounds: Scenario 3

6. Conclusion

Due to several advantages of T2FL, this paper presents a T2FLUCA for appropriate election of CHs and cluster size. T2FL is employed for CH and cluster size selection by the use of three input parameters. To validate, T2FLUCA is experimented on under different deployment scenarios based on the location of BS. A performance comparison is also made with LEACH, TEEN, DEEC, EAUCF are used interms of network lifetime, throughput and average energy consumption. The simulation results reported that the proposed T2FLUCA outperforms the existing algorithms and achieves uniform load distribution which eventually increases the network lifetime.

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