The Journal of Supercomputing (2021) 77:9947–9970
https://doi.org/10.1007/s11227-021-03668-w

Fuzzy rule-based system for energy efficiency in wireless sensor networks

Amruta Lipare[1] · Damodar Reddy Edla[1] · Saidi Reddy Parne[1]

Accepted: 2 February 2021 / Published online: 22 February 2021

Abstract
The sensor nodes consume a large amount of energy to transfer the sensed information directly to the base station (BS). To reduce the energy consumption from the direct transmission, clustering and routing techniques are used. In this paper, we propose clustering and routing algorithms called energy-efficient two-phase approach using fuzzy logic (EETPF). Here, the rule-based fuzzy logic is used to associate the input values of clustering and routing algorithm. The fuzzy system makes decisions according to the residual energy of sensor nodes, distance of sensor nodes from the BS and the number of nodes in the communication range. The crisp values of the input variables are converted into different fuzzy values. The fuzzy output values are converted to crisp values using centroid defuzzification method. The cluster heads (CHs) and routers are selected with respect to the output values. The sensor nodes get allocated to respective CHs according to the load handling capacity of CHs. The routing path is generated according to the capacity of routers. The simulations are conducted on evaluation factors such as energy consumption, active sensor nodes per round and sustainability period of the network. It is observed that EETPF outperforms state-of-the-art algorithms under these evaluation factors.

Keywords Clustering · Energy efficiency · Fuzzy system · Load balancing · Routing · Wireless sensor networks

✉ Damodar Reddy Edla
dr.reddy@nitgoa.ac.in

Amruta Lipare
amruta.lipare@gmail.com

Saidi Reddy Parne
psreddy@nitgoa.ac.in

1 National Institute of Technology Goa, Ponda, Goa 403401, India

1 Introduction

In the last decades, the field of wireless sensor networks (WSNs) has grown up considering one of the emerging extents in the world. It is used in various applications such as healthcare, agriculture and surveillance monitoring. The scale of the WSN arises various kinds of challenges to design an efficient algorithm in order to increase the lifetime [1, 2]. In the WSNs, the sensor nodes are composed of various sensing units, communication mechanisms, memory, data processing units and battery constraints. The sensor nodes are deployed in the area under observation to sense the local information from the environment such as temperature, humidity, etc [3, 4]. The sensed row information is processed to generate appropriate data. These data are sent to the local base station (BS). BS is connected to the internet. The data from each sensor node are collected at the BS and BS updates the local information of the area under observation. One of the most prominent constraints of sensor node is its limited battery unit [5, 6]. Several research studies have arisen following the core aim that, to optimize the sensor nodes' energy consumption by using innovative conservation techniques for improving the lifetime of the network and network performance. There are number of definitions existing for the lifetime of the network such as the percentage of dead sensor nodes or loss of coverage occurs, the round of first dead sensor node. A dead sensor node is termed as either a damaged sensor node or a sensor node with no power. A dead sensor node cannot transmit data to the BS. In some of the WSNs, the replacing or recharging the batteries of dead sensor nodes is crucial. Therefore, the efficient battery use of a sensor node is one of the challenging tasks [7–10]. Researchers opted solutions to defeat this challenge by applying different techniques such as clustering, routing, data collection algorithms, data aggregation methods etc. In the clustering technique, the clusters are created by gathering sensor nodes together. One of the sensor nodes from the cluster is considered as the leader of the cluster, called a cluster head (CH). CH collects the processed data from each sensor node from its particular cluster. The gathered data are aggregated and transmitted to the BS directly or through other CHs. In the direct transmission from CHs to BS, the CHs need to travel a longer distance toward BS. This leads to the faster energy depletion of CHs [11, 12]. The transmission of data from one CH to the BS through other CH in the network is called routing. Routing helps to minimize the energy consumption of CHs because, instead of transmitting data over a longer distance to the BS, CHs send data to other CHs nearer to them [13–16]. Figure 1 shows the WSN with clusters and routing path toward the BS.

In Fig. 1, there are 18 sensor nodes, and out of which 4 are playing the role of CH. Out of 4 CHs, 2 are playing the role of router also. Sensor nodes send data to CHs. Further, CHs forward it toward the BS through other CHs or direct to the BS.

The selection of CHs is also one of the critical challenges in WSN, as the CH has to take an extra effort compared to normal sensor nodes. The parameters affecting energy consumption of CH are its power, its distance from the BS

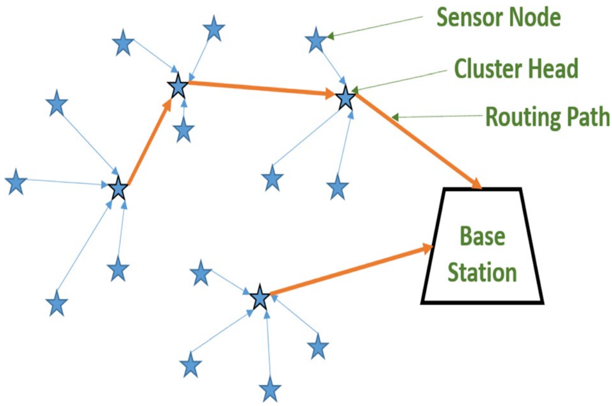


Fig. 1 WSN framework

and other communication parameters. Therefore, number of uncertainties are present in WSN. To deal with these uncertainities, in this paper, fuzzy logic is used. Fuzzy logic [17] is one of the computational intelligence techniques used in various real-time applications. Fuzzy logic is mainly composed of four parts: Fuzzifier, Fuzzy Inference System, Rule-base and Defuzzifier. Fuzzification is a process where the crisp values of input variables are converted to fuzzy values according to the defined fuzzy linguistic variables. Generated fuzzy input values are given to the Fuzzy Decision Block (FDB). FDB is a configuration connected with fuzzy inference system and rule-base. FDB processes the generated fuzzy input data and produces fuzzy outputs. The fuzzy outputs are sent to the defuzzifier to convert again to the crisp values [18]. In this paper, CH selection, cluster formation, router selection and routing path generation are carried out according to the output values of the fuzzy system. Figure 2 demonstrates the proposed fuzzy rule base system.

Our contributions to this paper are discussed below.

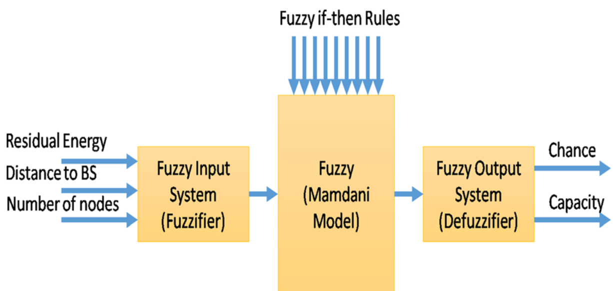


Fig. 2 Fuzzy system for clustering and routing in EETPF

1.1 Our contributions

1. Both clustering and routing techniques are designed for energy efficiency in WSN.
2. Fuzzy rule-based system is used to select the appropriate CHs and routers.
3. A novel and efficient cluster formation algorithm and the routing path for the routers are designed.
4. The routing algorithm is applied after clustering is done.
5. The input variables to fuzzy system for clustering are residual energy of sensor nodes, sensor nodes in the range and distance of sensor nodes to the BS.
6. The sensor node is selected as a CH according to its chance to work as CH and load handling capacity
7. The input variables to fuzzy system for routing are remaining energy of CHs, the sensor nodes connected to the CH and distance of CH to the BS.

The remaining paper is structured as Sect. 2 describes some of the existing work related to the proposed approaches and energy model to calculate the energy consumption of the sensor node in network. Section 3 describes the proposed clustering and routing algorithms using a fuzzy rule-based system. Experimental results are designated in Sect. 4. Section 5 concludes the paper with the synthesis of the proposed work and experiments.

2 Related work

We have studied different approaches regarding energy efficiency, load balancing, clustering, routing in WSN. Some of the conventional approaches and fuzzy approaches are discussed in the subsections below.

2.1 Conventional approaches

Low-Energy Adaptive Clustering Hierarchy (LEACH) algorithm [19] is a well-known clustering algorithm in WSN. In LEACH algorithm, CHs are selected stochastically at each round. Then the selected CH do not get a chance to work as CH for next P rounds. Hence, the probability of getting selected as CH for each sensor node is $1/P$. Each sensor node joins its nearest CH to send data. CH prepares a schedule for member sensor nodes to transmit the data. After a certain number of rounds, sensor nodes drain whole energy, therefore cannot send data further. So, there is no transmission in these rounds. To overcome this issue, Kumar et al. [20] proposed improved LEACH in which they applied one more factor affecting the network lifetime, i.e., residual energy of sensor node.

Also, in the HEED algorithm [21], the CHs are selected according to the remaining energy level of sensor nodes. If there is a tie between any two nodes, the node degree is used to select the CH. Due to the consideration of energy level at the time of selection of CH, HEED performs better than LEACH.

2.2 Fuzzy approaches

Kim et al. [22] have designed an energy-efficient fuzzy logic-based cluster head election method (CHEF). In CHEF, the CHs are elected among sensor nodes using fuzzy logic. Authors have considered residual energy and the distance of the sensor node from the BS to elect the CHs. The output variable is the chance of a sensor node to work as a CH.

Hagci et al. [18] designed energy-efficient unequal clustering using fuzzy logic (EAUCF). EAUCF pre-defines a threshold (T) value between 0 and 1. Each sensor node in the network randomly produces a number between 0 and 1. The sensor nodes with the random number below T are considered as tentative CHs. The input parameters to the fuzzy inference model are 'Distance to BS' and 'Residual energy'. EAUCF defines a new output variable, i.e., 'Competition radius'. Final CHs are selected according to competition radius of each tentative CH. Later on, sensor nodes are assigned to the nearest CH out of the set of final CHs.

As an extension to EAUCF, Logambigai et al. [23] proposed an unequal clustering for WSN based on fuzzy system. Along with the competition radius of CHs, a new parameter called $\mathrm{CH}_{\mathrm{choice}}$ is added. $\mathrm{CH}_{\mathrm{choice}}$ helps to form clusters. The sensor nodes choose the CH to send data according to the $\mathrm{CH}_{\mathrm{choice}}$ value. A sensor node chooses CH according to its distance and node degree of CH.

Baranidharan et al. [24] designed a Distributed Unequal Clustering using Fuzzy logic (DUCF). In this approach, CHs are selected according to the fuzzy outputs. Here, two output variables, 'chance' and 'size', are used to elect final CHs. The size of clusters nearer to the BS is kept smaller, because they work as a router for the CHs located far from the BS. Therefore, DUCF generates unequal clusters considering the distance between CHs and BS. The assignment of sensor nodes and CHs is carried out according to the second fuzzy output value, i.e., size of cluster.

2.3 Energy model regarding energy consumption of sensor nodes

We have used the radio energy model from [25] to calculate the overall energy consumption by the network. In WSN, each sensor node needs the energy to perform clustering activities, transmission and receiving the packets from other sensor nodes. The energy consumed by a sensor node to transmit a data packet of length 'l-bit' over the distance d is expressed in Eq. 1.

$$E_T(l,d) = \begin{cases} l * E_{\mathrm{elec}} + l * \epsilon_{\mathrm{fs}} * d^2, & d < d_0 \\ l * E_{\mathrm{elec}} + l * \epsilon_{\mathrm{mp}} * d^4, & d \geq d_0 \end{cases} \tag{1}$$

where ϵ_{fs} and ϵ_{mp} are the energies required to transmit data in free-space channel and multi-path communication channel, respectively. d_0 is a threshold value for transmission distance. E_{elec} is the amount of energy consumed by the electronic circuitry of a sensor node. The energy consumption for receiving ‘l-bit’ of data is formulated in Eq. 2.

$$E_R(l) = l * E_{\text{elec}} \tag{2}$$

3 Proposed EETPF approach for clustering and routing

The proposed EETPF approach is composed of two phases: clustering and routing in WSN using fuzzy inference system. Both the phases are discussed in the subsections below.

3.1 The proposed clustering approach

In the phase of clustering, the CHs are selected from the set of sensor nodes. After selection of CHs, clusters are formed by joining sensor nodes to the selected CHs. There are three sub-phases in the proposed clustering technique: Fuzzy CH competition phase, CH selection phase and Cluster formation phase.

3.1.1 Fuzzy CH competition phase

This phase yields the chance of a sensor node to work as a CH by using fuzzy system. The parameters used for fuzzy inference system as an input are mentioned below.

I. **Residual energy:** Sensor nodes utilize their energy to sense the environment. They process the information collected from the environment and transmit to the BS. Each sensor node in the network must have sufficient energy to perform these activities. Therefore, residual energy is one of the most important factors considered at the time of selection of CH.

II. **Number of nodes in range (NIR):** The CH carries the load from the nearby sensor nodes and consumes energy to process and transfer the collected data. Therefore, the NIR is one of the necessary components for selecting the CH.

III. **Distance to the BS:** This is also a necessary parameter affecting the amount of energy consumption of the sensor nodes. Unequal size of clusters is constructed according to the distance of sensor nodes to the BS. The cluster size increases with increase in the distance of the sensor node to the BS. The main reason behind this is, the sensor nodes near to the BS carry a large amount of routed data, so may get die soon. Therefore, minimizing the cluster size of nearby sensor nodes from BS minimizes its own load. This leads to energy savings and the saved energy can be processed for routing the data.

Two output are generated from the fuzzy system, i.e., Chance to be the CH and Capacity of data handling of the sensor node. These parameters are crisp values obtained by defuzzification method.

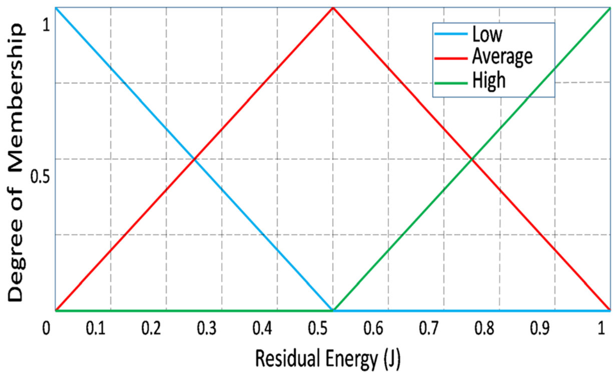


Fig. 3 Membership function for the input variable "Residual Energy"

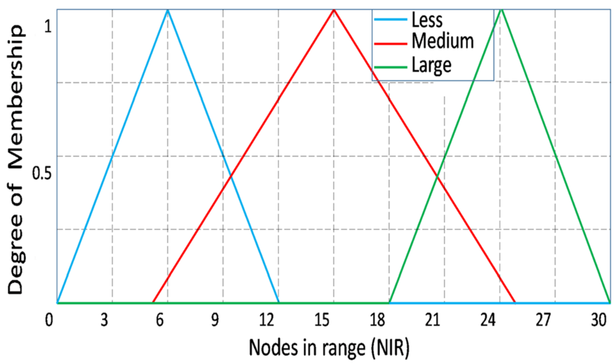


Fig. 4 Membership function for the input variable "NIR"

I. **Chance to be the CH (ChanceC):** This output parameter specifies the ability of the sensor node to be the CH. The nodes with higher ChanceC values may be considered as final CHs.
II. **Capacity of sensor node (CapacityC):** This output parameter specifies the capacity of the sensor node to carry the data load from other sensor nodes. The sensor nodes having higher CapacityC may be considered as final CHs.

Initially, all the sensor nodes are considered as the provisional CHs. Further, the sensor nodes get evaluated from the linguistic variables in the fuzzy system. The first input parameter 'Residual energy' has three linguistic variables High, Average and Low. The range of membership function is from 0 to 1 because the maximum residual energy of sensor node is 1 J. The second input parameter 'NIR' also has three linguistic variables Large, Medium and Less. The range of membership function of 'NIR' is from 0 to 17 and from 0 to 18 for scenario 1 and scenario 2, respectively. These scenarios are mentioned in Sect. 4. Similarly, the third input parameter 'Distance to BS' has three linguistic variables Long, Reachable and Short. The range of

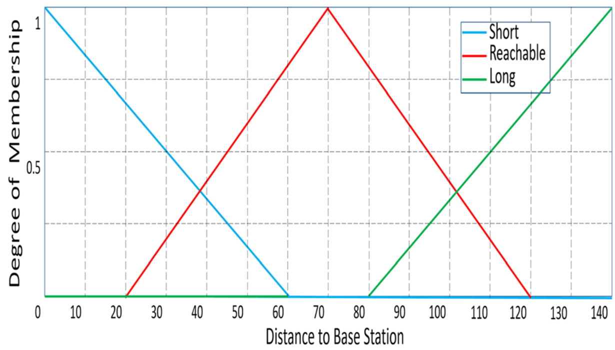


Fig. 5 Membership function for the input variable "Distance to BS"

membership function of 'Distance to BS' is from 0 to 142 and from 0 to 224 for scenario 1 and scenario 2, respectively. The membership functions are selected based on [18] and our own experimental findings. Figures 3, 4 and 5 depict all membership functions of the input parameters 'Residual energy, NIR and Distance to BS', respectively.

The first fuzzy output variable "ChanceC" denotes nine output linguistic variables such as Biggest, Bigger, Big, Big Moderate, Moderate, Small Moderate, Small, Smaller and Smallest. Figure 6 denotes the membership functions of the output variable "ChanceC". The second output variable "CapacityC" also has the nine fuzzy linguistic variables such as More Huge, Huge, Less Huge, Huge Bearable, Bearable, Little Bearable, Little, Rather Little and Less Little. Figure 7 denotes the membership function for "CapacityC" of sensor node. The ranges of all membership functions are selected wisely in order to accommodate each sensor nodes in a cluster by various experimental analysis.

The crisp input values are provided to the fuzzy system to generate fuzzified input values. Various fuzzy if-then rules evaluate these input values. The Mamdani model

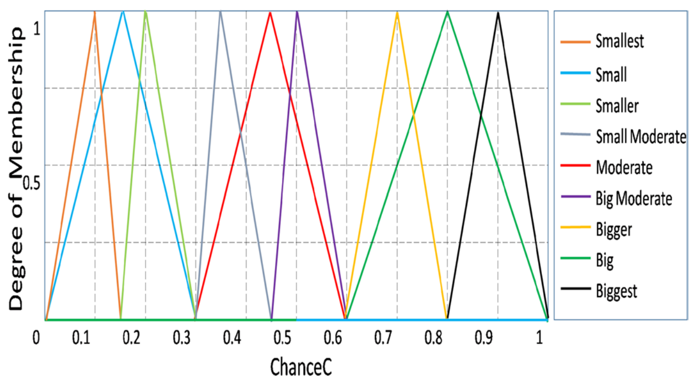


Fig. 6 Membership function for the output variable "ChanceC"

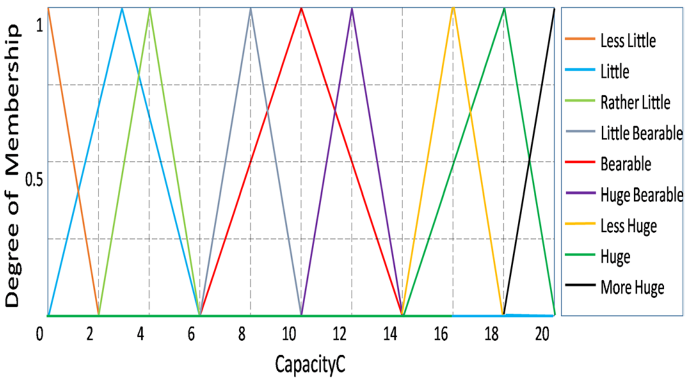


Fig. 7 Membership function for the output variable "CapacityC"

[26] is used to process these fuzzy rules because of its simplicity and popularity. Total 27 fuzzy if-then rules are defined with respect to different linguistic variables. Table 1 depicts these 27 fuzzy if-then rules. For defuzzification, we have used the centroid method, which gives crisp values for output variables.

3.1.2 CH selection phase

In this phase, each sensor node broadcasts a message 'candidateCH'. The message 'candidateCH' contains the information about ChanceC and CapacityC. Each sensor node compares its chance with neighbor node and sends 'joinCH' message to the sensor nodes having higher chance than its own. If a sensor node gets join requests more than its capacity, then it sends 'wonCH' message in its communication range. The sensor nodes sending 'wonCH' message are considered as CHs. So, in this way, CHs are elected in fuzzy clustering phase.

3.1.3 Cluster formation phase

According to the capacity of CH, CH sends 'acceptCM' message to its nearer sensor nodes, except other CHs, i.e., the sensor nodes from which it receives 'wonCH' message. If the number of join requests exceeds the capacity of CH, then it acknowledges with a 'rejectCM' message to the sensor nodes far from it. The normal sensor nodes may get multiple 'acceptCM' messages. In this case, it acknowledges its nearest CH by sending 'connectCH' message. If a sensor node does not receive any 'acceptCM' message from any of the CH, then it declares itself as a CH.

All of these messages and their description are given in Table 2. The flowchart of the entire clustering algorithm is given in Fig. 8.

Table 1 Fuzzy if-then rules for clustering in WSN

Sr. no	Input variables			Output variables	
	Residual energy	NIR	Distance to BS	ChanceC	CapacityC
1	High	Large	Long	Biggest	More Huge
2	High	Large	Reachable	Bigger	Huge
3	High	Large	Short	Big	Less Huge
4	High	Medium	Long	Biggest	More Huge
5	High	Medium	Reachable	Bigger	Huge
6	High	Medium	Short	Big	Less Huge
7	High	Less	Long	Biggest	More Huge
8	High	Less	Reachable	Bigger	Huge
9	High	Less	Short	Big	Less Huge
10	Average	Large	Long	Big Moderate	Huge Bearable
11	Average	Large	Reachable	Moderate	Bearable
12	Average	Large	Short	Small Moderate	Little Bearable
13	Average	Medium	Long	Big Moderate	Huge Bearable
14	Average	Medium	Reachable	Moderate	Bearable
15	Average	Medium	Short	Small Moderate	Little Bearable
16	Average	Less	Long	Big Moderate	Huge Bearable
17	Average	Less	Reachable	Moderate	Bearable
18	Average	Less	Short	Small Moderate	Little Bearable
19	Low	Large	Long	Smallest	Little
20	Low	Large	Reachable	Smaller	Rather Little
21	Low	Large	Short	Small	Less Little
22	Low	Medium	Long	Smallest	Little
23	Low	Medium	Reachable	Smaller	Rather Little
24	Low	Medium	Short	Small	Less Little
25	Low	Less	Long	Smallest	Little
26	Low	Less	Reachable	Smaller	Rather Little
27	Low	Less	Short	Small	Less Little

3.2 The proposed routing approach

In the phase of routing, from the set of CHs, some CHs are selected as routers. After selection of routers, the efficient routing path is formed joining the routers toward the BS.

There are three sub-phases in the fuzzy routing: Fuzzy router competition phase, Router selection phase and Routing path formation phase discussed below.

Table 2 Message descriptions

Sr. no	Message	Description
1.	candidateCH	Initially, each sensor node broadcast candidateCH in the communication range R CandidateCH(S.ID, S.ChanceC)
2	joinCH	If the chance of sensor node is less than received candidateCH, then it request to join by sending joinCH joinCH(S.ID)
3.	wonCH	If the number of join requests exceed the CapacityC, then broadcast wonCH wonCH(CH.ID)
4.	acceptCM	According to the CapacityC of CH, CH sends acceptCM to the most nearby sensor nodes acceptCM(CH.ID, S.ID)
5.	rejectCM	If the number of join requests exceed the capacity of CH, it acknowledges farther sensor nodes with rejectCM rejectCM(CH.ID, S.ID)
6.	connectCH	Sensor node acknowledges its nearest CH by sending connectCH and sends data to it connectCH(CH.ID, S.ID)

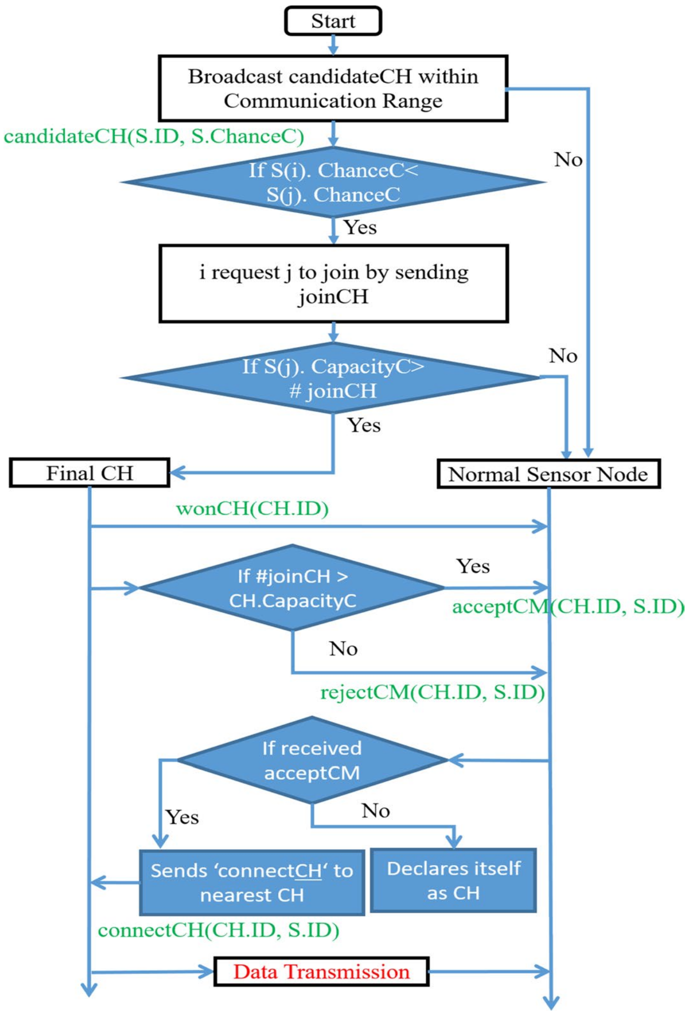


Fig. 8 Flowchart of clustering algorithm

3.2.1 Fuzzy router competition phase

Initially, all the CHs are considered as the provisional routers. Further, the CHs get evaluated from the linguistic variables and membership functions of the fuzzy system. The input parameters for routing the fuzzy approach are 'Residual energy', 'Distance to the BS' and 'Number of nodes connected after clustering (NCC)'. The linguistic variables of 'Residual energy' and 'Distance to BS' are the same as used in the clustering phase. The linguistic variables of 'NCC' are same as the variable 'NIR' in the clustering phase. The membership functions are selected based on our own experimental findings. Figures 9, 10 and 11 depict all membership functions of the input parameters 'Residual energy, NCC and

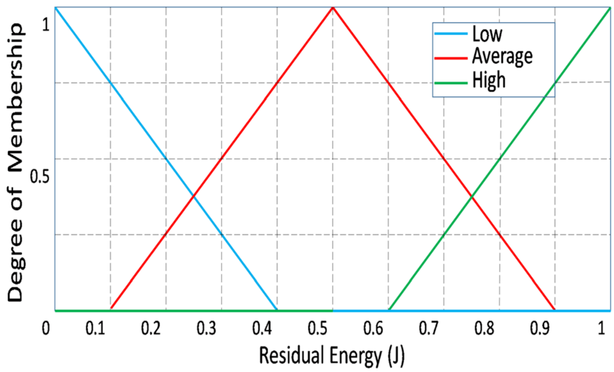


Fig. 9 Membership function for the input variable "Residual Energy"

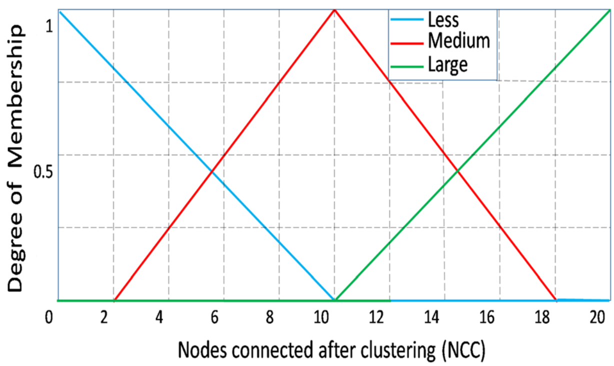


Fig. 10 Membership function for the input variable "NCC"

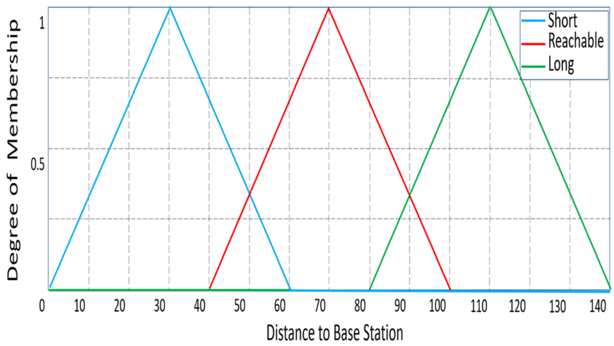


Fig. 11 Membership function for the input variable "Distance to BS"

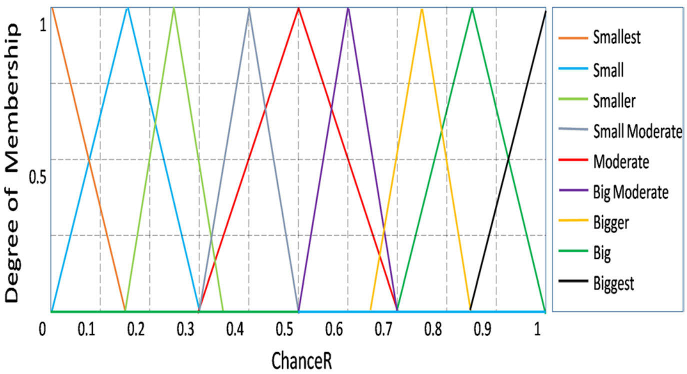


Fig. 12 Membership function for the output variable "ChanceR"

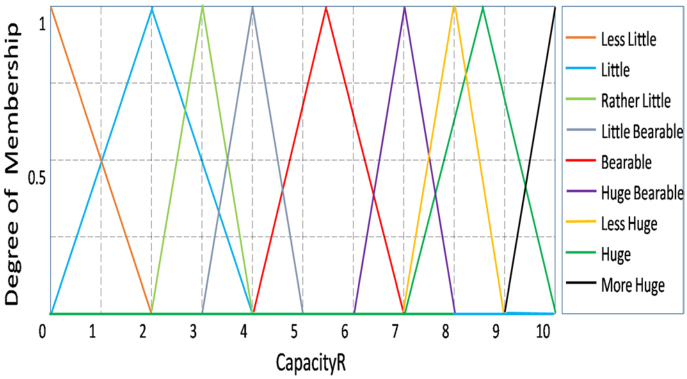


Fig. 13 Membership function for the output variable "CapacityR"

Distance to BS', respectively. The ranges of membership functions of the variables are the same as in fuzzy clustering phase.

The first fuzzy output variable "ChanceR" is considered as the chance of a CH to be a router. The linguistic variables of "ChanceR" are the same as the linguistic variable "ChanceC" in the clustering phase. Figure 12 denotes the membership functions of the output variable "ChanceR". The second output variable "CapacityR" also has the same as the linguistic variable "CapacityC" in the clustering phase. Figure 13 denotes the membership function for "CapacityR" of sensor node. The ranges of all membership functions are selected wisely in order to accommodate each CH in a routing path by various experimental analysis. Total 27 fuzzy if-then rules are defined for routing algorithm as shown in Table 3.

3.2.2 Router selection and routing path formation phase

Initially, sort all the CHs according to their distance to the BS. Broadcast 'candidateR' message in the range of CH. This message gets received by only CHs.

Table 3 Fuzzy if-then rules for routing in WSN

Sr. no	Input variables			Output variables	
	Residual energy	Distance to BS	NCC	ChanceR	CapacityR
1	Low	Long	Large	Smallest	Little
2	Low	Long	Medium	Smaller	Rather Little
3	Low	Long	Less	Small	Less Little
4	Low	Reachable	Large	Small Moderate	Little
5	Low	Reachable	Medium	Moderate	Rather Little
6	Low	Reachable	Less	Big Moderate	Less Little
7	Low	Short	Large	Big	Little
8	Low	Short	Medium	Bigger	Rather Little
9	Low	Short	Less	Biggest	Less Little
10	Average	Long	Large	Smallest	Little Bearable
11	Average	Long	Medium	Smaller	Bearable
12	Average	Long	Less	Small	Huge Bearable
13	Average	Reachable	Large	Small Moderate	Little Bearable
14	Average	Reachable	Medium	Moderate	Bearable
15	Average	Reachable	Less	Big Moderate	Huge Bearable
16	Average	Short	Large	Big	Little Bearable
17	Average	Short	Medium	Bigger	Bearable
18	Average	Short	Less	Biggest	Huge Bearable
19	High	Long	Large	Smallest	Huge
20	High	Long	Medium	Smaller	Less Huge
21	High	Long	Less	Small	More Huge
22	High	Reachable	Large	Small Moderate	Huge
23	High	Reachable	Medium	Moderate	Less Huge
24	High	Reachable	Less	Big Moderate	More Huge
25	High	Short	Large	Big	Huge
26	High	Short	Medium	Bigger	Less Huge
27	High	Short	Less	Biggest	More Huge

Table 4 Message descriptions

Sr. no	Message	Description
1.	candidateR	Initially, each CH broadcasts candidateR in the communication range R candidateR(CH.ID, CH.ChanceR, CH.CapacityR)
2.	availableR	If chanceR of neighbor node is less and capacity is Huge then, send availableR to the nearer CH availableR(CH.ID)
3	connectR	If availableR is received then, acknowledge nearest CH with connectR connectR(CH.ID, R.ID)

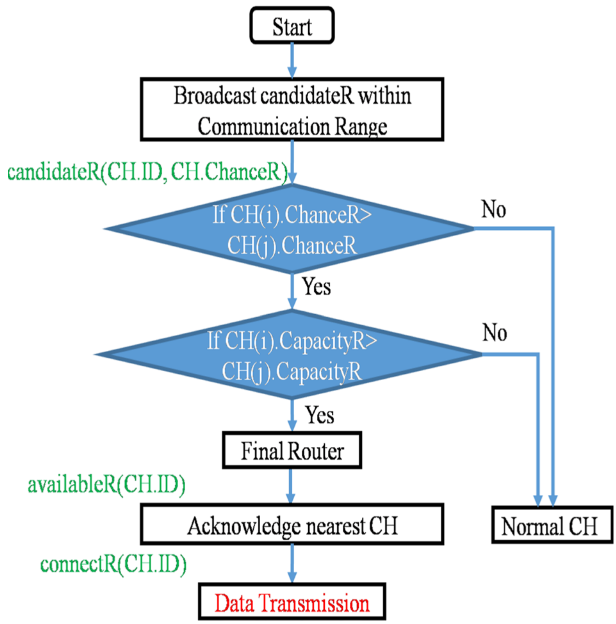


Fig. 14 Flowchart of clustering algorithm

'candidateR' message includes information about "ChanceR" and "CapacityR". The CHs farther from the BS get very less chance of being a router. All the CHs receive a various number of 'candidateR' messages. The CH compares chance and capacity with the received candidates. It sends a message 'AvailableR' to the CHs with a chanceR less than its own and not exceeding the value of its CapacityR. CHs may receive multiple 'availableR'. They acknowledge its nearest CH by sending a message 'connectR'. In this way, the selection of router process starts with farthest CH and ends at the BS along with the formation of the routing path. Here, the CHs may not receive any 'availableR' message, in this case, that CH directly sends data to the BS.

All of these messages and their description is given in Table 4. The flowchart of the entire routing algorithm is given in Fig. 14.

4 Experimental analysis

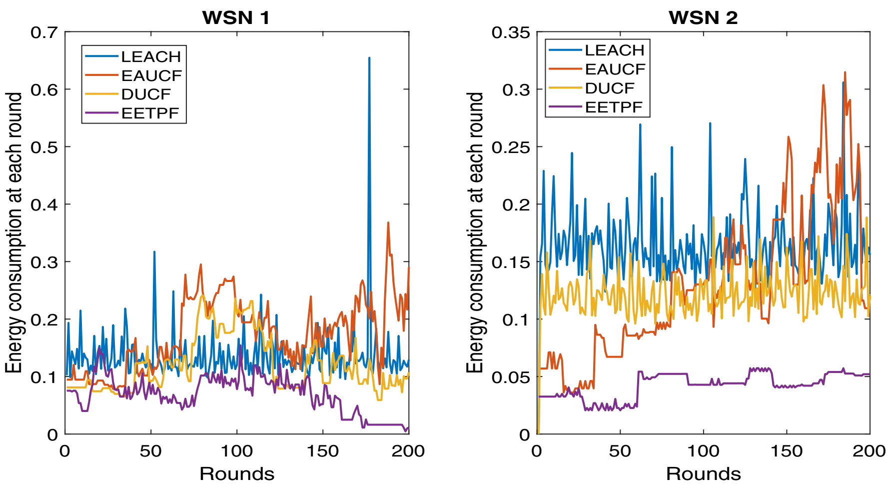
The simulations are performed under the area of 200×200 m^2 where 100 number of sensor nodes are deployed randomly. Later, their positions are constant throughout the experiments. The experiments are performed under two scenarios. In the first WSN scenario, the location of the BS is fixed at [100, 100], i.e., at the centre of the area. In the second WSN scenario, the location of BS is fixed at the [100, 200], i.e., at the side of the area. The purpose behind experimenting the second scenario is to monitor the energy consumption of sensor nodes and look

Table 5 Simulation parameters

Sr. no	Parameter	Value
1.	Packet size	4000 bits
2.	Message size	200 bits
3.	Data aggregation ratio	10%
4.	Communication range	40 m
5.	E_{elec}	50 nJ/bit
6.	ϵ_{fs}	10 pJ/bit/m^2
7.	ϵ_{mp}	0.001 pJ/bit/m^4

after the performance of the proposed fuzzy routing algorithm. The simulations are carried out in the MATLAB R2015. The proposed EETPF is compared with LEACH [19], EAUCF [18] and DUCF [24]. LEACH is one of the conventional algorithms used for clustering. EAUCF and DUCF are fuzzy logic-based distributed clustering algorithms. The remaining simulation parameters are declared in Table 5.

The experiments are conducted under the evaluation factors such as energy consumption at each round, total energy consumption at rounds, active sensor nodes per round, round number when first sensor node dies, residual energy of each sensor node at round number 300, standard deviation of quantity of energy consumed by sensor nodes and energy consumption rate till first sensor node die in the network. Following subsections describe overall performance of LEACH, EAUCF, DUCF and proposed EETPF based on these evaluation factors.



(a) For Senario 1 **(b)** For Scenario 2

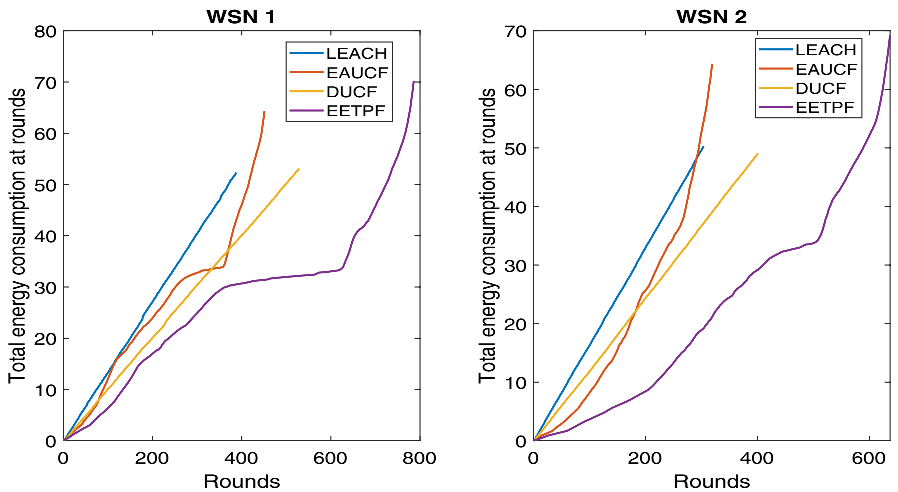
Fig. 15 Comparative study of EETPF with LEACH, EAUCF and DUCF for the parameter 'Energy consumption at each round'

4.1 Energy consumption at each round

The sensor nodes and CHs exhaust their energy after performing activities such as data collection, data transmission, as well as other intra-cluster activities. We noted the energy consumption at each round until the first sensor node dies in the network. Figure 15 shows the amount of energy consumed by the network from LEACH, EAUCF, DUCF and EETPF algorithms for scenario 1 and scenario 2. LEACH consumes the highest amount of energy. EAUCF also consumes a large amount of energy and the reason behind this is the probabilistic CH selection. EAUCF does not consider essential parameter 'number of neighbor nodes'. DUCF performs better than EAUCF because of the addition of an input variable 'number of neighbor nodes' to its fuzzy system. Even though DUCF performs better than EAUCF, it still consumes more energy than EETPF. The routing approach with fuzzy inference system is one of the strongest measures in the reduction in energy consumption. EETPF selects energetic and appropriate routers which help to balance the load of the network and consumes less amount of energy.

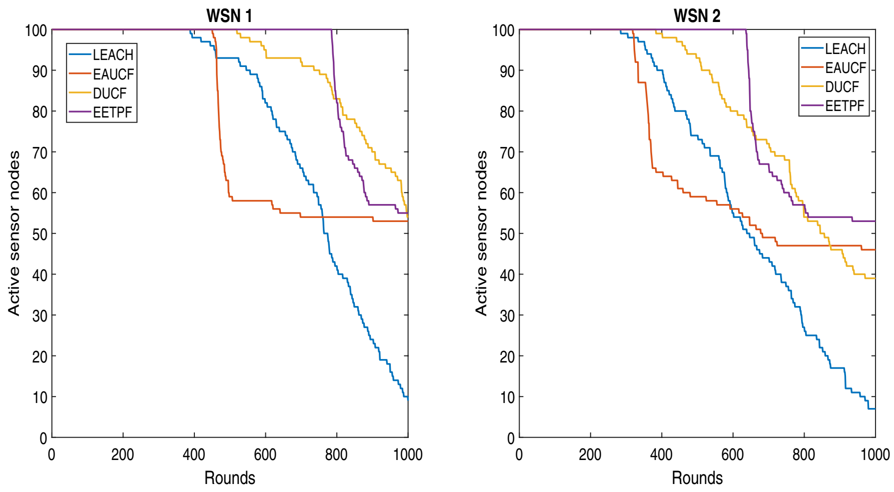
4.2 Total energy consumption at rounds

We have plotted this parameter to understand the lifetime and total energy consumption of the network. It is observed that, as the energy consumption at each round is less in the EETPF, the total energy consumption is also less in EETPF. Figure 16 shows the total amount of energy consumed by the network until the



(a) For Senario 1 **(b)** For Scenario 2

Fig. 16 Comparative study of EETPF with LEACH, EAUCF and DUCF for the parameter 'Total energy consumption at rounds'



(a) For Scenario 1 **(b)** For Scenario 2

Fig. 17 Comparative study of EETPF with LEACH, EAUCF and DUCF for the parameter 'Active Sensor Nodes at each Round'

first sensor node dies from LEACH, EAUCF, DUCF and EETPF algorithms for scenario 1 and scenario 2.

4.3 Active sensor nodes per round

The nodes are said to be active if they have energy level more than zero. The sensor nodes with energy extent zero are considered as inactive or dead sensor nodes since

Table 6 Comparison of EETPF with LEACH, EAUCF and DUCF in terms of sustainability of the network for scenario 1

Algorithms	FND	HNA	Difference	Energy consumption rate
LEACH	389	775	386	0.1342
EAUCF	451	1020	569	0.1427
DUCF	520	1146	626	0.1020
EETPF	**786**	**1447**	**661**	**0.0893**

Table 7 Comparison of EETPF with LEACH, EAUCF and DUCF in terms of sustainability of the network for scenario 2

Algorithms	FND	HNA	Difference	Energy consumption rate
LEACH	285	647	362	0.1765
EAUCF	319	683	364	0.2018
DUCF	384	857	473	0.1278
EETPF	**637**	**1257**	**620**	**0.1087**

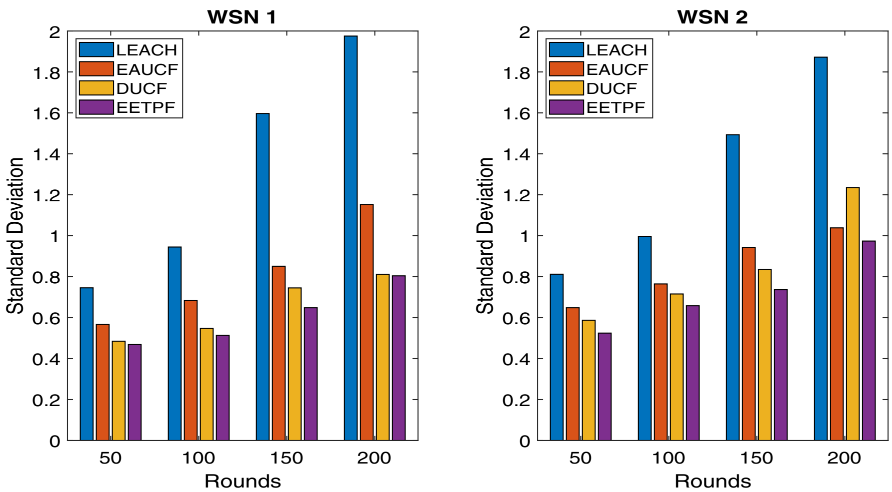
any activity cannot be performed without energy. Figure 17 denotes the total number of active sensor nodes per round for LEACH, EAUCF, DUCF and EETPF algorithms for scenario 1 and scenario 2. EETPF consumes less amount of energy than LEACH, EAUCF and DUCF. Therefore, the number of active sensor nodes at some of the rounds is higher in EETPF than LEACH, EAUCF and DUCF.

4.4 Sustainability of the network

The difference between the round at which first sensor node dies (FND), and half of the sensor nodes alive (HNA) is considered as sustainability period. Tables 6 and 7 indicate the values of rounds at which FND, HNA and its difference, i.e., sustainability period of the network for scenario 1 and scenario 2, respectively. It is observed that, in LEACH, the first sensor node dies in early stages than EAUCF, DUCF and EETPF. LEACH selects CHs with probability. Neither EAUCF nor DUCF considers the fuzzy routing in their algorithms. It is observed that EETPF has a larger difference between FND and HNA. Thus, it produces a more sustainable network than LEACH, EAUCF and DUCF.

4.5 Energy consumption rate per round

It is the ratio of total energy consumption by the sensor node to the number of rounds where the first sensor node dies from the network. Tables 6 and 7 show the energy consumption rate (Joules/Round) of sensor nodes until the first sensor node dies for scenario 1 and scenario 2, respectively. LEACH shows the highest energy



(a) For scenario 1 **(b)** For scenario 2

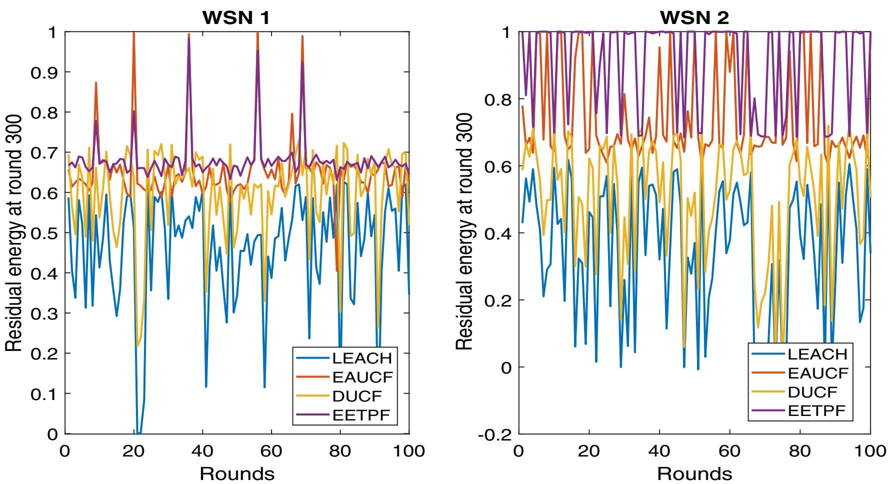
Fig. 18 Comparative study of EETPF with LEACH, EAUCF and DUCF for the parameter 'Standard deviation of the quantity of the energy consumed by the CHs per round' consumption rate. EETPF outperforms LEACH, EAUCF and DUCF because it correlates the load with respect to the transmission distance. The energy consumption rate in the case of scenario 2 is always higher than in scenario 1.

4.6 Standard deviation of the quantity of the energy consumption of the sensor nodes

The main purpose behind calculating the standard deviation of the quantity of energy consumed by the CHs is to check overall energy balancing in the network. From Fig. 18, it is observed that EETPF has least standard deviation at rounds 50, 100, 150 and 200. LEACH has highest deviation compared to other algorithms. In LEACH and EAUCF, the sensor nodes are connected to its nearest CH. This causes overload to the CH, where node density is high. Therefore, CHs from EAUCF consume a large amount of energy. In DUCF, sensor nodes are connected to the final selected CHs according to the size of the cluster. It is observed that EETPF outperforms LEACH, EAUCF and DUCF under the standard deviation of the quantity of the energy consumed by the sensor nodes per round.

4.7 Residual energy of each sensor node at round 300

We noted the residual energy of each sensor node at round 300 to observe the energy consumption of each sensor node. It is observed that, in EETPF, most of the sensor nodes carry a large quantity of residual energy than in other approaches. Figure 19 denotes the residual energy of each sensor node at round 300 for scenario 1 and scenario 2. From Fig. 19, we can see that each sensor node in the EETPF has a



(a) For scenario 1 **(b)** For scenario 2

Fig. 19 Comparative study of EETPF with LEACH, EAUCF and DUCF for the parameter ‘Residual energy of each sensor node at round 300’

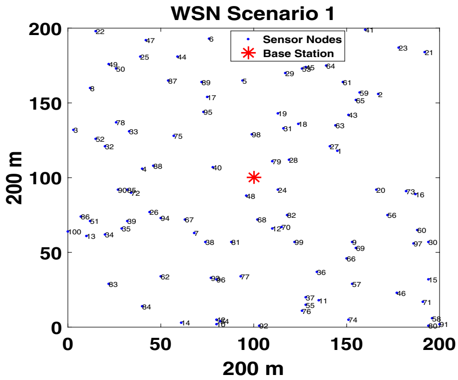


Fig. 20 Network structure of WSN1

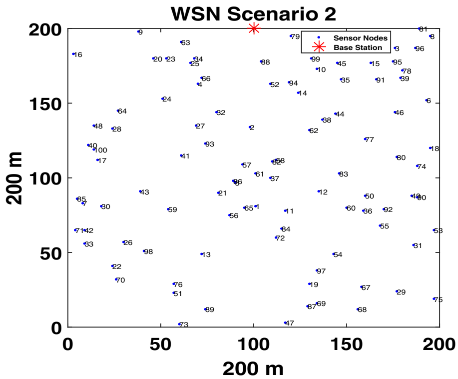


Fig. 21 Network structure of WSN2

nearly equal amount of residual energy. It is also observed that there is much fluctuation in the energy consumption of sensor nodes in LEACH, EAUCF and DUCF. In EETPF, the load of the network is distributed and balanced according to the distance between CH and BS. This guarantees a constant deviation in the energy consumption of sensor nodes.

4.8 Network structure

The network scenarios used in the experiments under the target area of $200 \times 200\ \mathrm{m}^2$ with 100 sensor nodes are shown in Figs. 20 and 21.

5 Conclusion

In this paper, the rule-based fuzzy logic is used to improve the lifetime of the WSN. Fuzzy logic is one of the computational intelligence techniques used in the various applications where the number of uncertainties is present. Here, fuzzy clustering and fuzzy routing algorithms are designed to generate an energy-efficient network.

The input variables to the fuzzy inference system are 'residual energy', 'number of nodes in range' or 'number of nodes connected after clustering' and 'distance to BS'. The output variables are 'Chance of a sensor node to be CH' or 'Chance of a CH to be a router' and 'capacity of CH or router to handle the data load'. The clusters are formed using the output values generated by the fuzzy system. Also, in the fuzzy routing phase, the routing path is formed.

The simulations are carried out according to the evaluation factors such as energy consumption, active sensor nodes per round, the sustainability of a network, energy consumption rate and standard deviation of the energy consumption. EETPF is compared with the state-of-the-art algorithms, namely LEACH, EAUCF and DUCF. It is observed that EETPF carries less amount of energy consumption rate and lasts longer. EETPF outperformed LEACH, EAUCF and DUCF under various evaluation factors.

References

1. Kai L, Rodrigues Joel JPC, Hongwei G, Naixue X, Xuedong L (2011) Energy efficiency QoS assurance routing in wireless multimedia sensor networks. IEEE Syst J 5(4):495–505
2. Iyengar SS, Wu HC, Balakrishnan N, Chang SY (2007) Biologically inspired cooperative routing for wireless mobile sensor networks. IEEE Syst J 1(1):29–37
3. Akyildiz Ian F, Weilian S, Yogesh S, Erdal C (2002) Wireless sensor networks: a survey. Comput Netw 38(4):393–422
4. Ahmed AA, Mohamed Y (2007) A survey on clustering algorithms for wireless sensor networks. Comput Commun 30(14–15):2826–2841
5. Shokouhi RA, Marzieh B, Farahnaz M, Rahmani HAA, Kumar SA (2018) Survey on clustering in heterogeneous and homogeneous wireless sensor networks. J Supercomput 74(1):277–323
6. Vinu S, Selvi M, Kumar RS (2018) An optimal cluster formation based energy efficient dynamic scheduling hybrid MAC protocol for heavy traffic load in wireless sensor networks. Comput Secur 77:277–288
7. Karim SF, Sherali Z (2016) Energy harvesting in wireless sensor networks: a comprehensive review. Renew Sustain Energy Rev 55:1041–1054
8. Halil Y, Kan CKT, Mohammed E-H, Hanzo HL (2017) A survey of network lifetime maximization techniques in wireless sensor networks. IEEE Commun Surv Tutor 19(2):828–854
9. Lipare A, Edla DR (2019) Shuffled particle swarm optimization for energy efficiency using novel fitness function in WSN. In: International Conference on Pattern Recognition and Machine Intelligence. Springer, Cham, pp 347–355
10. Lipare A, Edla DR, Cheruku R, Tripathi D (2020) GWO-GA based load balanced and energy efficient clustering approach for WSN. In Smart Trends in Computing and Communications. Springer, Singapore, pp 287–295
11. Reddy ED, Chowdary KM, Ramalingaswamy C (2019) SCE-PSO based clustering approach for load balancing of gateways in wireless sensor networks. Wireless Netw 25(3):1067–1081
12. Reddy ED, Chowdary KM, Ramalingaswamy C (2019) A PSO based routing with novel fitness function for improving lifetime of WSNs. Wireless Pers Commun 104(1):73–89
13. Reddy ED, Amruta L, Ramalingaswamy C (2018) Shuffled complex evolution approach for load balancing of gateways in wireless sensor networks. Wirel Pers Commun 98(4):3455–3476
14. Reddy ED, Amruta L, Ramalingaswamy C, Venkatanareshbabu K (2017) An efficient load balancing of gateways using improved shuffled frog leaping algorithm and novel fitness function for WSNs. IEEE Sens J 17(20):6724–6733
15. Lipare A, Edla DR (2018) Novel fitness function for sce algorithm based energy efficiency in WSN. In: 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT). Bangalore, India. IEEE, pp 1–7

16. Lipare A, Edla DR, Kuppili V (2019) Energy efficient load balancing approach for avoiding energy hole problem in WSN using Grey Wolf Optimizer with novel fitness function. Appl Soft Comput 84:105706
17. Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353
18. Hakan B, Adnan Y (2013) An energy aware fuzzy approach to unequal clustering in wireless sensor networks. Appl Soft Comput 13(4):1741–1749
19. Handy MJ, Haase M, Timmermann D (2002) Low energy adaptive clustering hierarchy with deterministic cluster-head selection. In: 4th international Workshop on Mobile and Wireless Communications Network, Stockholm, Sweden, Sweden. IEEE, pp 368–372
20. Kumar N, Kaur J (2011) Improved leach protocol for wireless sensor networks. In: 7th International Conference on Wireless Communications, Networking and Mobile Computing, Wuhan, China. IEEE, pp 1–5
21. Ossama Y, Sonia F (2004) HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. IEEE Trans Mob Comput 4:366–379
22. Kim J-M, Park S-H, Han Y-J, Chung T-M (2008) CHEF: cluster head election mechanism using fuzzy logic in wireless sensor networks. In: 10th International Conference on Advanced Communication Technology, Gangwon-Do, South Korea. IEEE, pp 654–659
23. Logambigai R, Arputharaj K (2016) Fuzzy logic based unequal clustering for wireless sensor networks. Wirel Netw 22(3):945–957
24. Baranidharan B, Santhi B (2016) DUCF: distributed load balancing unequal clustering in wireless sensor networks using fuzzy approach. Appl Soft Comput 40:495–506
25. Heinzelman Wendi B, Chandrakasan Anantha P, Hari B (2002) An application-specific protocol architecture for wireless microsensor networks. IEEE Trans Wirel Commun 1(4):660–670
26. Mamdani EH (1976) Application of fuzzy logic to approximate reasoning using linguistic synthesis. In: Proceedings of the Sixth International Symposium on Multiple-Valued Logic. IEEE Computer Society Press, pp 196–202