A Study on Multi-Hop Routing Scheme for Wireless Sensor Networks

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Abstract

Wireless sensor networks (WSN) play an important role in IoT (Internet of Things) as an interconnecting infrastructure. Working with a limited energy source, the vital challenge for WSN is to prolong the network lifetime as an important performance metric. Furthermore, the limitations of regular transmission technologies create localized network areas of a multi-hop fashion form that adds more constraints to enhance the network performance. Hence, the clustering strategies initially have solved these problems and received the attention of many studies, an approach using unequal clustering strategy has yielded some positive results since consumed energy gaps are avoided in regions near base stations. However, the routing strategy among cluster heads in multi-hop wireless networks is still a big challenge because of its inefficiency in energy consumption aspects. Therefore, in this paper, we propose a novel method that combining an unequal clustering problem and a simple multi-hop routing to prolong network life. The numerical results show that the proposed solution is more effective than other models in recent studies

Keywords: Wireless sensor network, fuzzy logic, clustering technique, routing algorithm, lifetime.

1. Introduction

The WSN act as a communication infrastructure in IoT with many applications in multiple fields like military, agriculture, smart control, etc. The WSN usually consist of a large number of small sensors to gather information or environment parameter based on single- or multi-hop wireless communication. The sensor network not only collects environmental data but also is used to control the actuators according to intelligent computational decisions. However, wireless sensor nodes often use a limited energy source like a battery (rechargeable and non-rechargeable) and thus leading to the need to save energy and prolong the life of the wireless sensor network. Therefore, one of the challenging sensor network performance issues is related to energy-saving operating mechanisms [1-4].

An effective approach to save energy consumptions of sensors in a network is clustering. Some geographically close sensors are organized into clusters and select a node to be the head of the cluster CH (Cluster Head). The information is sent from the sensors to the cluster head and from there forward to the BS (Base Station). Since the distance from sensors to CHs is limited and data is gathered at the cluster head before being transferred to the base station, the overall network lifetime is increased. From a basic energy-efficient clustering protocol called LEACH (Low Energy Clustering Hierarchy) [5], a series of variant protocols based on the principle of clustering form have been developed according to various criteria for selecting cluster heads such as probability, node residual energy, density, etc. [6]. To integrate multiple criteria with reasonable computational complexity, some fuzzy logic-based clustering algorithms have also been developed recently [7-9]. These protocols operate in both single-hop and multi-hop communication environments. For the multi-hop fashion, the appearance of energy holes nearby the base station has created new challenges for clustering solutions. In addition, the efficiency of multi-hop communication between cluster heads also poses a need to develop new algorithms to improve wireless sensor network performance.

In this paper, a novel multi-hop routing scheme is proposed. In which, the fuzzy logic-based clustering solution with a greedy routing algorithm is used to improve the lifetime of the wireless sensor network. The proposal is validated through numerical simulation in general scenarios. The results show the effectiveness of the proposed model when it comes to better load balancing and prolonging the life of the network compared to the previously researched model. The article includes the following sections: Session 2 presents the recent research on clustering and routing techniques. The proposed clustering method based on fuzzy logic and routing scheme between cluster head nodes is demonstrated in session 3. Simulation and comparison results with previous studies are given in section 4, and finally, conclusions about the research

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as well as future development directions are in the last session.

2. Related Work

In previous studies, many clustering algorithms based on the idea of LEACH protocol have been developed to improve the performance of WSN. Operating in a single-hop network, LEACH chooses randomly in the sensor nodes to elect a CH cluster head to get balance energy consumption. The detailed process of the LEACH protocol is described below.

The data communication process in wireless sensor networks based on LEACH protocol consists of two phases in a periodic time frame. This process consists of two stages: The first phase is the cluster building phase. The cluster head node is elected during an election process by voting. The cluster head node then sends a message to the member nodes informing them about the cluster head role. Member nodes send request messages to the cluster head to confirm cluster membership. The second phase is stable data communication. The sensor nodes in a cluster send data to their cluster head. The cluster head gathers data and sends it directly to the Sink node. It is easy to recognize that the CH node consumes more energy than the member nodes because it is responsible for sending all the data in its cluster. In other words, the cluster head node's energy is depleted too soon as compared to other cluster member nodes. Therefore, a random CH node selection mechanism is proposed to prolong the lifetime of the network. The algorithm is based on a simple principle, each node executes a random number process in the range *[0 1]* and takes that as its value to compare with the threshold $T(n)$. $T(n)$ probability is a function related to the probability of selecting the cluster head in the current round. The node that was selected as a cluster head in the previous round will have zero chance in the current round. The details of the LEACH algorithm are presented in [5].

Although LEACH has improved the lifetime of the network, random selection can select CH with low energy and lead to significant energy loss and energy hole formation. Hence, variants of LEACH aim to address this limitation by using more efficient parameters to select CHs such as residual energy, density, or distance to BS [10-12].

Instead of using a single parameter, some input parameters are combined to make decisions in a fuzzy method that gives positive results. These proposed models have brought a good performance and a reasonable complexity [13]. However, the above studies are conducted for single-hop wireless sensor networks, so they may not be suitable for large-scale networks.

In large-scale WSNs, multi-hop communication requires not only an appropriate clustering process but also an appropriate routing method. In [9], a routing algorithm is given based on the cluster radius of CH nodes and the cost function of transmission energy using an approximate optimization approach. This proposed scheme can prolong the lifetime of a multihop sensor network. However, it used three fuzzy inference sets to support the clustering process that makes increasing problem complexity. In fact, the complexity of clustering and routing based on fuzzy inference system (FIS) is dependent on input parameters and several rules. Some proposed multi-hop routing schemes based on FIS were focused on routing algorithm, traffic balancing, energy hole, and reliability [14-15].

In [14], it is shown that the lifetime of the network is strongly affected by the uneven distribution of cluster heads. Therefore, the authors [14] proposed a fuzzy clustering algorithm based on dynamic particle cluster optimization (PSO MF). In which, clusters are formed according to C-Means fuzzy algorithm to create stability for clusters. From these clusters, suitable cluster heads are selected through Mamdani fuzzy inference system (MFIS) through some key parameters. The input parameters of MFIS include residual energy, node degree, and distance to the Sink node. The novel method of the proposal is to use the particle swarm optimization algorithm to optimize the rules. Thus, the cluster head selection process will be adjusted according to the change predefined rules in Mamdani FIS. However, the introduction of the principle of forming clusters and the optimization algorithm also leads to an increase in computational complexity.

Based on the operating principle of the LEACH protocol, [15] highlights the limitation of the probability-based computational model. Clusters that form based on probability can lead to cluster heads being close together and subsequently reduce the energy efficiency of the network. From that perspective, the authors proposed a new protocol called LEACH-Fuzzy Clustering (LEACH-FC). This proposed LEACH-FC protocol performs cluster head selection based on fuzzy logic and cluster formation to maximize network lifetime. A cluster deputy head is proposed as a solution to increase the reliability of the cluster head selection problem. However, this is a centralized approach instead of distributed computing, so it is not suitable for wide-area wireless sensor networks.

A remarkable approach in previous studies is to use the entire fuzzy model for multi-hop communication networks presented in [9, 16]. In this study, the authors pointed out that the cause of the network exhausted energy is that the CHs near the base station is subjected to high transition loads; As a result, their energy depletes much faster than other CHs. To eliminate this phenomenon (hot spot), and unequal clustering approach based on distributed fuzzy logic and routing algorithm (DFCR) is proposed to solve this problem. After the clusters form, a fuzzy logic-based multi-hop routing algorithm is implemented for relaying the aggregate data between the cluster heads to the Sink node. Although hot spots are avoided, the number of rules of the two fuzzy models causes an increase in the problem complexity. Through these previous studies, we recognize that besides introducing an extra supported algorithm, the number of rules can bring more complexity to improve network lifetime.

Hence, to overcome these illustrated limitations, a combined scheme of a lightweight clustering problem and a simple greed routing algorithm is proposed to prolong the lifetime of the wireless sensor network. The numerical simulation results show a clear advantage of the proposal compared to recent studies.

3. The Proposed Model

3.1. Background

Fuzzy systems are an intelligent computational approach and are used to model noisy and imprecise environments. The biggest advantage of this approach is that it is compatible with the real environment with reasonable computational complexity because it is based on imitating human reasoning. This is important for many real-time applications and networks with limited resources.

Fuzzy systems allow inputs with relative values to give a smooth output function. A range of real values described by fuzzy sets is called a domain, and a membership function is defined. Each point in the fuzzy set domain will be assigned a truth value. The membership function can be one of a number of triangular, trapezoidal, Gaussian functions with domain values between *0* and *1*.

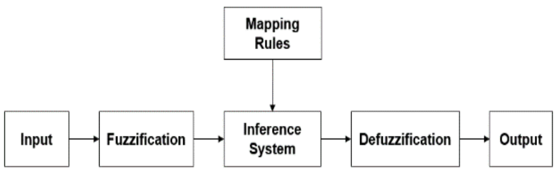

Fig. 1. A typical fuzzy inference system model

In wireless sensor networks, the problem of cluster formation and cluster head selection with input variables such as residual energy, distance, or density in a dynamic network are all uncertain factors. Therefore, the fuzzy logic approach would be advantageous to solve these problems. Proven through previous studies [8-9], fuzzy logic is suitable to solve the clustering for WSNs by calculating the choice in many different dependent parameters. Fig. 1 shows the general fuzzy inference system model. In the study, property parameters of a wireless sensor network are applied to function blocks according to the clustering goal for the sensor nodes. The main functions of the FIS model are described below.

- *Fuzzification:* The fuzzification has the effect of mapping each point of the input data to values in the range *[0, 1]* or retaining the fuzzy values at the input.
- *Mapping Rules*: Represents the relationship between input parameters and output parameters based on certain rules.
- *Inference System*: An inference system that maps input and output according to fuzzy rules.
- *Defuzzification*: The values obtained at the output will be back-mapped for correct identification.

The basic fuzzy inference system is divided into two types according to different principles: the one based on the non-additive principle called the Mamdani FIS model and the other based on the additive model called the addition rule model Takagi-Sugeno-Kang FIS. The main difference between the two FIS models is the way sharp outputs are generated from fuzzy inputs. The Mamdani FIS model uses the output fuzzy technique that has fuzzy sets in the consequent part. The TKS-FIS model uses a weighted average to calculate the output through the linear functions of the input variables [17].

A rule in the Mamdani FIS type rule base has a general form expressed by the formulation as

$$\begin{aligned} &\textit{If}\ \text{ input } x \text{ is } A1 \text{ and input } y \text{ is } B1 \\ &\textit{Then}\ \text{ output } z \text{ is } C1 \end{aligned} \tag{1}$$

A Sugeno FIS model type rule is in the form of the statement expressed by

$$\begin{aligned} &\textit{If}\ \text{ input } x \text{ is } A1 \text{ and input } y \text{ is } B1 \\ &\textit{Then}\ \text{ output } z \text{ is } z1 = p1.x + q1.y + r1 \end{aligned} \tag{2}$$

where $A1$ and $B1$ are the values of the membership functions associated with the input values x and y.

Due to the interpretable and intuitive nature of the rule base, Mamdani FIS is widely used in particular for decision support applications, artificial intelligence, and so on. Hence, this study used a Mamdani FIS to construct clusters based on several key input parameters such as residual energy and distance to the sink node. The input and output variables in the Mamdani FIS model are characterized by triangular membership functions.

The network lifetime is dependent on the energy consumption of whole sensor nodes. If the current energy of the node is less, then the sensor node becomes a dead node, resulting in broken links and decreasing network lifetime. Therefore the energy of the node should be a key factor of a network lifetime problem as a part of input parameters in the study.

In this paper, we use the energy model [9], which is calculated based on the distance $Dist_{(I,j)}$ between source and destination; free space channel f_s, and multipath channel m_p. The energy consumed when transferring data of l bits between node S_i and S_j with distance $Dist_{(I,j)}$ is determined by:

$$E_{TX} = \begin{cases} (E_{elec} + \varepsilon_{fs} Dist^2_{(i,j)}) \times l, Dist_{(i,j)} < d_0 \\ (E_{elec} + \varepsilon_{mp} Dist^4_{(i,j)}) \times l, Dist_{(i,j)} \ge d_0 \end{cases} \quad (3)$$

where, E_{elec} is the 1-bit data transmission power, ε_{fs} and ε_{mp} is the free space and multipath gain, respectively, d_0 is the calculated distance value threshold:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (4)$$

The energy received during data reception of l bits is calculated as:

$$E_r(S_i, S_j) = E_{elec} \times l \quad (5)$$

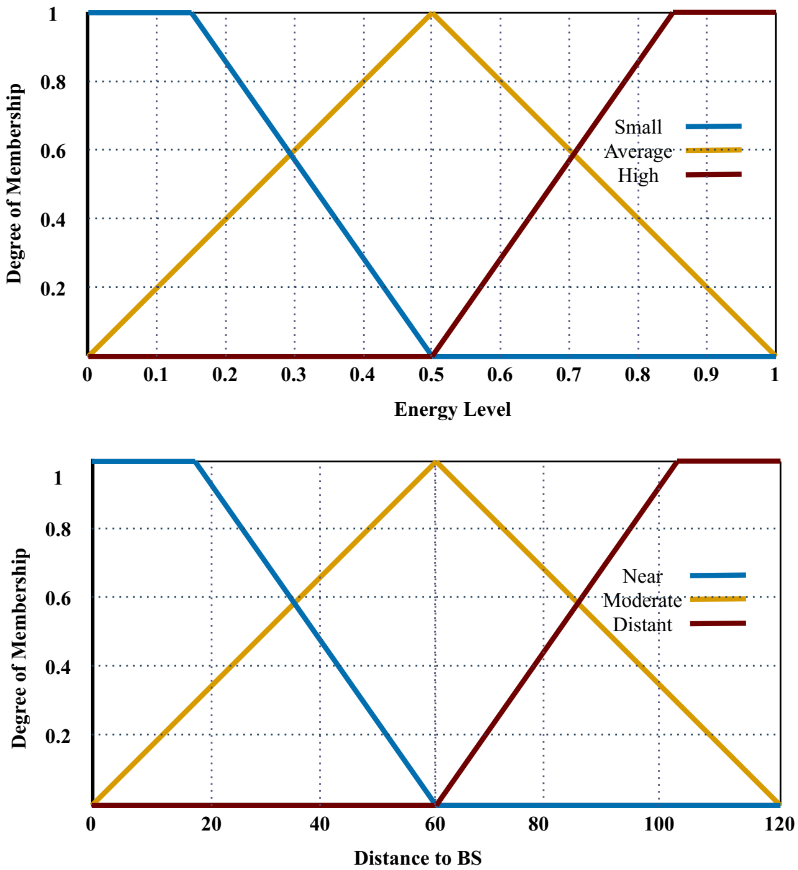

Fig. 2. Input parameters (a) Energy level; (b) Distance to the Sink node;

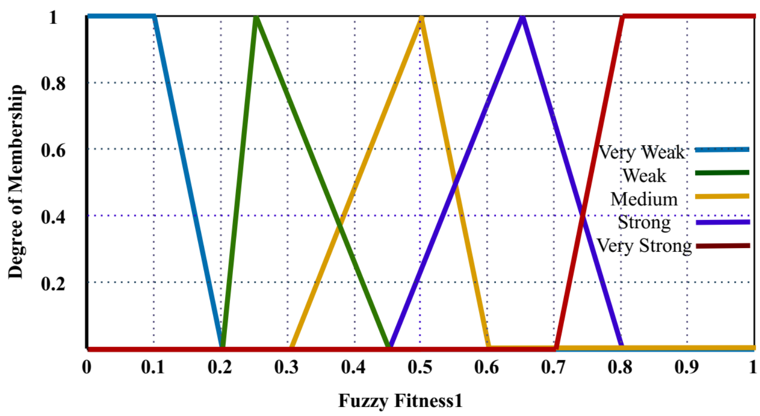

Fig. 3. Output probability of the Mamdani FIS

3.2. Clustering and Electing the Cluster Head

To cluster and elect the cluster head, this study uses two input parameters to reduce the complexity as the same previous approaches [9, 16]. In [9], to perform unequal clustering based on fuzzy logic, the nodes that are likely to be candidates for cluster master are selected through the fitness1 function. The proposed FIS model used two input parameters such as residual energy and distance to the sink node. The input variables of fitness1 are shown below

The input parameters of the fuzzy set are as follows:

- *Energy level:* The energy level of a S_i node is the ratio of the remaining energy to the initial energy. Nodes with higher energy levels will be selected as candidate nodes. Furthermore, as the energy level decreases with time, the cluster radius is adjusted to conserve its energy. The input energy script of sensor node is presented in Fig. 2(a).
- *Distance:* The path length from a S_i node to the BS root node is denoted $Dist_{BS}(S_i)$, this is to avoid the problem of having too many CH nodes located near the BS that have $Dist_{BS}(S_i)$ smaller than the cluster radius. This input distance script of sensor node to base station is presented in Fig. 2(b).

Table 1. If-then mapping rules for fuzzy fitness1

Rule	Energy level	Distance	Fuzzy fitness1
1	Small	Near	Medium
2	Small	Moderate	Weak
3	Small	Distant	Very weak
4	Average	Near	Strong
5	Average	Moderate	Medium
6	Average	Distant	Very weak
7	High	Near	Very strong
8	High	Moderate	Strong
9	High	Distant	Weak

After calculating through fitness1 as an outcome of the FIS model illustrated in Fig. 3, each S_i node will give a value that is the delay time T_d before self-select the CH node, T_d is determined by the following formula:

$$T_d(S_i) = \alpha \times (1 - Fuzzyfitness1) \times T_c \tag{6}$$

where α is a random variable in the interval *[0.9, 1]*, added to minimize the delay of the two nodes and T_c is the maximum waiting time when electing CH. When the delay time expires, it selects itself as the CH node and calculates the cluster radius. Then with the output of fitness1, we will recalculate the cluster radius based on the distributed rule of Fibonacci values. At the BS node, we extend the distance to the sensor nodes in the range of [10m 15m 20m 25m 30m]. In each hop, the CH nodes will increase the cluster radius according to the Fibonacci rule as follows:

$$\begin{cases} f(1) = 1, n = 1 \\ f(2) = 2, n = 2 \\ f(n) = f(n-1) + f(n-2), n \in [1, 6] \end{cases} \tag{7}$$

The cluster radius of the CH node in each hop is determined by the equation:

$$R_{CH} = f(n) \times \beta \tag{8}$$

where β is a random variable in the interval [1, 1.5], added to increase the accuracy of the cluster radius. After calculating the burst radius, a CH will broadcast a CH_ADVERTISE message within its cluster radius. CH_ADVERTISE contains the energy level of the CH, its location, and distance to the BS. If a node S_j receives the message, it does not elect a CH and considers it a non-CH node for that round. If a non-CH node receives a CH_ADVERTISE message from multiple CHs, it selects one of them based on cost. The cost function *CH_Cost(*S_j*,* CH_i*)* is defined as follows:

$$CH\_Cost(S_j, CH_i) = \frac{Dist(S_j, CH_i) \times Dist_{BS}(CH_i)}{Energy_{res}(CH_i)}$$

Clustering Algorithm

1. **For** each node S_i **do**
2. Compute delay *(*$T_d(S_i)$*)* using Equation 3
3. **End For**
4. **For** each node Si **do**
5. **If** ($T_d(S_i)$ == 0), ie, Delay time expires **then**
6. S_i becomes CH and calculates cluster radius using Fibonacci algorithm and broadcasts
7. CH_ADVERTISE message within-cluster radius
8. **End If**
9. **If** S_j receives the CH_ADVERTISE message from S_i **then**
10. S_j update S_i in Candidate(S_j) = [S_i]
11. **End If**
12. **End for**
13. CH of S_j is the most residual energy in Candidate(S_j)

3.3. Routing Scheme

The routing process is based on the transmission energy cost function and the CH node radius [9]. Each CH node after being clustered will be assigned the following level:

$$L(S_i) = \left\lceil \frac{Dist_{BS}(S_i)}{R_{\max}} \right\rceil \tag{9}$$

To determine the next CH nodes to the BS node, each CH S_i node will transmit a FIND message containing information about its $L(S_i)$ level and its id in the range $k \times R_{max}$ (where k is initially 2). If a lower level CH receives such a message, it returns an ACK packet containing the id, energy, and distance information to the BS. If no ACK is received within the timeout from any of the lower CH, then S_i increments to k (k = 3, 4,…, L). If the lower-level CH node does not exist, it will transmit directly to the BS, the routing process will be complete.

The Greedy algorithm uses vector concepts to construct routing strategies as illustrated in Fig. 4. At any node CHs_i, when routing to the BS node, it will open a scan angle with radius R_{max} such that vector [CHs_i, BS] is the bisector of that angle. During the scan, the CHs_i node will find the CHs_j nodes belonging to that scan angle and determine the projection length $R(S)$ of that node down the line connecting the CHs_i and the BS node. After determining all the projection lengths of the CH nodes in that angle, CHs_i will choose the CH node whose $R(S)$ is the largest to transmit data. Denote α is the scan angle, l is the scan length. Then, the network continues to be routed to the BS node until the distance from the intermediate CHs_j node to the BS is less than R_{max}.

$$R(S_j) = \max\{\cos(\alpha) \times l(S_j)\} \tag{10}$$

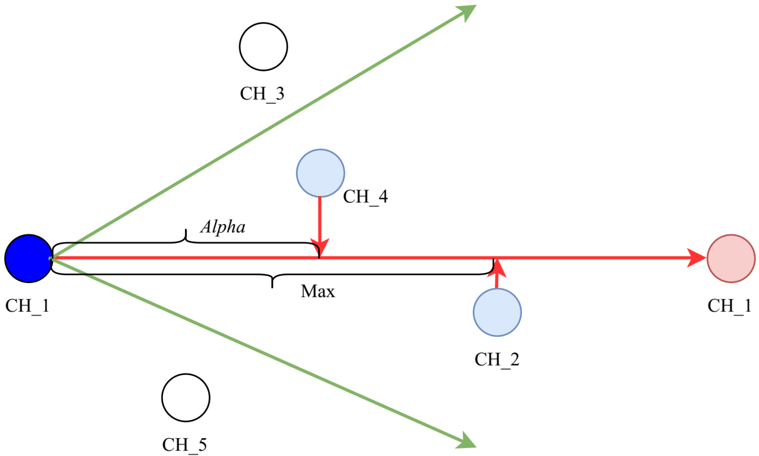

Fig. 4. Greedy routing algorithm

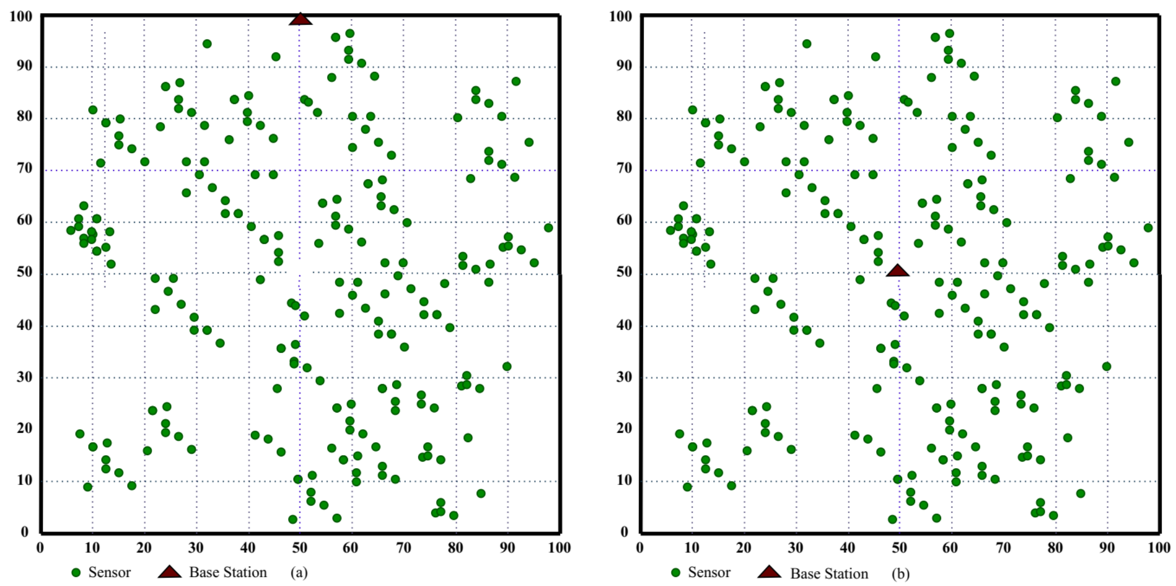

Fig. 5. (a) BS at the edge; (b) BS at the central

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Greedy routing Algorithm

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Function Greedy(R_max, angle, finish_id,start_id)
vector_to_finish_id = vector(start_id, finish_id)
Infr_path = []
While true
If length(vector_to_finish_id) ≤ R_max
update finish_id to Infr_path
break
End If
For each S_i in all nodes
vector = vector(CH, S_i)
cosine = cos(vector,vector_to_finish_id)
If(length(vector) ≤ R_max and cosine ≤ cos(angle))
R(S_i) = max(cosine*length(S_i))
End If
End For
update Si to Infr_path
Start_id = Si.id
End While
return Infr_path
End Function
```

Table 2. Parameters and values

Parameter	Symbol	Value
Network Size	A	100×100 m^2
BS location	BS	(50, 50); (50, 0)
Number of nodes	N	100
Initiation energy	$Energy_{init}$	0.5 J
Cluster radius	R_{max}	30 m
Transmission range	R_s	10 m
Packet Size	D_p	500
Free space coefficient	ε_{fs}	10 pJ/m^2/bit
Multipath delay factor	ε_{mp}	0.0013 pJ/bit/m^4
T_x and R_x signal	E_{tx} or E_{rx}	50 nJ/m^2/bit

To save energy, the routing algorithm considers the energy required to transmit messages between CH nodes. After determining the total energy consumed by the CH node, the routing will go through the cost function to determine the path to the BS node. The cost function will increase when the remaining energy of the node is low, so it must be routed to another node with higher residual energy.

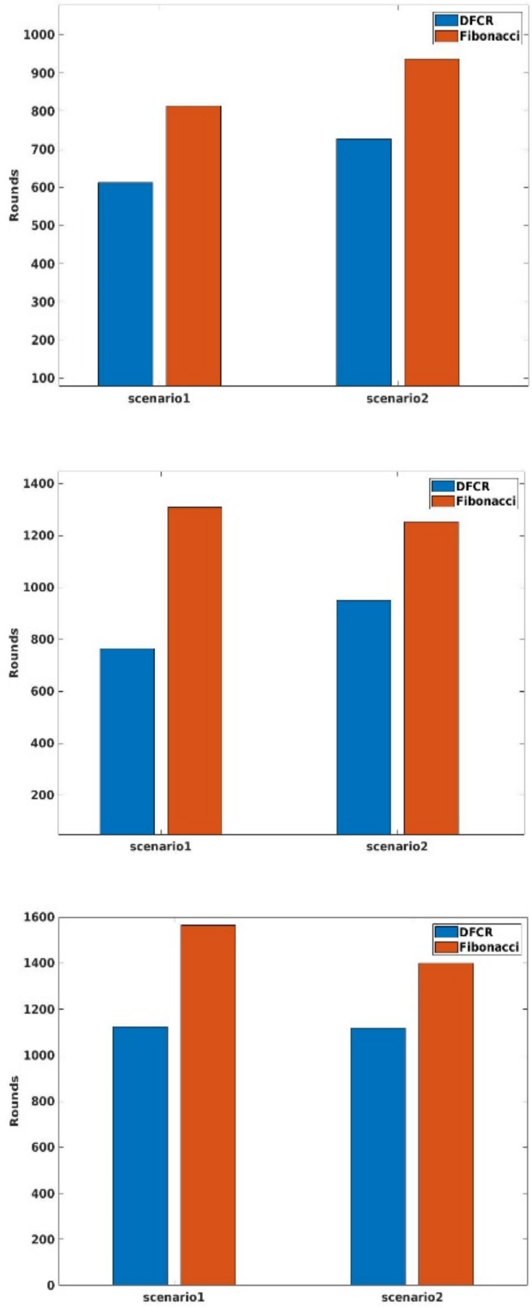

Fig. 6. Comparison of network life cycle results:

(a) Comparison of FND; (b) Comparison of HND; (c) Comparison of AND

4. Numerical Results

In this section, we conduct numerical simulations performed on MATLAB with input parameters as previously proposed [8, 9]. The BS base station is located at two locations (center and edge) as illustrated in Fig. 5, and the input parameters are presented in Table 2.

The criteria for evaluating network performance through the lifetime of the network include: the first node's energy depleted (FND : First Node Die) when

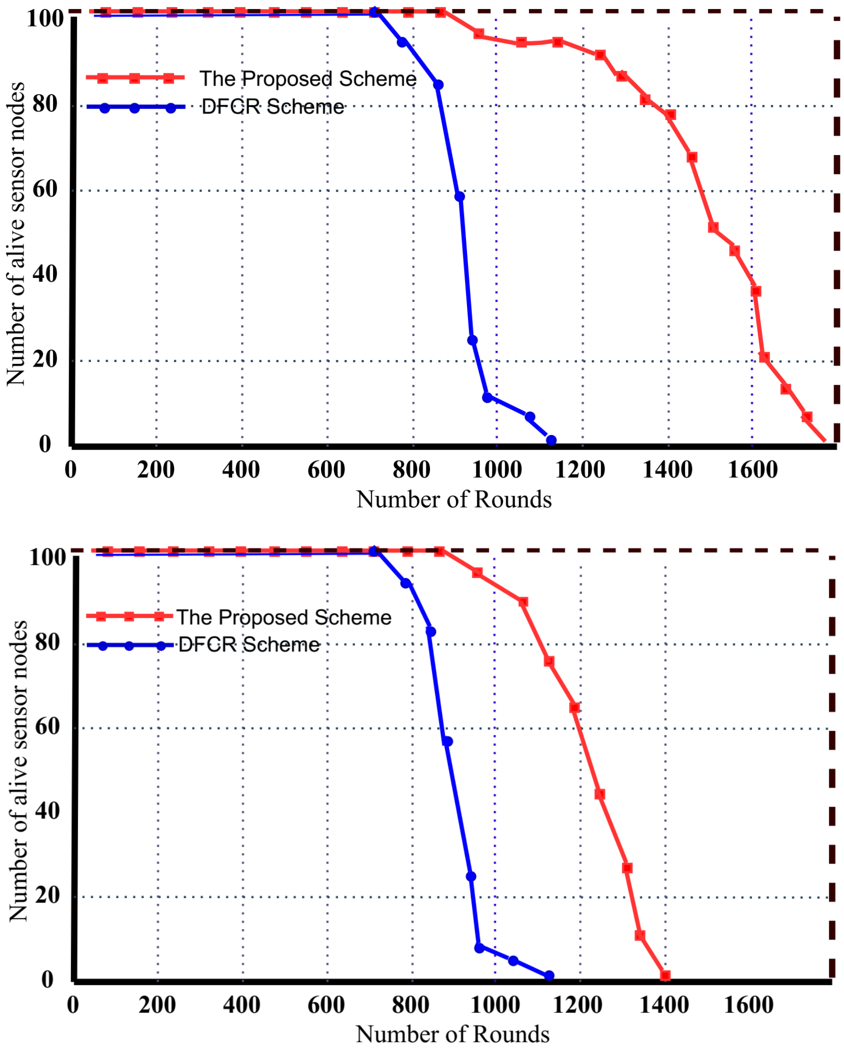

Fig. 7. Comparison of the number of alive nodes: (a) The BS is at the edge; (b) The BS node is at the center

half of all nodes are exhausted (HND: Half Node Die) and all nodes are exhausted (AND: All Node Die). The AND case will likely not occur, but we include it only to calculate the relative life of the network. A node is considered dead (out of energy) when it has no energy left to receive or transmit data. The main numerical results are presented in Fig. 6 for comparing the life of a sensor network in general cases. Fig. 7 presents two general cases with different position (a) for the base station located at the edge examples network and (b) for the center of the simulation network.

5. Conclusion

The lifetime of a multi-hop wireless sensor network has always been a practical criterion for evaluating network performance. A simple and efficient multi-hop routing scheme has been proposed in this paper, the intelligent computational approaches based on fuzzy logic provide effective solutions for the clustering process and cluster head selection. To avoid energy holes by efficient routing algorithms between cluster heads, the proposed algorithm has been proposed and proven through simulation. The validated numerical results show the ability to operate efficiently and respond well to the uncertain conditions of the multi-hop wireless sensor network. From the above initial results, cooperative calculations between cluster heads will be our next research.

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