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EEIT2-F: energy-efficient aware IT2-fuzzy based clustering protocol in wireless sensor networks

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ABSTRACT

Improving the network lifetime is still a vital challenge because most wireless sensor networks (WSNs) run in an unreached environment and offer almost impossible human access and tracking. Clustering is one of the most effective methods for ensuring that the relevant device process takes place to improve network scalability, decrease energy consumption and maintain an extended network lifetime. Many researches have been developed on the numerous effective clustering algorithms to address this problem. Such algorithms almost dominate on the cluster head (CH) selection and cluster formation; using the intelligent type1 fuzzy-logic (T1-FL) scheme. In this paper, we suggest an interval type2 FL (IT2-FL) methodology that assumes uncertain levels of a decision to be more efficient than the T1-FL model. It is the so-called energy-efficient interval type2 fuzzy (EEIT2-F) low energy adaptive clustering hierarchical (LEACH) protocol. The IT2-FL system depends on three inputs of the residual energy of each node, the node distance from the base station (sink node), and the centrality of each node. Accordingly, the simulation results show that the suggested clustering protocol outperforms the other existing proposals in terms of energy consumption and network lifetime.

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1. INTRODUCTION

Recent days have seen significant advances in the area of wireless sensor networks (WSNs). The implementations of these networks are visible in basic consumer electronic equipment and modern space technologies. However, many communication protocols were developed under the low energy adaptive clustering hierarchical (LEACH) protocol [1]–[5] to improve energy consumption efficiency in the WSN nodes. Different factors such as the network size, the position of the base station (BS), and the initial sensor node energy will influence the performance of a wireless network. When the energy from sensor nodes is retained by LEACH, its energy efficiency is still somewhat disadvantaged because of random, faster power drainage, In particular, smaller nodes per cluster are induced by the unequal distribution of nodes in clusters and time limit due to the use of the time division multiple access (TDMA) media access control (MAC) Protocol, Thereby, just one parameter, such as energy in the probabilistic model should not be assumed to elect the cluster heads (CHs). More criteria such as distance to BS, concentration, centrality, number of neighbors may be used to select the CHs. But, since there are some complexities in the relationship between the network lifetime and the other parameters of the sensor nodes, thus many researchers have suggested the use of optimization algorithms such as bat algorithm (BA), ant colony optimization (ACO), practical swarm optimization (PSO), flower pollination algorithm (FPA), and swarm intelligence [6]–[12] as an effective approach to reduce the consumed energy in WSNs and thus increase the network lifetime. Meanwhile, other researchers have also suggested using neuro-fuzzy and deep learning approaches to optimize the cluster-based routing protocol issues, some of them are: Thangaramya *et al.* [13] which introduce a new cluster formation and routing protocol based on the neuro-fuzzy rule for performing efficient routing in LEACH protocol. Also, Thakur and Sakravdia in [14], proposes an efficient method based on fuzzy deep learning for improving the reliability of energy irregularity models.

Nevertheless, numerous researchers have emphasized the concept of fuzzy logic (FL) in decision-making for CH efficiency in WSNs. These approaches are scalable, versatile, and intelligent enough to spread the load between sensor nodes and eventually improve network lifetime. Among these, recent research in [15]–[17], They suggested different cluster head (CH) selection algorithms based on type 1 fuzzy logic, each of which employs effective parameters such as Residual energy, distance to the BS, and others as an input parameter to the fuzzy inference system to decide on the best solution for choosing the suitable CHs and cluster formation. Ayati *et al.* [18] proposed a super CH election scheme using fuzzy logic in three levels Mamdani inference engine. On the contrary, interval type-2 fuzzy logic was also introduced by some researchers to assume the decision of uncertain levels to be more efficient than the T1-FL model. For example, Nayak and Vathasavai [19] proposed a clustering algorithm based on interval type-2 FL model using the remaining battery power, distance to BS, and concentration as input parameters to fuzzy inference system (FIS), the simulation results show that it provides better scalability and better network lifetime than T1-FL LEACH protocol. Several studies in [20]–[22] presented efficient CHs selection methods relying on T2-FL as a controller for decision making, compared to the traditional LEACH. Such methods can prove a good quality of services (QoS) of the network performance via improving the residual energy and the network lifetime.

To achieve the highest QoS performance, this paper presents a new approach that depends on modifying the threshold equation of the LEACH protocol taking into account the Sugeno IT2-FLC model as a powerful tool in the election of the optimal number of CHs. Such modified LEACH is so-called energy efficient based interval type2-Fuzzy LEACH (EEIT2-FLEACH). It can work in two phases, the Set-Up phase, and the Steady-state phase. The IT2-fuzzy inference system depends on three effective key parameters: i) residual energy (REN), ii) The node's distance from the base station (DBS), and iii) the node's centrality (CEN). The output represents the chance of choosing the CHs. the proposed protocol efficiently improves the network lifetime and reduces the energy consumption during its rounds.

The rest of this paper will be structured as follows. Firstly, the network and energy models are addressed in section 2. In section 3, the proposed protocol is described in detail. Section 4 displays and discusses the simulation results. Finally, in section 5, the conclusion has been drawn.

2. NETWORK AND ENERGY MODEL

2.1. Network model

The network model is assumed to be a set of sensor nodes (N) distributed uniformly around the (M X M) interested area, all nodes are stationary (nonmobile), and have the capability to sense, aggregate, and forward the data to the BS (act as a sink node). Also, they are non-rechargeable and homogeneous in terms of initial energy. It is presumed that communication links between nodes are symmetric. So that, the data rate and the energy consumption between any two nodes are symmetric in terms of packet transmission.

On the other hand, the sink node (BS) is also assumed to be nonmobile. Meanwhile, its location is assumed to be changed in three scenarios (at the center of the network field, at the upper right corner, and out of the network area) to investigate the impact of BS position on WSN performance. Moreover, in each round of the proposed protocol, the cluster heads are still selected randomly but with extra IT2-fuzzy logic criteria to improve the LEACH protocol's CH selection process.

2.2. Radio energy model

Energy consumption is an important factor in designing WSNs protocols. Sensor nodes are highly energy limited since it consumes energy for sensing data, processing, and wireless communication [23]. In particular, communication mainly causes higher energy consumption on both sides of the communications (sender and receiver). Thus, in This paper, we depend on the first-order energy dissipation model (traditional energy model of LEACH protocol) [24], [25]. However, in this model to transmit the data packet of K bits along with a distance d from the sender to the receiver, Energy consumption can be estimated using a free space channel model or a multi-path fading channel as (1):

$$E_{TX}(K,d) = \begin{cases} K * E_{elec} + K * \varepsilon_{amp} * d^4 & if\ d \geq d_0 \\ K * E_{elec} + K * \varepsilon_{fs} * d^2 & if\ d < d_0 \end{cases} \tag{1}$$

where, E_{elec} indicates the energy consumption per bit of a functioning transmitter or receiver circuitry, K denotes the data packet length, d is the distance from the transmitter to the receiver, ε_{fs} and ε_{amp} are the proportional constants of the energy consumption of the transmitting amplifier in the model of the free space channel.

$$d_0 = \left(\frac{\varepsilon_{fs}}{\varepsilon_{amp}}\right)^{1/2} \tag{2}$$

And the consumed energy to receive these bits is estimated as (3):

$$E_{RX}(K) = E_{elec} * K \tag{3}$$

3. THE PROPOSED PROTOCOL

3.1. Interval type 2-fuzzy inference system (IT2-FIS)

In general, the interval type 2 fuzzy inference system operates in five stages, as seen in Figure 1:

- Fuzzification: a fuzzifier determines the value of inputs depending on the intersection points of trapezoidal membership functions and generates fuzzy sets.
- Fuzzy rule: it consists of a compilation of 27 IF-THEN rules running in parallel order on fuzzy inputs. Since IF-THEN rules have several entries, the AND operator is applied with minimum selection to choose at least three memberships to attain the single output value.
- Aggregation: to merge multiple output values into a single fuzzy set, we used the fuzzy union operator (OR), which chooses the limit of our fuzzy rule base output to construct the fuzzy output set.
- Type-reduction: the Kuhn–Munkres (KM) algorithm is used to reduce an interval type-2 fuzzy set to an interval-valued type-1 fuzzy set before defuzzification will take place.
- Defuzzification: the defuzzified value is simply the average of the two-interval end-points produced from the type reducer.

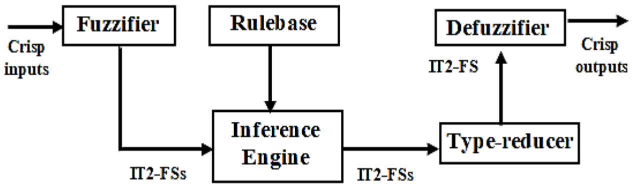


Figure 1. IT2-fuzzy inference system

To measure the chance of a node being CH, we use three fuzzy inputs and if-then fuzzy rules in our proposed process. The fuzzy inputs are defined as follows:

- REN: the nodes with high residual energy will have a high chance to be selected as CHs.
- The node's distance from the base station (DBS): the nodes close to BS will have a high chance to be selected as CHs. The Euclidean distance calculated of each node from the BS calculated as (4):

$$DBS_i = \sqrt{(X_i - X_{BS})^2 + (Y_i - Y_{BS})^2} \tag{4}$$

- 3- Centrality (CEN): The centrality of the node can be defined as the total of distances from nodes within a certain range R of the node. Thus, the range R is expressed by (5):

$$R = \sqrt{\frac{M}{\pi N\ P}} \tag{5}$$

where M is the sensor space's size, P is the Probability of CHs selection (typically, P=0.05), and N is the total number of nodes (N=100). Figure 2 explains the concept of node centrality.

$$CEN = d1 + d2 + d3 + d4 + d5 \tag{6}$$

The node with less centrality has a higher chance to be selected as CH.

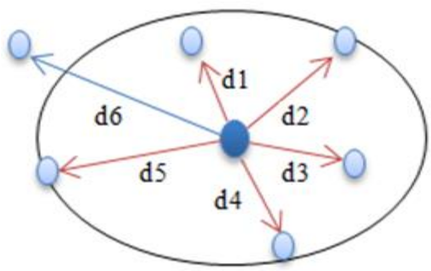
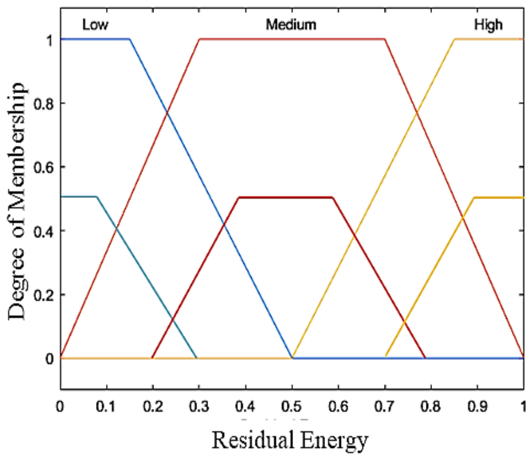
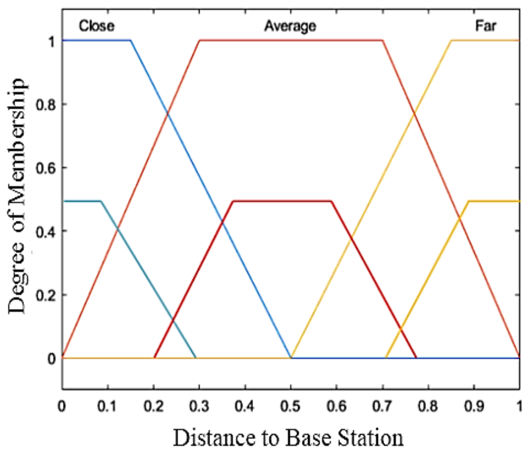


Figure 2. Node centrality

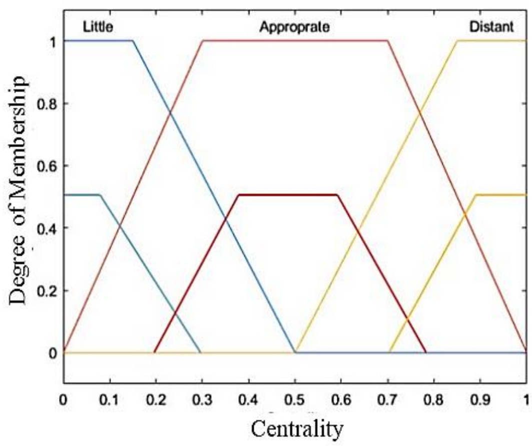
In our proposed FLC, three separated parameters (REN, DBS, and CEN) are considered as inputs for IT2-FIS to select CH's. Each parameter is normalized with the universe set to [0, 1]. Trapezoidal membership functions are defined for the input linguistic variables as shown in Figures 3(a), 3(b), and 3(c), respectively. Consequently, the linguistic variables for the input/output MFs with output MFs intervals are shown in Tables 1 and 2 as well. Meanwhile, each input parameter divides into three levels, so it requires 3^3=27 rules listed in Table 3.



(a)



(b)



(c)

Figure 3. The MFs of input variables in proposed FIS model (a) MFs of input variable REN, (b) MFs of input variable DBS, and (c) MFs of input variable CEN

Table 1. Inputs/output linguistic variables

Parameter	Linguistic variable
Residual energy (REN)	Low (Low), Medium, (Med), High (Hig)
Distance to BS (DBS)	Close (Cls), Average (Avg), Far (Far)
Centrality (CEN)	Little (Lit), Approprate (App), Distant (Dst)
Chance	Very low (VL), Low (LW), Rather Low (RL)
	Low Medium (LM), Medium (MD), High medium (HM)
	Rather high (RH), High (HG), Very high (VH)

Table 2. Intervals of output MFs

O/P MFs	Intervals
VL	0.0-0.1
LW	0.0-0.4
RL	0.2-0.4
LM	0.4-0.5
MD	0.4-0.7
HM	0.6-0.7
RH	0.7-0.8
HG	0.7-1.0
VH	0.9-1.0

Table 3. Input/output rules

No.	REN	DBS	CEN	Chance	No.	REN	DBS	CEN
1	Low	Cls	Lit	RL	15	Med	Avg	Dis
2	Low	Cls	App	LW	16	Med	Far	Lit
3	Low	Cls	Dst	VL	17	Med	Far	App
4	Low	Avg	Lit	RL	18	Med	Far	Dst
5	Low	Avg	App	LW	19	Hig	Cls	Lit
6	Low	Avg	Dst	VL	20	Hig	Cls	App
7	Low	Far	Lit	RL	21	Hig	Cls	Dst
8	Low	Far	App	LW	22	Hig	Avg	Lit
9	Low	Far	Dst	VL	23	Hig	Avg	App
10	Med	Cls	Lit	HM	24	Hig	Avg	Dst
11	Med	Cls	App	MD	25	Hig	Far	Lit
12	Med	Cls	Dst	LM	26	Hig	Far	App
13	Med	Avg	Lit	HM	27	Hig	Far	Dst
14	Med	Avg	App	MD				

3.2. Proposed IT2-fuzzy logic-based clustering protocol

EEIT2-F LEACH performs its operation at rounds based on LEACH protocol. Thereby, each round starts in two phases: set-up phase and steady-state phase.

- The set-up phase provides a selection for the CHs based on the IT2-FIS. The BS sends a request for ID, residual energy, distance to BS, and the Centrality for each sensor node in the network and waits for a response from the sensor nodes (SN). Once these values are received from the sensors, a CHs chance is calculated by the BS according to the modified threshold equation together with a fuzzy chance, which is defined as (7):

$$T(n) = \begin{cases} \frac{P}{1-P(r \bmod 1/P)} + \frac{E_S}{E_i} * P & if n \in G \\ 0 & Otherwise \end{cases} \tag{7}$$

  where P denotes the desired percentage of CHs, r represents the current round's number, n is the number of sensor nodes (SNs), G is the set of nodes that have not become CH within the last $1/p$ rounds, E_s, and E_i are the current energy of the sensor node, and Initial Energy of the sensor node respectively, and $1/P$ indicates the expected number of nodes in a cluster. As the CHs are elected, each CH sends advertisement (ADV) messages to all sensor nodes to join it. and based on the strength of the received signal (RSSI), the sensor nodes join its CH.
- In the Steady-State phase each CH makes a TDMA schedule based on the number of Cluster Members (CMs), and each SN sends its data packet within its time slot. The selected CHs gather the information from their CMs and transmits it to the BS. Algorithm 1 describes the general steps of the EEIT2-F LEACH. Thus, the General Flowchart of EEIT2-F LEACH Protocol can be obtained as in Figure 4.

Algorithm 1. The Proposed EEIT2-F LEACH

Begin:
The BS sends a request for ID, residual energy, distance to BS, centrality for each sensor node in the network and waits for a response from the sensor nodes.
Define REN, DBS, and CEN as inputs to IT2-FIS to produce a fuzzy chance.
Select CH based on the following criteria:
If (rand (0,1) < $T(n)$ & Chance >=Q) then the node is selected as a CH.
Otherwise, the node is selected as a CM.
$T(n)$ represents the threshold value of LEACH protocol which was modified by adding (E_s/E_i) to avoid the random selection of the CHs in the set-up phase and Q is the fuzzy threshold value (0.5).

$$T(n) = \begin{cases} \dfrac{P}{1 - P(r \bmod 1/P)} + \dfrac{E_s}{E_i} * P & if\, n \in G \\ 0 & Otherwise \end{cases}$$

For each CH
Sends advertisement (ADV) messages to all sensor nodes to join it.
Based on the strength of the received signal (RSSI), the sensor nodes join its CH.
Makes a TDMA schedule based on the number of CMs
CH collects the data from its CMs and sends it to the sink (BS)
End For
End

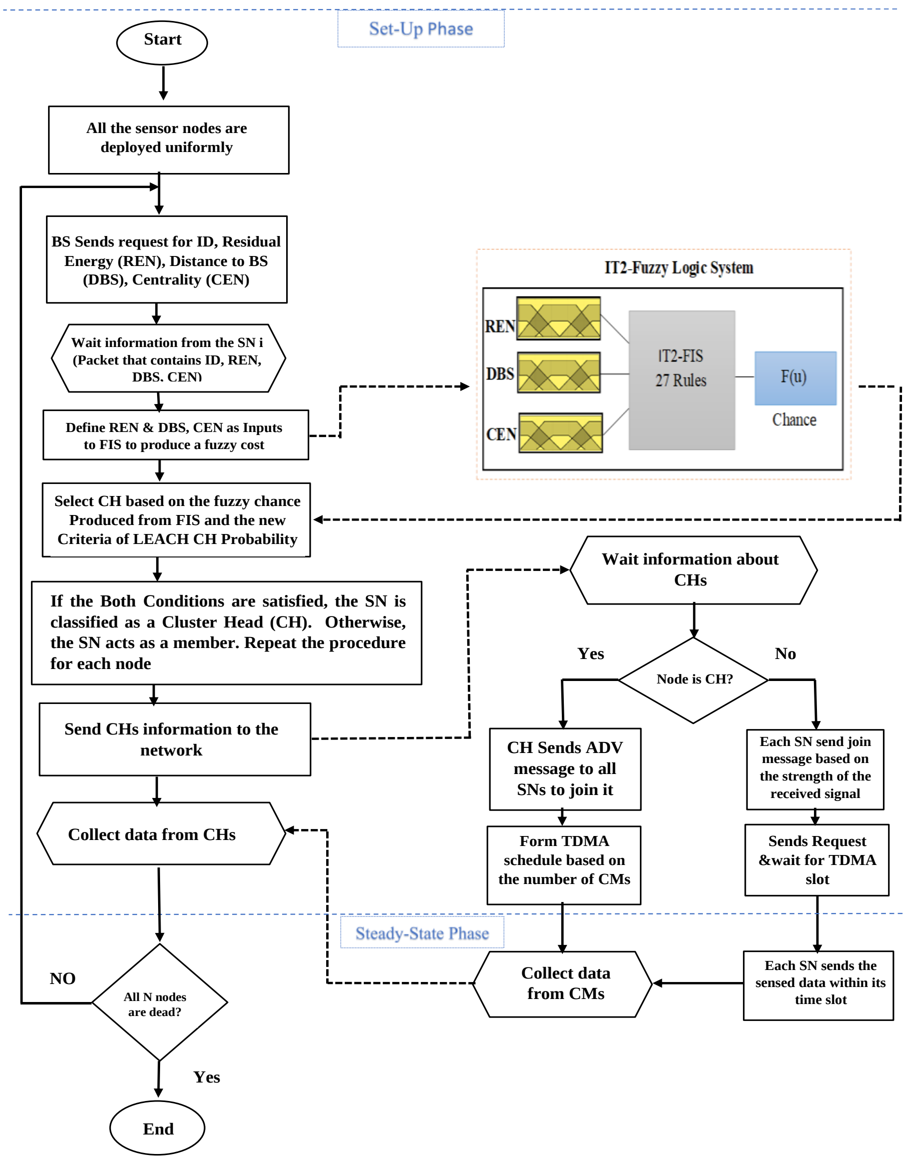


Figure 4. The general flowchart of EEIT2-FLEACH protocol

4. RESULTS AND DISCUSSION

In this section, the efficiency of our proposed EEIT2-F LEACH protocol was assessed using the MATLAB simulation tool. The proposed protocol was tested using the simulation parameters in Table 4. Moreover, the results obtained are contrasted with the traditional LEACH protocol.

Table 4. Simulation parameters

Parameters	Value	Parameters	Value
Network Size	100×100 m^2	E_{elec}	50 nJ/bit
No. of Nodes	100	ε_{amp}	0.0013 PJ/bit/m^4
Percentage of CHs	0.1	ε_{fs}	10 PJ/bit/m^2
Location of BS	50×50 m	Simulation time	3000 s
Node distribution	Random	Hello Packet Size	25 Bytes
Initial Energy	1 Joule	Data Packet Size	2000 Bytes

4.1. Experimental case I

Figure 5 shows the first node dead (FND), half nodes dead (HND), and last node dead (LND). The results reveal that the EEIT2-F LEACH protocol outperforms the LEACH in terms of FND, HND, and LND by 49.98%, 48%, and 49.8%, respectively. Now, Figure 6 illustrates the significant increase in the network lifetime after the first 20% of nodes are dead nodes up to 3073, while the LEACH Lifetime is limited to 1452.

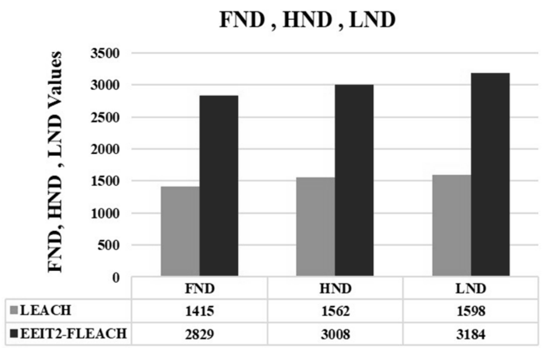


Figure 5. FND, HND, and LND of EEIT2-F LEACH

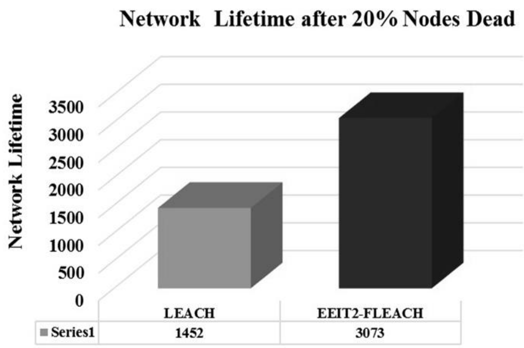


Figure 6. The lifetime of EEIT2-F LEACH

In addition, the average consumed Energy was examined in Figure 7. In LEACH protocol, the consumption becomes nearly 68.16% of the sensor energy during the first 1500 rounds; while the proposed protocol consumed just 45% of the sensor energy. Furthermore, Figure 8 also depicts the average energy of all sensors in EEIT2-F LEACH that can efficiently save 54.91% of the energy at 1500 rounds compared to energy savings of 31.9% for LEACH protocol.

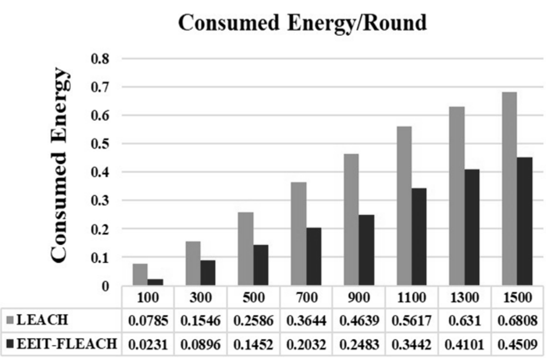


Figure 7. Consumed energy of EEIT2-F LEACH

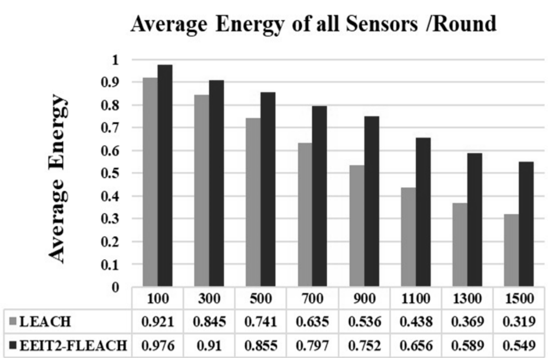


Figure 8. Average energy of EEIT2-F LEACH

4.2. Experimental case 2

This experiment represents the performance evaluation of EEIT2-F LEACH based on three scenarios. To address the effect of changing the BS location (position) on the overall network performance: scenario 1: BS at (50, 50), scenario 2: BS at (100, 100), and scenario 3: BS at (50, 175). The tests of these scenarios are performed with 100 sensors distributed uniformly over 100×100 m^2, and all of the sensors are homogeneous with initial energy equal to 0.5 Joule. The obtained results:

- Figure 9 in scenario 1. The values of FND, HND, and LND are 66.4%, 19.95%, and 12% superior to scenario 2. While it is 54.4%, 21.51%, and 16% superior to scenario 3 in terms of FND, HND, and LND respectively.
- Figure 10 displays the network lifetime of scenario 1 increased by 37%, 37.86% compared to scenarios 2 and 3.

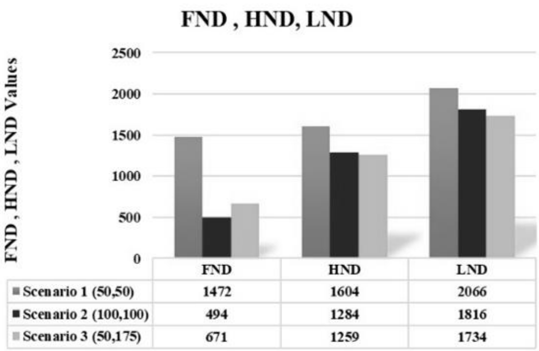


Figure 9. FND, HND, and LND in three scenarios

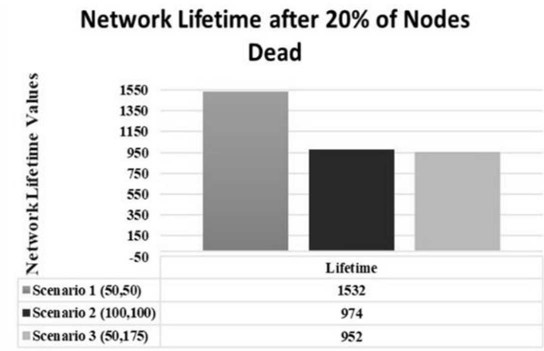


Figure 10. Network lifetime in three scenarios

5. CONCLUSION

This paper has proposed a new approach for the application of the IT2-fuzzy scheme to improve sensor node performance in WSNs and to compare them to the LEACH. Within this methodology, utilizing interval type-2 fuzzy logic supported in dealing with the uncertainties that prevailed in WSN environments. The simulation results demonstrate that the proposal efficiently minimizes energy consumption, resulting in energy savings in network nodes and an improvement in the expected network lifetime. Notice that the results of the three scenarios related to the BS location obviously show that the BS location at the center of the network area (scenario 1) has more efficient effect on the proposed protocol than the other two scenarios in terms of the network lifetime, and the corresponding FND, HND, and LND. For future improvement, the intelligent algorithms such as FPA, grey wolf optimizer (GWO), ant colony optimization (ACO), artificial bee colony (ABC) algorithms can be employed to improve the routing strategy in sensor networks.

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