Fuzzy Logic Approach to Zone-Based Stable Cluster Head Election Protocol-Enhanced for Wireless Sensor Networks

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Abstract

Energy is a scarce resource in wireless sensor networks (WSNs). A variety of clustering protocols for WSNs, such as the zone-based stable election protocol-enhanced (ZSEP-E), have been developed for energy optimization. The ZSEP-E is a heterogeneous zone-based clustering protocol that focuses on unbalanced energy consumption with parallel formation of clusters in zones and election of cluster heads (CHs). Most ZSEP-E research has assumed probabilistic election of CHs in the zones by considering the maximum residual energy of nodes. However, studies of the diverse CH election parameters are lacking. We investigated the performance of the ZSEP-E in such scenarios using a fuzzy logic approach based on three descriptors, i.e., energy, density, and the distance from the node to the base station. We proposed an efficient ZSEP-E scheme to adapt and elect CHs in zones using fuzzy variables and evaluated its performance for different energy levels in the zones.

Keywords: Wireless sensor networks, clustering, optimization, zones, cluster head, probabilistic election, fuzzy-logic, energy, density, distance.

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1. Introduction

Wireless sensor networks (WSNs) are highly distributed networks with micro-sensor nodes deployed in large numbers to handle complex data acquisition and processing functions. WSN technology has been used in a wide range of applications, such as military surveillance, environmental monitoring in disaster prone areas, monitoring remote areas, fire detection, monitoring hospital patients, nuclear reactor control, and traffic monitoring [1–5]. Three major functions performed by the sensors are environmental sensing, processing sensed data, and information exchange between neighboring nodes [6]. Energy-saving solutions for these nodes are a critical issue. Sensor nodes can be deployed deterministically or randomly and can be homogeneous or heterogeneous in nature. To monitor a sensor area for a longer period, the node energy must be used judiciously because sensors cannot be powered by external batteries. One way to prolong network lifetime is to introduce node heterogeneity in terms of link, computation, and energy. Energy heterogeneity can improve data reliability and decrease data transport latency. Clustering is a common technique to improve the efficiency of a network and allocate role assignments.

However, the clustering paradigm causes uneven energy consumption between cluster heads (CHs) and cluster members. To balance this energy expenditure, previous research has proposed a CH rotation mechanism. This technique balances energy consumption between CHs and their members but not between CHs in multi-hop communication. CHs that are close to a base station (BS) consume energy quickly due to heavy relay traffic and will exhaust their power supplies sooner than other CHs, reducing network coverage and partitioning. In WSNs, this characteristic is called the hotspot problem. To address this problem, clustering techniques to balance energy consumption between CHs have been proposed [7–13].

To reduce energy consumption and prolong network lifetime, only processed information should be delivered to the BS. Only a few nodes, i.e., the CHs, aggregate and communicate with the BS [14]. Although clustering reduces energy consumption, CHs exhaust their power supplies faster than other nodes because they perform complex functions. The low-energy adaptive clustering hierarchy (LEACH) [14] uses same amount of energy for all nodes using homogeneous nodes. The physical environment, operating conditions, and associated tasks performed by a sensor node change dynamically. Note that nodes take on specific roles or functions without manual intervention. As the network and node properties change over time, deployment and role assignments must be adapted to the changes. Several protocols have been proposed to maximize network lifetime using cluster-based network architectures and to allocate role assignments to nodes. Various hierarchical energy-aware routing protocols, such as the LEACH [14], power-efficient gathering in sensor information system (PEGASIS) [15], TEEN [16], hybrid energy-efficient distributed clustering (HEED) [17], and APTEEN [18] protocols, have been proposed to address load balancing and increase network lifetime.

In clustering techniques, clusters close to sink nodes are smaller than clusters that are more distant. Thus, CHs close to the BS can preserve some energy for communication. Nodes farther from the BS transmit packets over longer distances than nodes closer to the BS; consequently, they consume more energy [19]. Organizing WSNs into clusters enables efficient utilization of the limited energy resources of the sensor nodes. However, the problem of unbalanced energy consumption exists, and it is closely related to the role and location of a particular node in the network [20]. Although it is important to investigate algorithms and protocols that use the existing design space as efficiently as possible, it is equally important to explore new design paradigms for future sensor networks. The zone-based stable election protocol-enhanced (ZSEP-E), which has heterogeneous and homogeneous zones to create local clusters, has been proposed to reduce the energy consumption of nodes that are distant from the BS and to provide balanced energy consumption for role assignment and location [21]. The motivation behind the zone-based protocol is that, as system complexity increases, it becomes increasingly difficult to make precise statements about the behavior of the nodes in a single large area and CH election requires a long time to converge. Thus, the protocol focuses on parallelizing the entire clustering and CH election processes.

However, uncertainty in CH election must be considered. An ideal CH has high residual energy, the maximum number of neighbors (density), and the smallest distance to the BS. Simultaneous consideration of these criteria in CH selection is a very tedious task that can be solved using multiple attribute decision-making (MADM) approaches. A number of MADM approaches that select alternatives quantitatively based on multiple attributes/criteria have been proposed [22–25]. In a real-time problem, estimation of exact values for all three criteria is difficult. Fuzzy-based approaches [26–28] are effective and efficient in such cases. In this study, we attempted to employ a fuzzy-based approach for CH election in the ZSEP-E to increase the lifetime of WSNs. The proposed approach is called the fuzzy logic zone-based stable CH election protocol-enhanced (FLZSEP-E).

The remainder of this paper is organized as follows. Section 2 briefly describes related work. We present an overview of the existing ZSEP-E, including the network model and specifications, and the problems associated with probabilistic selection clustering algorithms in Section 3. The proposed FLZSEP-E method for WSNs is described in Section 4. The results are discussed in Section 5, and the conclusions and suggestions for future work are provided in Section 6.

2. Related Work

To prolong the lifetime of WSNs, proposed routing protocols can be categorized as location-based, QoS-based, flat-based, and hierarchical [29]. Location-based protocols, such as greedy anti-void routing [30], minimum energy communication networks [31], and geographical energy-aware routing protocols [32], use node position information to forward data. QoS-based routing protocols, such as the sequential assignment routing protocol [33], stateless protocol for real-time communication in sensor networks [34], and energy-aware routing [35] protocols, use metrics (e.g., energy, delay, and bandwidth) to balance energy consumption and data quality. Flat-based protocols, such as negotiation [36], directed diffusion [37], and rumor routing [38], use a flood-based transferring scheme to route data. Hierarchical protocols cluster nodes in an initial phase and transmit data transmission in a second phase. The LEACH-C, LEACH-M, and LEACH-V protocols [14,19] cluster nodes based on received signal strength and elect CHs probabilistically over time.

The TEEN protocol [16], which employs a user-friendly physical parameter, was proposed by Manjeshwar and Agarwal for mission-critical applications. The PEGASIS method [15] is an improved version of the LEACH protocol discussed by Lindsey and Raghavendra that uses chains of sensor nodes to transmit data to CHs. However, it is unsuitable for large networks due to excessive delay. Smaragdakis et al. proposed a stable election protocol [39] that uses hierarchical clustering and two-tier heterogeneity nodes. A node becomes a CH based on the weighted election probabilities of each node. A distributed energy-efficient clustering [40] protocol was proposed by Li et al. for multi-level heterogeneous WSNs. Nodes with high initial and residual energies are selected as CHs. Nodes close to the BS require more energy than those farther from the BS due to the extra burden of nodes within the neighborhood of the BS. Thus, smaller clusters are formed using closer nodes to balance the load among CHs in different regions and vice versa.

The HEED protocol [17] proposed by Younis and Fahmy selects CHs based on node degree and residual energy. The node degree helps balance the load among CHs. In this method, in addition to supporting data aggregation, clusters are formed in all iterations, achieve fairly uniform CH distribution across the network, and prolong network lifetime. The HEED protocol has low overhead in terms of processing cycles and message exchange. It does not assume any distribution of nodes or location awareness. A variant of the HEED protocol, called the integrated HEED method [41], has integrated data aggregation in multi-hop routing by considering data aggregation operators. Another variant of the HEED protocol proposed by Huang and Wu [42] considers a constant-time clustering mechanism. The nodes with high energies participate in CH election, and the remaining nodes are eliminated. This variant of the HEED technique requires fewer rounds to select CHs. Khedo and Subramanian also proposed a variant of the HEED protocol called the MiSense hierarchical cluster-based routing algorithm [43], which maintains balanced node energy consumption to increase network lifetime. The authors have proposed stable CH election by partitioning the entire network into zones with localized CH election [15]. However, other parameters that are vital for performance were not considered for CH election. Faisal et al. proposed the zone-stable election protocol (Z-SEP). In the Z-SEP, the network is partitioned into zones, and some nodes transmit data directly to the BS while others use a clustering technique [50]. The authors proposed a zone-based routing protocol for edge-based WSNs to avoid the hotspot problem using an unequal clustering mechanism [51].

Gupta et al. [44] proposed fuzzy logic-based CH election by considering three input variables, i.e., energy, concentration, and centrality. Here, the BS chooses a CH by evaluating the node status information, such as the node's location and remaining energy. This centralized CH election approach results in high energy inefficiency due to overhead and control communication. It also imposes heavy load on the BS. The CH election mechanism using fuzzy logic in WSNs (CHEF) [45] protocol proposed by Kim et al. increases WSN lifetime using localized CH election through fuzzy logic. Even though the CHEF protocol avoids electing CHs that are close to each other, CH election remains probabilistic. Lee [46] proposed a fuzzy logic-based clustering protocol with parameters based on the residual energies and expected residual energies (EREs) of nodes that elects a node with higher chance value as the CH. Here, another parameter, i.e., expected energy consumption, is required to derive the ERE in each round. Rogaia et al. proposed an energy-efficient fuzzy logic cluster formation protocol in WSNs for cluster formation that uses the energy level of the CH, the distance between the CH and the node, and the distance to the BS as parameters [47]. Here, a non-CH node computes the chance value for a CH using Mamdani's fuzzy inference system (FIS) [48] on the above three descriptors. Yadav and Saxeena [52] proposed appropriate CH selection for the LEACH protocol based on fuzzy logic that considers energy level, distance from the CH, and density into consideration.

Krishnan and Kumar [54] proposed a heterogeneity-aware protocol to elect CHs based on assigned weights that provide information about previously elected CHs. However, this method requires additional energy to share the information among the candidate nodes. Rana et al. [55] proposed a clustering mechanism that implements two fuzzy logic levels. In the first level, CHs are elected based on energy and the distance between the nodes. In the second level, CH leaders are elected based on the energy level of the CH and its distance to the BS. This mechanism has more computational load and complexity in a fuzzy inference system (FIS).

Nayak and Anurag [56] proposed a protocol to select a new super CH (SCH) among all of the CHs using fuzzy logic by considering the remaining energy of each CH, the mobility of the BS, and the centrality of all of the other CHs. Here, CHs that are closer to the BS will communicate using the SCH, which increases communication overhead. In addition, there is no guarantee that the elected SCH will follow the optimal path to the BS.

The ZSEP-E [21] deterministically partitions the network into zones and probabilistically elects CHs in the zones based on the maximum residual energy. A fuzzy logic approach was used in this study to apply and evaluate diverse parameters for CH election in the zones. Three different parameters, i.e., node energy level, node density, and distance to the BS, were considered to improve the ZSEP-E. Herein, the FLZSEP-E is proposed to increase WSN lifetime by minimizing total energy consumption with limited control overhead on sensor nodes.

3. Overview of ZSEP-E

The performance and lifetime of a WSN are highly influenced by the clustering scheme. However, the efficiency of the network is drastically affected by the early death of the sensor nodes farthest from the BS. Also in clustering, unbalanced energy consumption at the nodes due to role assignments and location affects network lifetime. The ZSEP-E protocol has heterogeneous and homogeneous zones that are created using the dimensions of the field to parallelize the formation of clusters and the election of suitable CHs in the zones [21]. Partitioning the network into zones improves the coverage and connectivity of cluster nodes that are distant from the BS.

3.1 Network Model and Specifications

Some assumptions were made about the underlying network model of area $A = X \times Y$ square meters. Here, $X = a$, $Y = b_1 + b_2 + b_3$, where $b_1 = b_3$ and $b_1 + b_2 + b_3 = a$, and the sensor nodes are deployed as shown in **Fig. 1**. A zone partition algorithm was used to partition A into three zones. Each zone was considered separately as a geographical division of the sensing field. Appropriate energy-level sensor nodes were deployed depending on the distance and orientation from the BS. m proportion of the total number of nodes n were equipped with α times more energy than the normal nodes. Such nodes are referred to as advanced nodes. q proportion of the total number of nodes n were equipped with μ times more energy than the normal nodes. These nodes are referred to as intermediate nodes. The zone partition algorithm is as follows.

1) Zone 1 = $a \times b_1$, lying between $0 \leq Y \leq Y_1$, deployed with $n \times m \div 2$ static homogenous energy-rich advanced nodes, where $Y_1 = a \times m \div 2$.
2) Zone 2 = $a \times b_2$, lying between $Y_1 < Y \leq Y_2$, deployed with q static intermediate nodes and $(1 - m - q) \times n$ normal nodes, where $Y_2 = a - Y_1$.
3) Zone 3 = $a \times b_3$, lying between $Y_2 < Y \leq Y_3$, deployed with $n \times m \div 2$ static homogenous energy-rich advanced nodes where $Y_3 = a$.

The following assumptions were made [21].

(1) In Zones 1 and 3, all sensor nodes are homogeneous with the same capabilities.

(2) In Zone 2, sensor nodes are heterogeneous with different capabilities.

(3) Nodes are not equipped with global positioning systems and are location-unaware.

(4) Every node can change its transmission power level depending on the distance to the receiver.

(5) The network has continuous data to send.

(6) The links are symmetric. Based on received signal strength indication, any node can compute the approximate distance to another node for a given transmission power.
(7) Connectivity-interference assumption: interference always comes from connectivity and connectivity always leads to interference.
The interference-connectivity assumption was first addressed in [53]. We observe that this assumption is usually violated in the case of strong links, i.e., when the transmitter is close to the receiver and has a very strong signal that dominates the interfering signal. In a zone-based environment, dense clusters with strong links exist, and the strong signal dominates the interfering signal.

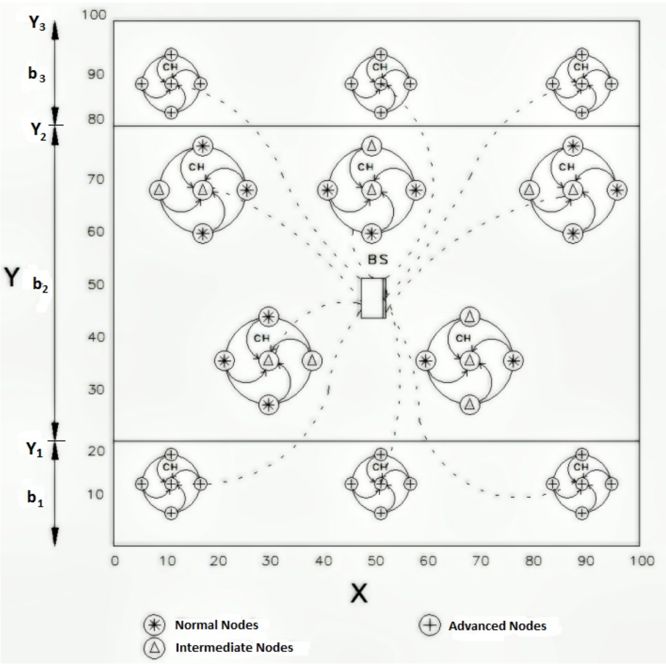

Fig. 1. Zonal heterogeneous settings

3.2 Problems in Probabilistic Selection of Cluster Heads and Motivation

There are some problems associated with probabilistic selection clustering algorithms [14–21]. A priori probability assigned to each sensor node is used to determine the initial CHs, and they often serve as the primary criterion for the nodes to determine their election as CHs individually. However, other secondary criteria may also be considered for CH selection, which is a tedious process. Fuzzy-based approaches are effective and efficient for the estimation of the exact values of all criteria [26–28].

4. Proposed Fuzzy Logic Approach to Zone-Based Stable Cluster Head Election Protocol-Enhanced for Wireless Sensor Networks

In this paper, we discuss a previously proposed network organization scheme [21] that can be used to partition a network, to organize sensor nodes into clusters, and to provide identities for sensor nodes. It is assumed that the BS in the network is equipped with a directional antenna with power control capability. The directional antenna provides a location identity to every sensor node in the network by varying its transmission power level in different directions. Using these identities, the sensor nodes are organized into hierarchical clusters, with the exception of the nodes in Zone 2. This arrangement avoids relay traffic burden on the Zone 2 CH, and the nodes in this zone communicate directly with the BS.

The proposed clustering method follows the basic principle of the ZSEP-E, and fuzzy logic is used to optimize the metrics used to select the CH as it combines and evaluates diverse parameters efficiently. The protocol operates in rounds, and each round begins with a cluster set-up phase and steady-state phase. Clusters are formed in the cluster set-up phase, and data transmission from the CH to the BS occurs in the steady-state phase. To form clusters and select a CH, we use a fuzzy logic-based approach with three fuzzy descriptors, i.e., node energy (e), node density (ds), and the node's distance to the BS (dt). The fuzzy descriptors are used to calculate the chance of a node becoming a CH that can transmit the message to the BS.

In the cluster steady-state phase, the CH employs a time-division, multiple-access time slot to each of the sensor nodes in the cluster. The CH uses equal time intervals for each of the sensor nodes and informs the time schedule to a sensor node by transmitting a HELLO message that contains the ID of the sensor node in order of the time schedule, the start time of the time slot, and the time interval. The first sensor node begins to transmit the data in the initial start time within the time interval, and all of the other nodes begin their transmission subsequently. The CH adopts local data fusion to compress the data being sent from the clusters to the BS. The CH sends the data to the BS using a fixed spreading code and carrier-sense, multiple-access approach.

4.1 Fuzzy Model

The proposed method prolongs network lifetime by improving the ZSEP-E based on an FIS [14] by mapping the given inputs to outputs using fuzzy logic. The FIS architecture consists of a fuzzification module, a knowledge base, an inference engine, and a defuzzification module **(Fig. 2),** which are described as follows.

1. Fuzzification module: The system inputs, which are crisp values, are transformed into fuzzy sets. A truth value or degree of membership for each fuzzy set is assigned.

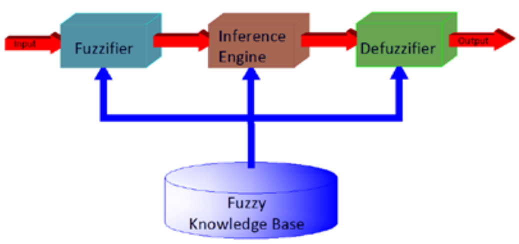

Fig. 2. FIS architecture

2. Knowledge base: The fuzzy rules are the IF-THEN rules stored in a fuzzy rule base referred to as the knowledge base.
3. Inference engine: A human inference system is simulated by performing fuzzy inference on the inputs and IF-THEN rules.
4. Defuzzification module: The defuzzification module transforms the fuzzy set obtained by the inference engine into a crisp output value. The defuzzifier calculates the centroid and uses it to calculate the probability.

The objective of our fuzzy logic-based system is to determine and select an optimized CH using the defined inputs. We use Mamdani's method [41] for the inference process in the proposed model. The method allows the system to be described in a simple mathematical manner using inference techniques and fuzzy logic design.

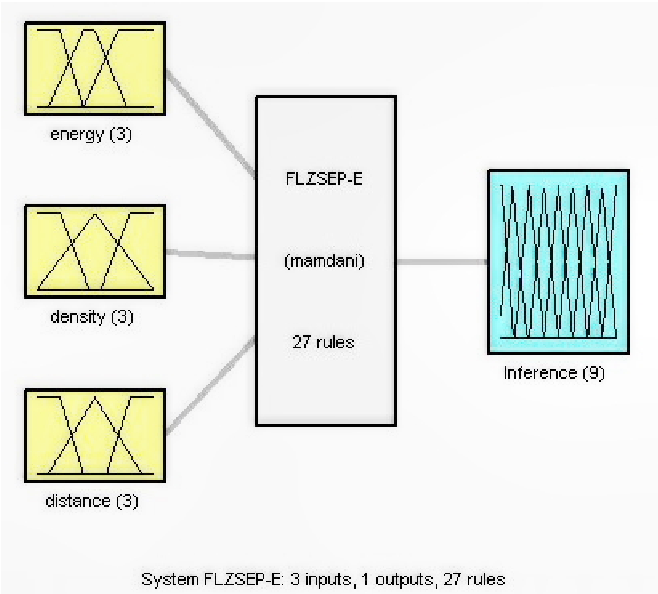

Fig. 3. FLZSEP-E system architecture

The input fuzzy variables considered are energy level, distance to the CH, and density. The output fuzzy variable, i.e., inference, is the defuzzified value, which determines the chance of a node to be elected as an efficient CH. The architecture of the FLZSEP-E model is shown in **Fig. 3**, which consists of three parts: fuzzification functions, an inference engine with 27 rules, and a defuzzification module.

4.1.1 Fuzzification Module

Our fuzzy system has three input parameters, i.e., node energy level, distance between the node and the BS, and node density. Each of these input variables has three membership functions , i.e, energy has low, medium, and high ; distance has close, medium, and far ; density has scattered, medium, and crowded. **Table 1** shows the membership functions of the input variables and their degrees.

Table 1. Membership functions for input variables

Input Variable	Membership Function		
Energy level(e)	low(0)	medium(0.5)	high(1)
Distance (dt)	close(0)	medium(0.5)	far(1)
Density(ds)	scattered(0)	medium(0.5)	crowded(1)

The input variables are defined as follows.

- Energy: residual energy of the node
- Density: number of nodes in its neighborhood
- Distance: distance between the node and the BS

Table 2. Membership functions for output variables

Membership Function	Inference
Very weak	0
Weak	0.5
Little Weak	1
Lower Medium	1.5
Medium	2
Higher Medium	2.5
Little Strong	3
Strong	3.5
Very Strong	4

A precise output function containing nine membership functions is given in Table 2. Fuzzy inference is the process of formulating a mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made or patterns can be discerned. The process of fuzzy inference involves all of the pieces described in the membership functions, logical operations, and IF-THEN rules. Table 3 shows the FIS IF-THEN rules of the proposed system. In the fuzzy rules, triangular and trapezoidal membership functions are used for the variables to simplify the computations.

Table 3. Fuzzy inference system IF-THEN rules

Energy Level (e)	Density(ds)	Distance (dt)	Inference
0	0	1	0
0	0	0.5	0.5
0	0	0	1
0	0.5	1	0.5
0	0.5	0.5	1
0	0.5	0	1.5
0	1	1	1
0	1	0.5	1.5
0	1	0	2
0.5	0	1	1
0.5	0	0.5	1.5
0.5	0	0	2
0.5	0.5	1	1.5
0.5	0.5	0.5	2
0.5	0.5	0	2.5
0.5	1	1	2
0.5	1	0.5	2.5
0.5	1	0	3
1	0	1	2
1	0	0.5	2.5
1	0	0	3
1	0.5	1	2.5
1	0.5	0.5	3
1	0.5	0	3.5
1	1	1	3
1	1	0.5	3.5
1	1	0	4

The most commonly used fuzzy inference technique is the Mamdani method. A fuzzy rule base drives the inference system to produce fuzzy outputs. The defuzzification of the fuzzy outputs gives the system outputs. The fuzzification functions for energy, distance, density of the nodes, and inference are shown in **Figs. 4(a), 4(b), 4(c),** and **4(d),** respectively.

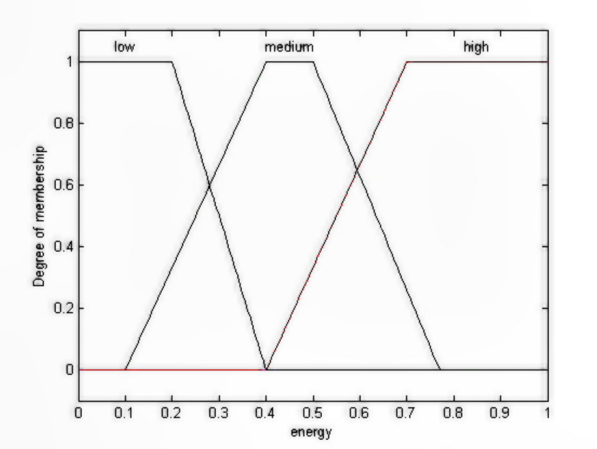

Fig. 4(a). Energy fuzzification function

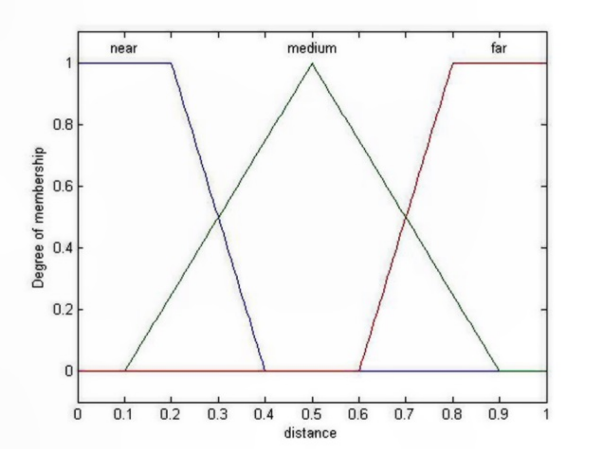

Fig. 4(b). Distance fuzzification function

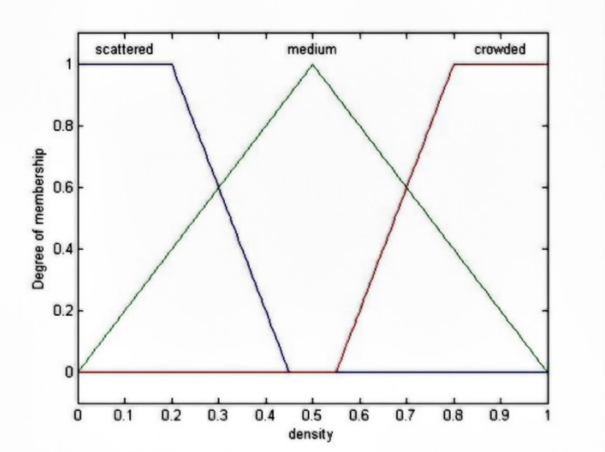

Fig. 4(c). Density fuzzification function

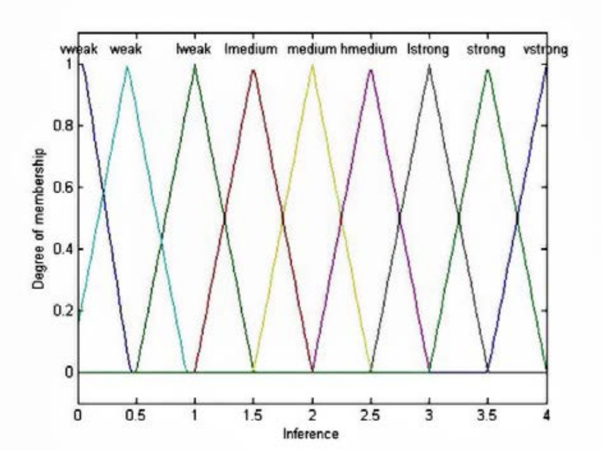

Fig. 4(d). Degree of membership vs inference

To obtain both endpoints of the interval, linear interpolation is used in the trapezoidal function, including the triangular membership function (a particular case of the trapezoidal membership function). It works well in all applications and is widely used in fuzzy systems [49]. The trapezoidal membership function represents a very weak inference, and triangle membership functions represent all other inferences, as shown in **Fig. 4(d).**

The membership function for the trapezoidal fuzzy number for fuzzy set $A_1 = \{a_1, b_1, c_1, d_1\}$ where $a_1 < b_1 < c_1 < d_1$ is given by

$$\mu_{A_1}(x) = \begin{cases} \frac{x-a_1}{b_1-a_1} & if\ a_1 \le x \le b_1 \\ 1 & if\ b_1 \le x \le c_1 \\ \frac{d_1-x}{d_1-c_1} & if\ c_1 \le x \le d_1 \\ 0 & otherwise \end{cases} . \tag{1}$$

The membership function for the triangular fuzzy number for fuzzy set $A_2 = \{a_2, b_2, c_2\}$ where $a_2 < b_2 < c_2 < d_2$ is given by

$$\mu_{A_2}(x) = \begin{cases} \frac{x-a_2}{b_2-a_2} & if\ a_2 \le x \le b_2 \\ \frac{c_2-x}{c_2-b_2} & if\ b_2 \le x \le c_2 \\ 0 & otherwise \end{cases} . \tag{2}$$

4.1.2 Knowledge Base

The fuzzy inference consists of 27 rules of the form IF premise, THEN consequence, where the premise is a set of fuzzy input variables joined by the logical AND function. The maximum values of the parameters can be computed using

$$Inference = 2e + ds + 1 - dt \, . \tag{3}$$

Here, e is the energy of the node, ds is the density, and dt is the distance from the node to the BS. The rules fall in the range 0 to 4, where 0 is a very weak inference and 4 is a very strong inference.

Very weak inference (0): IF (energy level is low) and (distance to the BS is far) and (density of nodes is scattered) THEN (inference is very weak).
Very strong inference (4): IF (energy level is high) and (distance to the BS is close) and (density of nodes is crowded) THEN (inference is very strong).

4.1.3 Defuzzification Module

The conclusions from each rule are aggregated, and the centroid defuzzification method is used to transform the fuzzy variable into a crisp value output. The center-of-area method, which finds the centroid *Z** of the area under the respective membership function, is given by

$$Z^* = \frac{\int \mu_Z(x) * x dx}{\int \mu_Z(x) dx}. \quad (4)$$

Here, $\mu_Z(x)$ is the degree of the membership function for the fuzzy set *A* defined by Eqs. (1) and (2).

5. Results and Discussion

The simulations were performed with MATLAB. The expectation of a node to be elected as a CH depends on the different attributes of the nodes, as shown in **Fig. 5.**

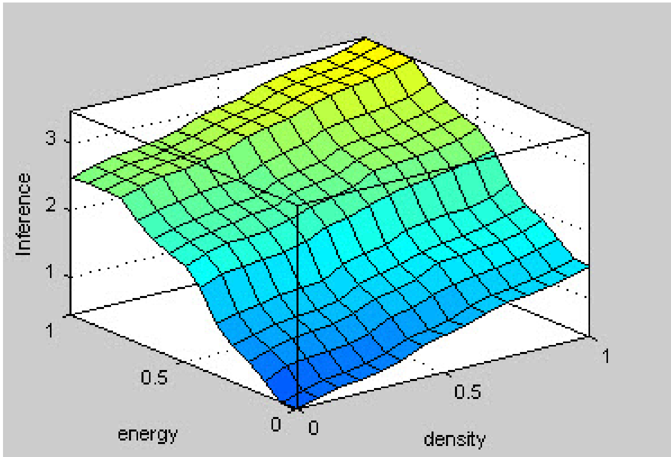

Fig. 5(a). Surface view: inference vs. energy and density

The chance that a node will be elected as a CH increases with increased node energy and density, as shown in **Fig. 5(a).** Increase in the distance from a node to the BS decreases the expectation of a node to be elected as a CH. In addition, with increased density, less distance between the BS and the node with low energy level has a lower chance to be elected as a CH, as shown in **Figs. 5(b)** and **5(c).**

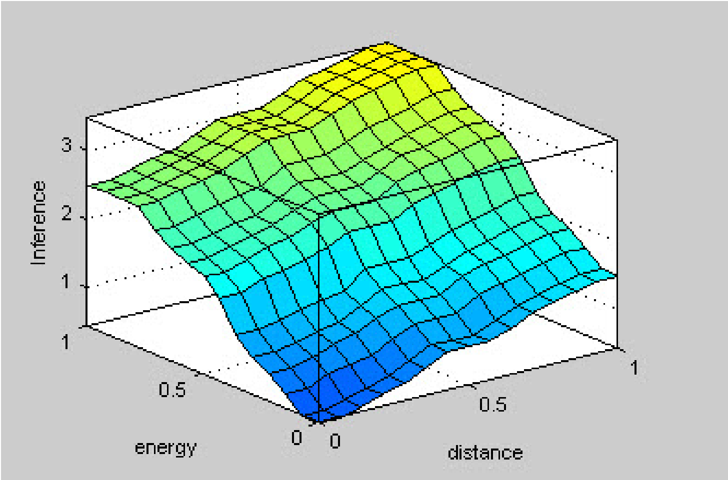

Fig. 5(b). Surface view: inference vs. energy and distance

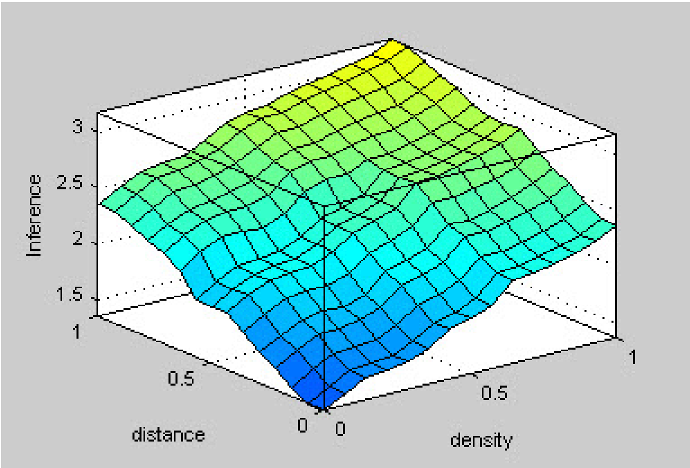

Fig. 5(c). Surface view: inference vs. distance and density

We simulated a square clustered WSN with dimensions 100 m × 100 m and partitioned the field into three rectangular zones as in ZSEP-E using MATLAB. The total population (n) of the sensors deployed randomly in all the zones was 100. Advanced nodes with α times more energy than normal nodes were deployed in Zones 1 and 3 equally. In Zone 2, intermediate nodes with μ times more energy than the normal nodes were distributed along with normal nodes. The total population (n) of the sensors deployed randomly in all zones was 100, of which 20% were advanced nodes, i.e., $m = 0.2$. Thus, the zone dimensions will be Zone 1 lying between $0 < Y_1 \leq 10$ with area 100 m × 10 m , Zone 2 lying between $10 < Y_2 \leq 90$ with area 100 m × 80 m, and Zone 3 lying between $90 < Y_3 \leq 100$ with area 100 m × 10 m, as shown in **Fig. 6(a).**

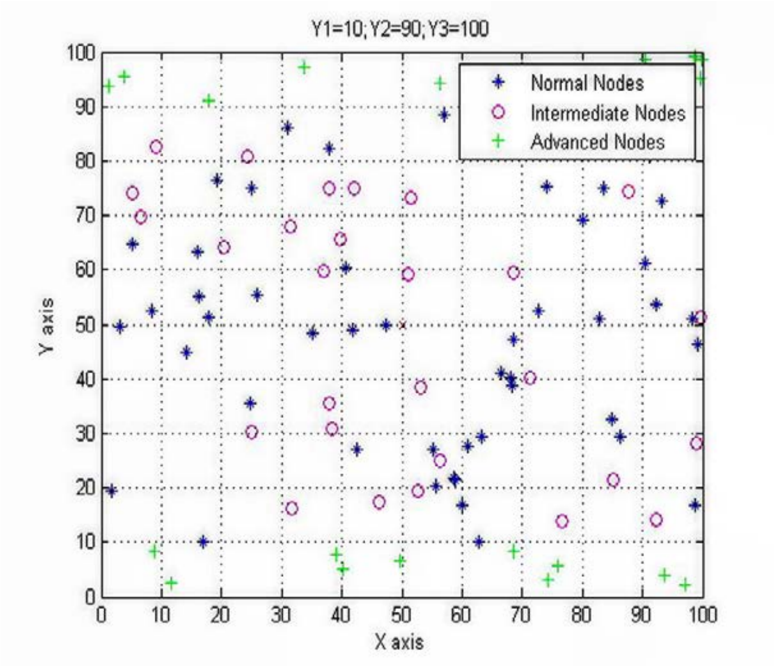

Fig. 6(a). Node distribution with $Y_1 = 10$, $Y_2 = 90$, and $Y_3 = 100$

The performance of the FLZSEP-E was compared to that of the ZSEP-E. For fair comparison, we maintained the same zone-based heterogeneous node setting and the same energy levels in all zones as in the ZSEP-E. Thus, the total initial energy of the system was the same in both the ZSEP-E and the FLZSEP-E. We compared the performances of the FLZSEP-E and the ZSEP-E with m = 0.2, b = 0.3, α = 3, μ = 1.5, and E_{total} = 102.5 J in the presence of high energy heterogeneity, as shown in **Figs. 6(b)** and **6(c).**

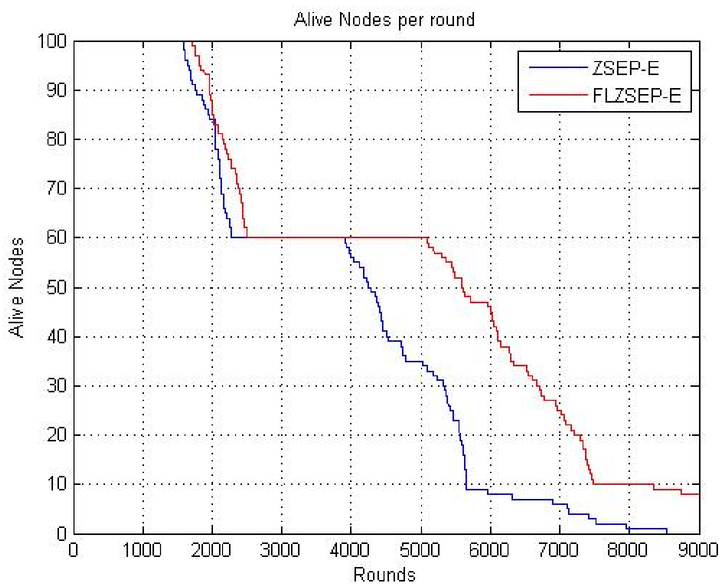

Fig. 6(b). Alive nodes per round for FLZSEP-E and ZSEP-E (m = 0.2, b = 0.3, α = 3, μ = 1.5, and E_{total} = 102.5 J; zone area: $Y_1 = 10$, $Y_2 = 90$, and $Y_3 = 100$)

Fig. 6(b) shows the number of alive nodes per round. The proposed FLZSEP-E demonstrates stability over a greater period than the ZSEP-E does when the CHs are chosen with different input functions. Better performance in terms of throughput is shown in **Fig. 6(c)** for the proposed fuzzy approach because dense clusters with high energy nodes are elected as CHs. The simulation results demonstrate that the proposed FLZSEP-E delays the time at which the first node dies (FND) by nearly 8% compared to the ZSEP-E, which is a significant network lifetime improvement.

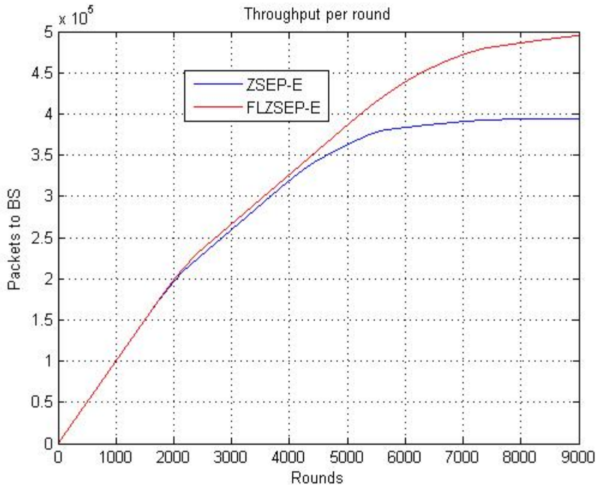

Fig. 6(c). Throughput of FLZSEP-E and ZSEP-E (m = 0.2, b = 0.3, α = 3 and μ = 1.5, and E_{total} = 102.5 J; zone area: Y_1 = 10, Y_2 = 90, and Y_3 = 100)

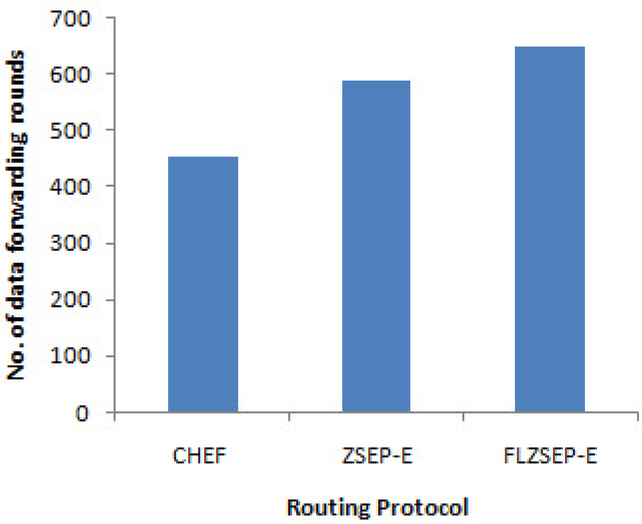

Fig. 7(a). Network lifetime (200 nodes)

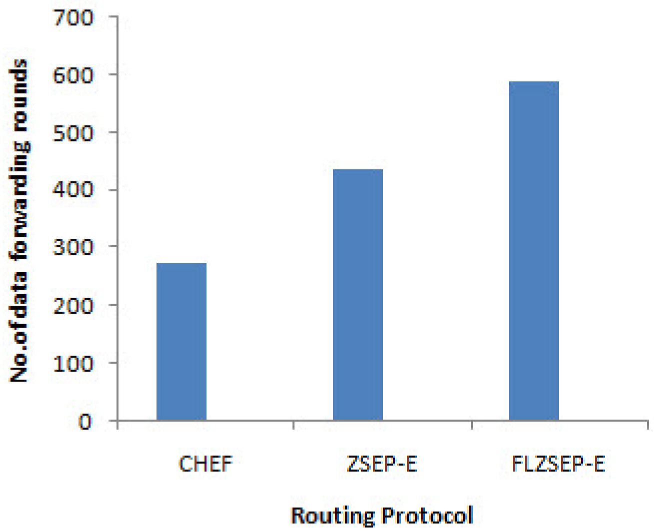

Fig. 7(b). Network lifetime (400 nodes)

Figs. 7(a) and 7(b) show the network lifetimes for the three algorithms with 200- and 400-node networks, respectively. It is evident that the FL-ZSEPE improves the network lifetime compared to the CHEF and ZSEP-E. CH selection is fine-tuned with the fuzzy logic approach across the zone-based network and conserves individual sensor node energy. We conducted paired T-test statistical analysis for 10 independent experiments using MINITAB to compare the mean difference of the FND metric for both protocols using the same simulation parameters **(Fig. 8).** Here, we tested to determine if the mean difference was significantly different from zero, i.e., we tested $H_0 : \mu_{\text{difference}} = 0$ versus an alternative hypothesis, such as $H_1 : \mu_{\text{difference}} \neq 0$. The rounds when the FND of the FLZSEP-E was higher than the ZSEP-E with the mean difference between them was 123.60. In addition, the standard deviation was 14.10 rounds, with a standard error of the mean of 4.46 rounds. This result indicates a 95% confidence interval for the mean difference of 113.51 to 133.69 rounds.

```
Paired T for FLZSEP-E - ZSEP-E

             N     Mean  StDev  SE Mean
FLZSEP-E    10  1721.10  10.98     3.47
ZSEP-E      10  1597.50   9.89     3.13
Difference  10   123.60  14.10     4.46


95% CI for mean difference: (113.51, 133.69)
T-Test of mean difference = 0 (vs ≠ 0): T-Value = 27.71  P-Value = 0.000
```

Fig. 8. Confidence intervals of corresponding network lifetime

The statistical significance (two-tailed *p*-value) of the paired t-test (*p*-value) was 0.0. As the *p*-value is 0, it can be concluded that there is a statistically significant difference between the FLZSEP-E and the ZSEP-E.

6. Conclusion and Future Work

Fuzzy logic is a form of multi-valued logic to deal with reasoning that is approximate rather than precise. In this study, a fuzzy logic approach was used to combine and evaluate diverse parameters for efficient CH election in the FLZSEP-E. The FLZSEP-E is a new approach that uses three criteria, the residual energy of the node, node density, and the distance from the node to the BS, for CH election. The results of simulations demonstrated significant energy savings and increased network lifetime compared to the ZSEP-E. In the future, we will focus on specific applications in order to optimize the energy consumption of an entire network, as well as QoS, such as bandwidth, latency, and packet loss rate.

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