IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 23, 2021, accepted February 14, 2021, date of publication March 2, 2021, date of current version March 15, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3063097

An Unequally Clustered Multi-hop Routing Protocol Based on Fuzzy Logic for Wireless Sensor Networks

MOHD ADNAN, LIU YANG, TAZEEM AHMAD, AND YANG TAO
School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
Corresponding authors: Mohd Adnan (l201820045@stu.cqupt.edu.cn) and Liu Yang (yangliu@cqupt.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61801072, in part by the Chongqing Science and Technology Commission under Grant cstc2018jcyjAX0344, in part by the Science and Technology Research Program of Chongqing Municipal Education Commission under Grant KJQN202000641, and in part by the National Key Research and Development Program of China under Grant 2019YFB2102001.

ABSTRACT Wireless sensor networks (WSNs) is associated with a new exemplification of a real-time embedded system used for various applications that make the traditional infrastructure-based network seem infeasible. Due to imbalanced energy consumption among nodes, WSN has challenges with better utilization of energy and system enhancement. Clustering has been a better approach in this sequence. Therefore, this paper will utilize a fuzzy logic-based clustering protocol (unequal clustering) with multi-hop transmission for load balancing, energy consumption minimization, and network lifetime prolongation. The protocol forms unequal clusters with cluster head (CH) being selected by fuzzy logic with competition radius. Node distance to the base station, concentration, and residual energy are input variables. The simulation and results section displays the outperformance of the proposed protocol, where the low-energy adaptive clustering hierarchy (LEACH), energy-aware multi-hop multi-path hierarchical (EAMMH), energy-aware unequal clustering fuzzy (EAUCF), and two-tier distributed fuzzy logic-based protocol (TTDFP) for efficient data aggregation in multi-hop wireless sensor networks algorithms.

INDEX TERMS Wireless sensor network, fuzzy logic, clustering, network lifetime.

I. INTRODUCTION

Due to their wide usage in various applications such as disaster management, health, and home applications, wireless sensor networks (WSNs) have amassed a lot of attention. Developments such as micro-electrical-mechanical, wireless communication, and digital systems have allowed the use of miniaturized wireless sensors. A WSN consists of several miniature detector nodes. These nodes are deterministically/randomly deployed to monitor specific target areas [1]. During sensing, processing, and transmitting the collected data, the sensor nodes exhaust a lot of energy. These nodes are supplied with a low-powered battery that is unique but rechargeable. The nodes' energy needs to be sparingly used so as long the life of the network is attained. One of the finest ways to decrease energy consumption by the network is grouping the sensor nodes in a certain characteristic that forms a cluster. Each cluster has a cluster head (CH) that allows communication with a base station (BS). The CHs gather data from the other member nodes of their specific cluster [2].

CH-BS communication is made up of either multi-hop or single-hop communication models. In the latter model, a CH communicates directly to a BS. On the other hand, multi-hop communication is characterized by a CH sending its data through other CHs to get to the BS eventually [3]. The approach is found to be logical in prolonging the network lifetime of WSNs.

Also, multi-hop communication in a cluster reduces the number of links, thus avoiding congestion. Besides, multi-hop communication can allow member nodes to assist the CH to share data fusion, thus efficiently decreasing the energy consumption by the CHs. This will help in the extension of the lifetime of the networks [4].

However, in multi-hop communication, the CHs close to the BS is characterized by massive data trafficking. This is

The associate editor coordinating the review of this manuscript and approving it for publication was Hongwei Du.

known as an energy hot spot [5]. To avoid an energy hole problem, unequal clustering algorithms can be utilized. The algorithms include keeping the clusters in the proximity of the BS trivial in size than the clusters away. This ensures CHs near the BS are more ready to allot the data traffic. The scalable nature of WSNs is also improved.

Studies on clustering approaches in WSNs has mainly focused on establishing distributed and centralized protocols in computing groups of CHs. Centralized approaches are, however, inefficient in large-scale networks because collecting the whole amount of crucial details at the central BS is energy and time-consuming [6]. Distributed protocols are further efficient in large-scale networks. Here, a node can decide to emulate a CH or unite with an existing cluster. The process is determined by the nature of details obtained from adjacent nodes. Several dispersed clustering protocols have been suggested in different literature [7]–[10]. For [7], a majority of the protocols are either in the case of the iterative or probabilistic state. Probabilistic protocols are characterized by the probabilistic determination of a decision to become a CH [9], [10]. Iterative protocols include an iterative process performed on the nodes to decide the becoming of a CH. Differently, clustering protocols can be contemplated as being static or dynamic. The clusters are permanent in static clustering. In dynamic clustering, the protocol is split into different rounds [8]. The clusters are then devised again in the next round. The additional overhead comes about when the repeated cluster is formed on the system.

Some protocols take full advantage of fuzzy logic [11]. Even with incomplete information on environmental factors, real-time decisions are possible in fuzzy logic. Combining various environmental features based on preset rules and eventually coming up with a decision according to the finding is another important use of fuzzy logic. In turn, fuzzy clustering algorithms use the same logic for combining different clustering frameworks to choose CHs. Fuzzy logic is a structure that functions almost similar to human logic. Fuzzy logic is made up of 4 main components, including fuzzifier, defuzzifier, fuzzy rule, and inference engines [12].

(a) Fuzzifier: This component maps every input value into the correlating fuzzy set. It assigns a degree of membership or truth value to each set.
(b) Inference engine: This component processes fuzzified values. It includes a variety of methods used to deduce the rules and a rule base.
(c) Fuzzy rule: This component is a sequence of IF-THEN directives where the output fuzzy variables are related to the input linguistic variables.
(d) Defuzzifier: Defuzzification is done by this component, where a solution space is mapped into one crisp input value.

The distance decides the inequality in cluster formation between the sink and the CHs. Therefore, CHs near the sink is smaller than the CHs away from the sink.

In this study, we propose fuzzy logic as the algorithm of choice. The algorithm includes unequally-sized clusters, where their cluster radius is determined through a distributed fuzzy logic approach. To minimize energy consumption, we use multi-hop transmission in the wsn with unequal clustering. Intelligence techniques of computation, such as particle swarm optimization [14], ant colony optimization [13], fuzzy logic, and genetic algorithms [15], have previously been used to solve several WSN issues. Here, we utilize three fuzzy variables- node's residual energy, concentration, and base station distance for computation of competition radius and choices CHs. The emergence of lots of uncertainties will include the use of the fuzzy logic approach [16], [17]. To improve the chance of cluster radius and the chance of cluster head selection, we use one new variable, node concentration. It is important to consider this node concentration because it ameliorates the fuzzy logic algorithm, hence prolonging the WSN network lifetime. The multi-hop hotspot problem is familiar in WSNs. The nodes close to the sink expire quickly because of the inter-cluster congestion. Reducing such a problem includes an approach known as unequal clustering.

We have performed experiments for the proposed algorithm to evaluate its efficacy in terms of energy consumption and network lifetime over the existing algorithms, namely, two-tier distributed fuzzy logic-based protocol for clustering phase (TTDFP Tier-1), energy-aware fuzzy approach to unequal clustering (EAUCF), energy-aware multi-hop multipath hierarchical (EAMMH), and low-energy adaptive clustering hierarchy (LEACH).

II. RELATED WORK

In designing the WSN, energy is the most obligatory resource, so its battery life confines the sensor nodes' lifetime. The reduction in the energy consumption of nodes can lead to better network life. Several routing protocols have been developed to enhance network performance and lifetime. In this part, some famous clustered based routing protocols are explained. We have divided them into two categories. In the first category, few protocols where cluster heads are elected in a probabilistic manner are discussed. In the second category, some of the fuzzy logic clustering-based protocols are discussed.

A. HIERARCHICAL ROUTING PROTOCOLS BASED ON CLUSTERING

LEACH is a clustering algorithm, where the sensor nodes are probabilistically selected as viable CH in WSNs [24]. Each node selects an arbitrary number. A node automatically becomes the CH if the selected number is lower than the set threshold. After the CHs are determined, based on their distance, non-CH nodes join the CHs. The performance of the determined CH is initially low. Also, there is no consideration of residual energy during the selection of a CH. This does not support the proper performance of the heterogeneous network. There are many disadvantages in selecting the CH using the local information from the nodes. Besides, this algorithm involves low-energy nodes that may be chosen as CHs, resulting in further quick depletion in their energy. This eventually creates energy holes in this network.

PEGASIS [25] is a protocol that is chain-based and near-optical and an upgrade of LEACH. In this protocol, each node communicates with an adjacent node. The nodes alternate in transmitting signals to the BS. This process reduces the quantity of energy eventually spent with each round. One major problem of this protocol includes the CHs directly sending data to the BS. This is a single-hop communication process that is energy-consuming and not appropriate for a large-scale network, such as WSN.

The EAMMH protocol was started by inducing the attributes of multi-hop intra-clustering and energy-aware routing [26]. The utilization of the EAMMH protocol is divided into rounds. Each round starts with a launching phase where there is an organization of clusters. The initial phase is then followed by a steady-state phase, which includes data transfer to the BS. The second phase involves organizing the sensor nodes into clusters, forming a multi-hop intra-cluster communication. Multiple paths are established from every node to the CH. This provides energy-aware heuristic connectivity where the optimal path is chosen. Therefore, this protocol chooses CHs regarding their residual energy, especially when the survival time of the network is short.

In [27], the authors proposed a reliable routing distributed learning automaton (RRDLA) algorithm which determines the smallest number of nodes to protect the desired QoS requirements. In routing election, it takes various QoS routing constraints such as end-to-end reliability and delays into account.

In the paper [28], the authors aim to defend sensor protection and provide efficiency of the wsn while using an irregular cellular learning automaton (ICLA)-based algorithm, also called SPLA. Learning automaton at each cell of ICLA with proper rules aims to investigate the minimum possible number of nodes to guarantee the network's self-protection requirements.

The aim of this paper [29] is to improve the energy efficiency and maximize the lifetime of WSNs by using enhanced clustering hierarchy (ECH). This algorithm is implemented in both homogeneous and heterogeneous networks.

In [30], the authors proposed an enhanced routing-Gi protocol for a mobile sink in WSNs to enhance the energy efficiency, minimize the packet loss rate and maximize the network lifetime. By optimizing the distance between the mobile sink and each CH at a specific time at a specific location, this proposed protocol conserves energy of CHs. At each round, based on the ratio between the energy level of CH and grid numbers, the mobile sink moves in a predetermined trajectory.

B. FL BASED CLUSTERING PROTOCOL

Multiple studies have discussed Fuzzy Logic (FL) and how it is usable in clustering, especially in enhancing energy-consumption. Some associated protocols will be discussed as follows:

In Hybrid Energy-Efficient Distributed Clustering (HEED) protocol, the primary parameter for selecting CHs is nodal residual energy. The process involves probabilistic election [7]. The distance between the node and BS is utilized to decide the CH whenever there is was a tie between two nodes. Experiments have been used to evaluate this protocol. They have demonstrated that data aggregation and clustering can, at least, double the duration of a WSN.

In a fuzzy clustering protocol that was proposed by Gupta *et al.* [11], the CHs are chosen at the BS. Input subjected to the system is characterized by residual energy, node centrality, and degree. In each round of selection, each node passes on its clustering output to the BS. This approach is incompatible with large-scale networks, such as WSN, because it suffers from scalability offsets.

CHEF is another protocol similar to fuzzy clustering [8]. The BS does not have to gather clustering outputs from all nodes. This is because it selects CH in a diffused manner. A probabilistic process selects the provisional CHs. Fuzzy logic is then used to narrow the selection to the eventual CHs. Inputs administered to the fuzzy system are characterized by residual energy. The CHEF protocol provides a greater duration of network use. However, different from other protocols such as LEACH, CHEF may have non-uniformly distributed CHs in the network. This is mainly because of the probabilistic selection of the provisional CHs.

SEP-FL is a fuzzy logic clustering protocol. It considers residual battery, node distance to BS, and the threshold value for CHs selection [26]. One major setback for this protocol is direct communication between the CHs and the BS, which is a single-hop communication that consumes a lot of energy. This setback makes this protocol inappropriate to use in a large network, such as WSNs.

In [31], this paper explains improved low-energy adaptive clustering hierarchy (LEACH) protocol for mobile sensor networks, which prolong the network lifetime and using fuzzy logic reduce the packet loss in a mobile sensing environment.

Recently, some unequal clustering protocols have been developed. These protocols are mainly based on creating smaller clusters around the sink. A significant distance to the BS also characterizes the smaller clusters. Sensor nodes near the sink are in smaller cluster sizes than other nodes located far away.

EEUC protocol includes diffused unequal clustering in selecting CH through local competition [12]. A competitive radius is assigned to each node. This radius becomes more trivial when the nodes near the BS. The EEUC protocol, therefore, is characterized by unequal clustering. This protocol cannot support the processing load.

The authors Bagci and Yazici in EAUCF protocol recommend unequal clustering algorithm [33]. In that study, fuzzy logic was used to process the competition range by considering the node's distance to the BS and residual energy.

This protocol increases the network duration and solves the energy holes problem. The main offset here is the increased energy depletion at the CHs.

In Two-Tier Distributed Fuzzy Logic-Based Protocol (TTDFP) [34], the authors proposed enhancing the data aggregation efficiency in the two-tier sensor networks. At first, optimum CH was selected based on probabilistic models. TTDFP utilizes the optimization framework to tune the two parameters in this tier, which are the threshold radius and the maximum competition radius, rather than the use of a trial-and-error approach to find the right blend of these parameters. In the second tier, fuzzy sets enhance the routing performance. In clustering, TTDFP uses three linguistic parameters, distance to BS, node energy, and node connectivity. In this, the residual energy. In this situation, using relative distance and average connection, the residual energy was resolved and elected CHs based on the availability of node connectivity, which has ignored the energy in the networks.

MOFCA-35 is an unequal clustering protocol with multiple objectives. This protocol utilizes three parameters: node's residual energy, density, and distance to the sink. Also, the provisional CHs are selected through the use of fuzzy logic. Different from the other protocol, the competition radius in this algorithm is calculated.

FBUC [36] takes three parameters residual energy, distance to the BS, and node degree, for cluster radius computation. This protocol uses fuzzy logic for non-cluster nodes to join with a CH. This protocol uses the CH competition ranges and the separation between CH and non-cluster members for selecting CHs. The drawback of this protocol is there inter-cluster energy consumption is very high.

In [37], the authors improves the performance and efficiency of fuzzy-rule based routing algorithms using the modified clonal selection algorithm (CLONALG-M). The modified version of the clonal selection algorithm is applied to find the nearest form of the output membership functions, which help to improve the overall fuzzy routing algorithm performance.

The authors [38] proposed an Energy-efficient fuzzy logic cluster head (EEFL-CH) algorithm, which is the improvement of the LEACH protocol. The aim of this algorithm is to reduce energy consumption while increasing the network lifetime by using fuzzy logic. CH selection is based on three fuzzy parameters residual energy, expected efficiency, and closeness to the base station.

The author LEE [39] proposed a fuzzy-logic-based clustering approach with an extension to the energy predication, which enhances the network lifetime by evenly distributing the workload. This approach uses two fuzzy parameters, residual energy, and expected residual energy, for elected CHs.

This study aims to use unequal clustering in a fuzzy logic approach to reduce energy consumption in sensor nodes and address the energy-hole problem common in older algorithms. This study aims to outline the routing advantages of the suggested algorithm, such as using multi-hop communication to reduce energy consumption. The study will also demonstrate an unequal adaptive clustering used in the suggested fuzzy logic algorithm. Compared with older algorithms, such as EAMMH, EAUCF, TTDFP Tier-1, and LEACH, this study will also demonstrate advantages in the suggested protocol, including efficient energy-saving distances and CH selection effective energy-consumption parameters.

III. SYSTEM MODEL AND TERMINOLOGIES

In this work we consist the network model along with the energy model and terminologies used in it.

A. NETWORK MODEL

In our network model, we have considered a network where a number of homogeneous sensor nodes are randomly deployed in an area and BS is located outside of the network area. For our proposed network model, we make some assumptions, which are as follows.

1) All the sensor nodes and the base station are considered to be static after deployment.
2) Sensor nodes can join just a single CH inside its imparting range.
3) The BS has no energy limitation.
4) Wireless connection is symmetric and bidirectional.
5) Initially, all the sensor node contains the same amount of energy.

B. ENERGY MODEL

Consider nodes are distributed uniformly in M*M region. If there is a cluster k, then the average is N/K nodes per cluster. The area engaged by each cluster is approximately M^2/K. The required squared distance from the nodes to the CH is given by

$$E\left[d_{toCH}^2\right] = \rho\,(x, y)\,dxdy \tag{1}$$

We assume that this area is a circle with a radius $R = \left(\frac{M}{\sqrt{\pi K}}\right)$ and $\rho\,(r, \theta)$ is constant for r and θ, so equation 1 simplifies to:

$$E\left[d_{toCH}^2\right] = \rho \int_{\theta=0}^{2\pi} \int_{r=0}^{\frac{M}{\sqrt{\pi K}}} r^3 \partial r \partial \theta = \frac{\rho}{2\pi}\frac{M^4}{K^2} \tag{2}$$

If the density of the nodes is uniform throughout the cluster area, then the diameter $D = \frac{2M}{\sqrt{\pi K}}$ and

$$E\left[d_{toCH}^2\right] = \frac{1}{2\pi}\frac{M^2}{K} \tag{3}$$

The Average distance between CH nodes to BS:

$$D_{toBS} = \int_A \sqrt{x^2 + y^2}\frac{1}{A}\partial A = 0.765\frac{M}{2} \tag{4}$$

$$D_{toBS} = \frac{0.755M}{2} \tag{5}$$

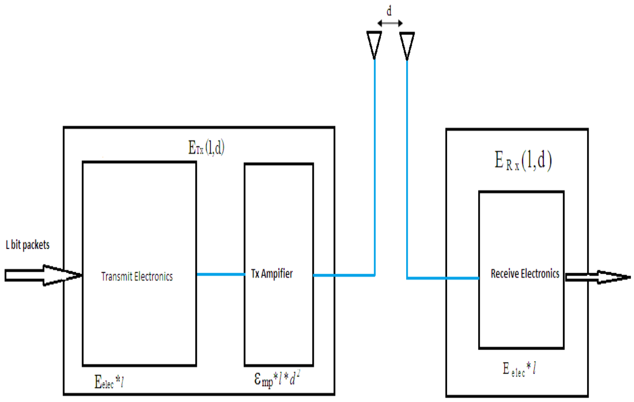


FIGURE 1. Radio model.

Now first, we consider all cluster are equal in size, so the radius is R, and the area of each cluster is $\frac{M}{K}$, therefore the radius of a cluster is $R = \frac{M}{\sqrt{\pi K}}$, Now the diameter of the cluster or distance between two cluster head is $D = \frac{2M}{\sqrt{\pi K}}$

The energy model considered in our work is alluded from [40] as shown in Fig.1. The signal-to-noise ratio (SNR) during broadcasting l-bit packet over distance d so the energy dissipated by radio is determined as:

$$E_{TX}\,(l,d) = \begin{cases} lE_{elec} + l\in_{fs} d^2, & if\ d \le d_o \\ lE_{elec} + l\in_{amp} d^4, & if\ d \ge d_o \end{cases} \tag{6}$$

where, E_{elec} denotes energy depleted per bit to operate the electronic circuitry, $\in_{fs}$ and $\in_{amp}$ shows the energy consumption by free space and multifading channel, d indicate the distance among sender and receiver and d_0 denotes the threshold transmission distance. The threshold distance d_0 is given by equating the equation for $d = d_o$

$$lE_{elec} + l \in_{fs} d_o^2 = lE_{elec} + l \in_{amp} d_o^4$$

$$d_o = \sqrt{\frac{\in_{fs}}{\in_{amp}}} \tag{7}$$

To obtain l-bit message, the radio uses:

$$E_{RX}\,(l,d) = lE_{elec} \tag{8}$$

So the total energy consumption we get:

$$E_t = l\left(2\,N_s\,E_{elec} + N_s \in_{fs} d_{toCH}^2 + N_s\,E_{DA} + k \in_{fs} D^2 + \in_{mp} k\, d_{toBS}^4\right) \tag{9}$$

To find the optimal number of cluster, we differentiate equation (9) with k and put the value 0.

$$K_{opt} = \frac{M}{d_{toBS}^2}\sqrt{\frac{N_s}{2\pi}}\sqrt{\frac{\in_{fs}}{\in_{mp}}} \tag{10}$$

where M is the side of the deployment area, so area A = M∗M m^2. E_{elec} indicates energy consumed in transmitting or receiving one bit, depends upon coding and modulation. $\in_{fs}$ indicates free space loss coefficient. N_s shows sensing nodes and E_{DA} is aggregation energy.

Algorithm 1 CH Selection and Clustering

TH ←Threshold probability for selection of a provisional CH
for each node **do**
  Provisional CH = False
  $\mu \leftarrow$ rand(0, 1)
  if ($\mu < TH$) **then**
    Provisional CH = True
  else Provisional CH = False
  end if
  if Provisional CH=True **then**
    for each provisional CH **do**
      Using if then mapping rules, calculate radius and CH chance
      Radius = Fuzzy logic (distance, residual energy, node concentration)
      CH chance = Fuzzy logic (distance, residual energy, node concentration)
    end for
    Inside the range of Provisional CH send CH message (ID, chance) to other CHs
    Select Provisional CH having maximum CH chance as Prime CH
  end if
  if Provisional CH ≠ Prime CH **then**
    Provisional CH = node
  end if
  Send Prime CH message (ID, chance)
  for (each node) **do**
    join with Prime CH having maximum as a cluster member
  end for
  for each Prime CH **do**
    calculate the distance among all clusters
    if (distance between Prime CH and BS > min (Distance between Prime CH −Prime CH')) **then**
      transmit to BS
    else(transmit to Prime CH)
    end if
  end for
end for

C. UNEQUAL CLUSTERING

In the wireless network, to reduce energy consumption, sensor nodes chose a CH to forward their data. As the distance from the BS is one of the main factors for a node to be selected as a CH, a number of CM nodes can choose them for their data forwarding leading the CH to drain its battery rapidly. As the node's distance from BS increases, the energy required in data transmission also increases, leading to the node's rapid battery drainage. To reduce CH's rapid battery drainage, we propose an unequal clustering scheme where the radius of a CH varies depending on their distance from BS. i.e., if the cluster is near the base station, then the cluster size will be small, and if the cluster is far from the BS, then the cluster size will be large. In this scheme, we first select candidate CHs, and later, based on other properties, we select final CHs for data transmission. The scheme is discussed as follows. In this scheme, based on a probabilistic approach, we select initial CH and provisional CH. For initial CH selection, In each clustering round, every sensor node creates an arbitrary number between the two binary numbers (0 and 1). If the arbitrary numbering for a specific node is lower than the threshold (T), this node spontaneously becomes an initial CH. The competition radius from every provisional CH dynamically changes in the proposed model. This is because the proposed model utilizes the node concentration, distance to the BS, and residual energy in calculating the relevant competition radius. Therefore, it is logical to reduce the network service area for a CH whose residual energy is proportionally decreasing. The sensor node rapidly runs out of its battery if the competition radius does not reduce while its residual energy reduces. Radius calculation is achieved by utilizing preset fuzzy IF-THEN delineated regulations to manage the uncertainty. The fuzzy IF-THEN described regulations are shown in Table 1. To assess the regulations, the Mamdani Method (one of the most utilized methods) is utilized as a fuzzy inference technique[10]. The Center of the area (COA) practice is used for the de-fuzzification process in competition radii. In each round, initial CHs are selected by creating a random number that is allocated to every node. If the produced random number allocation is less than the threshold value (TH) of adjacent nodes allocated in Eq. 12, then that node becomes a provisional CH.

$$TH = P/(1 - P * (r \bmod 1/p)) \tag{11}$$

where r is the value of the present round of selection, P is the preferred percentage of CH (e.g. P = 0.05). This section will describe the unequal clustering process by making use of fuzzy logic. Different from other studies, three linguistic variables are used. These linguistic variables used are residual energy in the provisional CH, distance to the BS, and concentration.

- **Input distance to BS-**Distance to the BS is a crucial metric in avoiding energy holes. The shorter distance of a CH to the BS has a smaller number of cluster member nodes, hence spends considerable energy to relay data packets. However, distant CHs can have large clusters because data is propagated in a multi-hop communication process.
- **Residual energy-** CH node functions more than its member nodes. These functions include data collection, aggregation, and transmission to the BS. It should, therefore, have enough energy to support all relevant functions.
- **Concentration-** This the number of adjacent nodes in the vicinity of the preferred CH.

This section includes a description of the unequal clustering process using fuzzy logic. In this paper, three variables were used. The variables used include residual energy of the provisional CHs, distance to the BS, and concentration of nodes adjacent to the CH. The existing fuzzy-based unequal clustering process has one output variable only. The suggested process includes two output variables. These are CH probability and its competition radius. The latter variable is made up of eight linguistic values: small, very small, rather small, medium, medium-small, large, rather large, medium-large, and very large. The values with trapezoidal membership functions are very large and very small. The rest have triangular functions.

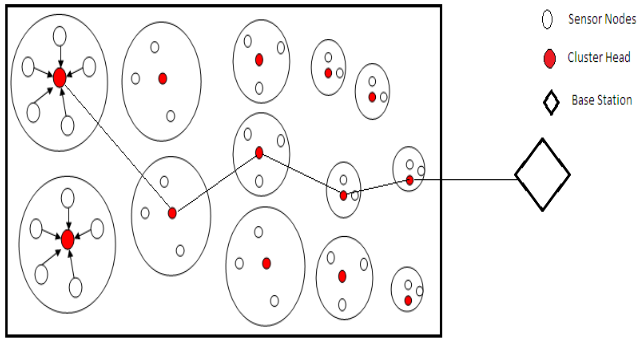


FIGURE 2. Proposed model for multi-hop clustering.

The former variable is made up of seven fuzzy linguistic values. They include poor, very poor, average, below average, above average, strong, and very strong. The values with trapezoidal membership functions are very strong and very poor. Triangular functions characterize the rest. The careful selection of membership function extent is supposed to subject all the nodes to a repeated experimental analysis on different network magnitudes. The fuzzy theory engine fuzzifies the crisp data values into suitable linguistic variables. The engine makes use of availed membership functions. The Mamdani practice is utilized to come up with regulations with which the fuzzified data values are refined. Twenty-seven regulations are eventually specified (as in Table 2), which blend various linguistic variables. The output variable is also a fuzzy value. The trapezoidal and triangular membership function used in our FIS is shown in the following figure:

$$\mu_{A1}(x) = \begin{cases} 0 & x \le a1 \\ \dfrac{x - a1}{b1 - a1} & a1 \le x \le b1 \\ \dfrac{c1 - x}{c1 - b1} & b1 \le x \le c1 \\ 0 & c1 \le x \end{cases} \tag{12}$$

$$\mu_{A2}(x) = \begin{cases} 0 & x \le a2 \\ \dfrac{x - a2}{b2 - a2} & a2 \le x \le b2 \\ 1 & b2 \le x \le c2 \\ \dfrac{d2 - x}{d2 - c2} & c2 \le x \le d2 \\ 0 & d2 \le x \end{cases} \tag{13}$$

The COA method is utilized to de-fuzzify the output variable into a crisp variable. After completing the CH selection, non-CH nodes unite with the nearest CH. The COA method is used in the given equation:

$$COA = \frac{\int \mu_A(x)\, xdx}{\int \mu_A(x)\, dx} \tag{14}$$

For illustration, let us consider a 100 × 100 m^2 network size where sensor nodes are randomly deployed and the BS is located outside of the network at the position (150, 50). As the BS is located outside of the network are the minimum distant sensor node may be found at 50m, and the farthest node can be found at 160m. For the calculation of competition radius, we consider the minimum and maximum values for the input variables of fuzzy logic, i.e. Distance to BS, residual energy and concentration in such a way that they can cover the entire range of network size, nodes residual energy and adjacent nodes in the vicinity of the preferred CH respectively. Table 2 represents the input variables of fuzzy logic control for the computation of competition radius.

For the computation of competition radius, we consider an example of a node whose Distance to BS is 160, residual energy (RE) is 0.7, and concentration is 30. The linguistic values are farthest for Distance to BS, avg, high for residual energy (RE) and medium, high for concentration.

Rule 1: If Dist. to BS is farthest and residual energy is avg and concentration is medium, then the competition rad. is large.

Rule 2: If Dist. to BS is farthest and residual energy is avg and concentration is high, then the competition rad. is rather large.

Rule 3: If Dist. to BS is farthest and residual energy is high, and concentration is med. then the competition rad. is rather large.

Rule 4: If Dist. to BS is farthest and residual energy is high, and concentration is high, then the competition rad. is large.

Apply trapezoidal member function to the linguistic value far. X = 145 (far)

$$\begin{aligned} f(x:a,b,c,d) &= \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \\ &= \max\left(\min\left(\frac{145-112}{147-112}, 1, \frac{161-145}{161-160}\right), 0\right) \\ &= \max(0.9, 0) \\ &= 0.9 \end{aligned}$$

Apply triangular for linguistic value avg, high of residual value. X = 0.6 (avg)

$$\begin{aligned} f(x:a,b,c) &= \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \\ &= \max\left(\min\left(\frac{0.6-0}{0.5-0}, \frac{1-0.6}{1-0.5}\right), 0\right) \\ &= \max(\min(1.2, 0.8), 0) \\ &= \max(0.8, 0) \\ &= 0.8 \end{aligned}$$

TABLE 1. Fuzzy input parameters and min. and max. values for competition radius.

variable name	min. value	max. value
Distance to BS	50	161
Residual Energy	0	1
Concentration	0	30

X = 0.6 (high)

$$\begin{aligned} f(x:a,b,c,d) &= \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \\ &= \max\left(\min\left(\frac{0.6-0.5}{0.9-0.5}, 1, \frac{1.2-0.6}{1.2-1}\right), 0\right) \\ &= \max(\min(0.25, 1, 3), 0) \\ &= 0.25 \end{aligned}$$

Apply triangular for linguistic concentration (med, high) X = 17 (medium)

$$\begin{aligned} f(x:a,b,c) &= \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \\ &= \max\left(\min\left(\frac{17-0}{15-0}, \frac{30-17}{30-15}\right), 0\right) \\ &= \max(\min(1.13, 0.86), 0) \\ &= 0.86 \end{aligned}$$

X = 17 (high)

$$\begin{aligned} f(x:a,b,c,d) &= \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \\ &= \max\left(\min\left(\frac{17-15}{27-15}, 1, \frac{32-17}{32-30}\right), 0\right) \\ &= \max(\min(0.16, 1, 7.5), 0) \\ &= 0.16 \end{aligned}$$

Now Apply values in fuzzy rules:

Rule 1: min (0.94, 0.8, 0.86) = 0.8

Rule 2: min (0.94, 0.8, 0.16) = 0.16

Rule 3: min (0.94, 0.25, 0.86) = 0.25

Rule 4: min (0.94, 0.25. 0.16) = 0.16

From Rule 1 to Rule 4 the Max. value is 0.8 which is large and crisp value lies between 60 and 80.

For defuzzification, the fuzzy output is given as input to COA. So, competition radius is 58.70.

D. CLUSTER FORMATION

Algorithm 1 gives the pseudocode for CH selection and cluster formation in each round. The algorithm is explained as follows. At the beginning of every round, each sensor node creates an arbitrary value between 1 and 0. If the arbitrary value created by a specific node is less than the threshold (TH) value, that node becomes a provisional CH. This algorithm utilizes the node's distance to the BS, residual energy, and concentration to determine the relevant competition radius.

TABLE 2. Fuzzy rules.

Distance	Residual Energy	Concentration	Cluster Radius	CH Choice
close	less	high	very small	very poor
close	less	med	small	poor
close	less	low	rather small	below average
close	avg	high	small	avg
close	avg	med	rather small	below avg
close	avg	low	medium small	poor
close	high	high	rather small	very strong
close	high	med	small	strong
close	high	low	medium small	above avg
far	less	high	medium small	avg
far	less	med	rather small	below avg
far	less	low	small	poor
far	avg	high	medium large	below avg
far	avg	med	medium	avg
far	avg	low	medium small	below avg
far	high	high	medium large	strong
far	high	med	medium	above avg
far	high	low	medium small	avg
farthest	less	high	large	poor
farthest	less	med	medium large	very poor
farthest	less	low	medium	below avg
farthest	avg	high	rather large	avg
farthest	avg	med	large	below avg
farthest	avg	low	medium large	above avg
farthest	high	high	large	very strong
farthest	high	med	rather large	strong
farthest	high	low	very large	above avg

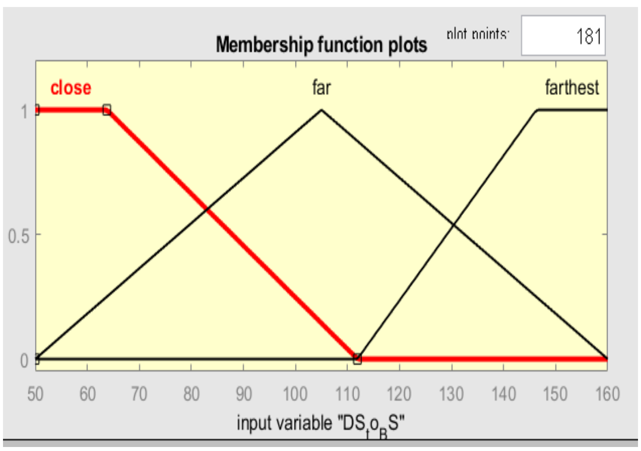


FIGURE 3. Fuzzy input variable DS to BS.

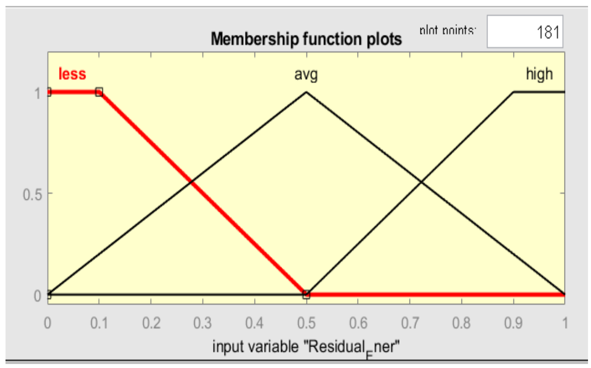


FIGURE 4. Fuzzy input variable res. energy.

It should be noted that in some cases, the hotspot problem might occur with the increasing number of clusters and inter cluster routing. With this problem, a number of clusters may be generated with too small radius. As a solution to this problem, we set a lower radius to prevent the network from becoming divided into too many clusters. The provisional CH will then compute radius and chance. Every node relays a discovery CH-MSG in the cluster radius to generate its routing table carrying a list of adjacent nodes and their residual energy. The CH will broadcast CH-MSG to all adjacent nodes in its radius, which is determined by FIS. This provisional CH-MSG will have information about the node's chance value and id. The Provisional CH with the hight chance value within the cluster is declared the Prime cluster head (PCH). The PCH then relays ELECTED-CH-MSG to adjacent nodes. The rest of the nodes that do not become the PCH will relay JOIN-CH-MSG to the adjacent CH. Finally, the PCH transmits a message which contains a time slot table to its member nodes. According to this slot table, the member nodes send raw data to the PCH. After the completion of clustering, the packet transmission is similar to EAMMH and EAUCF schemes. Thus the data transmission and synchronization process in the cluster is not introduced in detail in this work.

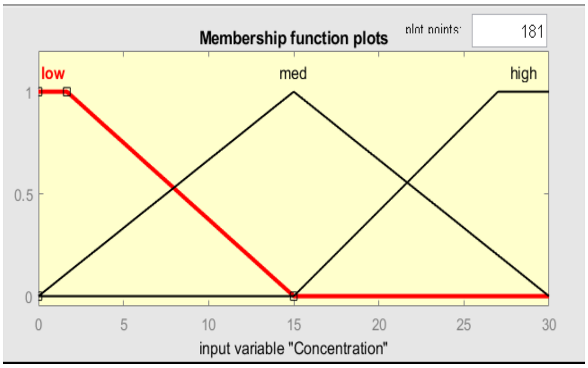


FIGURE 5. Fuzzy input variable Concentration.

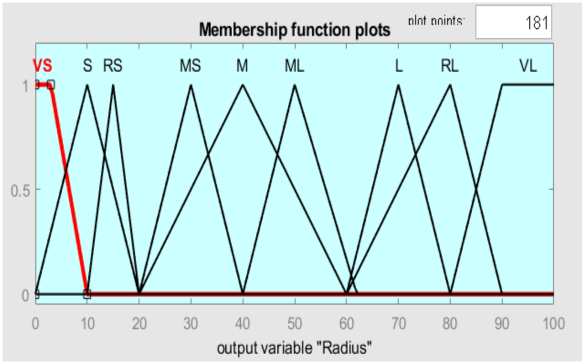


FIGURE 6. Fuzzy output variable (radius).

There is a dynamic change in the provisional CH competition radius of this suggested algorithm, as it utilizes energy, shorter distance to the BS, and low concentration in the parameters for CH chance calculation. Reducing the CH radius is the best option to reduce its energy consumption. The preset fuzzy IF-THEN regulations determine the CH chance. By using the fuzzy process, unpredictability is integrated into the WSN and is computed efficiently.

The input variable takes the fuzzy values that are equivalent. In the initial input variable, the node's distance to the BS is characterized by close, far, and farthest as the fuzzy linguistic values. Farthest and close have trapezoidal functions, while far has triangular functions. The next input variable, node's residual energy, is characterized by less, average, and high as the linguistic values. High and less have trapezoidal functions. The average has a triangular membership function. The third input variable is concentration, which is made up of low, medium, and high as the linguistic values. Low and high have trapezoidal functions. Medium has triangular functions. The non-CH nodes relay sensed data to their specific CHs after clusters are formed. The eventual CHs then combine all the received input and relay it farther to another CH using multi-hop transmission, and then CH sends the data to the sink. Figure 6-8 shows the fuzzy input and output variables.

E. SELECTION OF CLUSTER HEAD

The linguistic values are farthest for Dist. to BS, avg, high for residual energy (RE), and med, high for concentration.

For cluster head:

Rule 1: If Dist. to BS is farthest and residual energy is avg and concentration is med then cluster head is avg.

Rule 2: If Dist. to BS is farthest and residual energy is avg and concentration is high then cluster head is below avg.

Rule 3: If Dist. to BS is farthest and residual energy is high and concentration is med then cluster head is strong.

Rule 4: If Distance to BS is farthest and residual energy is high and concentration is high then cluster head is very strong.

TABLE 3. Fuzzy input variables and their min. and max. values for CH.

variable name	min. value	max. value
DS to BS	50	162
Residual Energy	0	1
Concentration	0	22

Now take the min. and max. values given in Table 3 for the input variables of fuzzy logic control.

Apply trapezoidal member function to the linguistic value farthest.

X = 150

$$\begin{aligned} f(x:a,b,c,d) &= \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \\ &= \max\left(\min\left(\frac{150-110}{155-110},1,\frac{162-150}{162-160}\right),0\right) \\ &= \max(\min(0.89,1,12),0) \\ &= 0.89 \end{aligned}$$

Apply triangular member function to the linguistic value average.

X = 0.6 (avg)

$$\begin{aligned} f(x:a,b,c) &= \max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \\ &= \max\left(\min\left(\frac{0.6-0.2}{0.4-0.2},\frac{0.7-0.6}{0.7-0.4}\right),0\right) \\ &= \max(\min(2,0.34),0) \\ &= 0.34 \end{aligned}$$

Apply trapazoidal member function to the linguistic value high.

X = 0.6(high)

$$\begin{aligned} f(x:a,b,c,d) &= \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \\ &= \max\left(\min\left(\frac{0.6-0.4}{0.7-0.6},1,\frac{1.1-0.6}{1-0.6}\right),0\right) \\ &= \max(\min(2,1,1.4),0) \\ &= 1.4 \end{aligned}$$

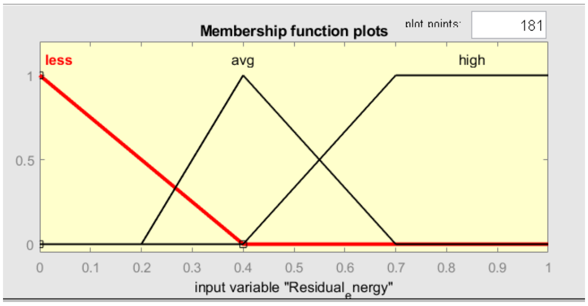


FIGURE 7. Fuzzy input variable residual energy.

Apply concentration triangular member function to the linguistic value med.
X = 12 (med)

$$\begin{aligned} f\left(x : a, b, c\right) &= \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \\ &= \max\left(\min\left(\frac{12-5}{10-5}, \frac{16-12}{16-10}\right), 0\right) \\ &= \max\left(\min\left(1.4, 0.67\right), 0\right) \\ &= 0.67 \end{aligned}$$

Apply concentration triangular member function to the linguistic value high.
X = 12(high)

$$\begin{aligned} f\left(x : a, b, c, d\right) &= \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \\ &= \max\left(\min\left(\frac{12-10}{20-10}, 1, \frac{23-12}{20-12}\right), 0\right) \\ &= \max\left(\min\left(0.2, 1, 1.4\right), 0\right) \\ &= 0.2 \end{aligned}$$

Now Apply values in fuzzy rules:

Rule 1: minimum (0.89, 0.34, 0.34) = 0.34
Rule 2: minimum (0.89, 0.34, 0.4) = 0.34
Rule 3: minimum (0.89, 1.4, 0.67) = 0.67
Rule 4: minimum (0.89, 1.4. 0.2) = 0.2
The max. value of Rule 1 to 4 is 0.67 which is strong and crisp value lies between 50 and 75.
For defuzzification the fuzzy output is given as input to COA. Therefore, CH chance is 55.6.

F. SIMULATIONS AND RESULTS

The proposed algorithm has been assessed using MATLAB because its Fuzzy Toolbox examines all fuzzy membership functions, hence suitable for use. This suggested algorithm was simulated using MATLAB. One hundred sensor nodes were reviewed after distribution over a 100 × 100m^2 area. Assumptions made included initial energy in every node as 0.5J. The MATLAB simulation frameworks utilized in the suggested system are tabulated in Table 4. Shown in Table 5 is

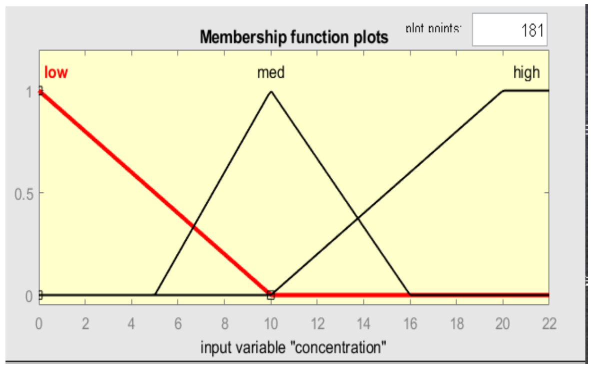


FIGURE 8. Fuzzy input variable Concentration.

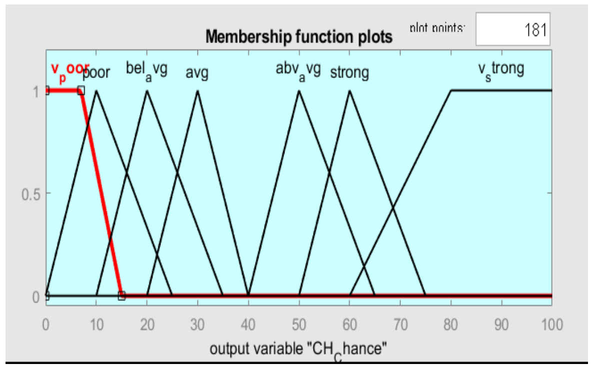


FIGURE 9. Fuzzy output variable (CH chance).

TABLE 4. Simulation parameters.

Area	100*100
Nodes	100
Packets size	4000 bits
ϵ_{mp}	0.0013 pj/bit/m4
ϵ_{fs}	10 pJ/bit/m2
E_{elec}	50 nJ/bit
Initial Energy	0.5j
Control Packet Size	200 bits

TABLE 5. The results of the simulation for HND and FND.

Algorithm	FND	HND
LEACH	118	372
EAMMH	164	416
EAUCF	109	515
TTDFP Tier-1	285	593
PROPOSED	353	610

the suggested protocol outperforming in FND. The network duration has been evaluated as the period at the beginning of the operation to the initial node death or the eventual node death.

We tested the suggested algorithm extensively. Experimental results were presented in a tabulated design. The suggested algorithm is compared to EAUCF, LEACH, TTDFP Tier-1, and EAMMH algorithms. The results show the suggested algorithm performs greater than EAUCF, LEACH, EAMMH, TTDFP Tier-1 algorithms in both scenarios. The limited energy is the major constraint in the WSN.

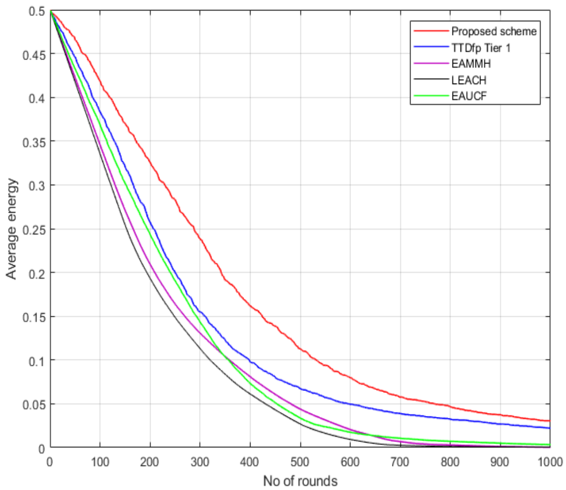


FIGURE 10. No. of round vs average energy.

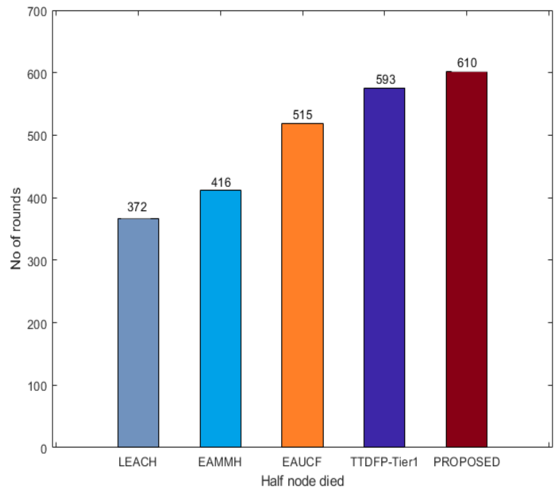


FIGURE 12. N0.of round vs HND.

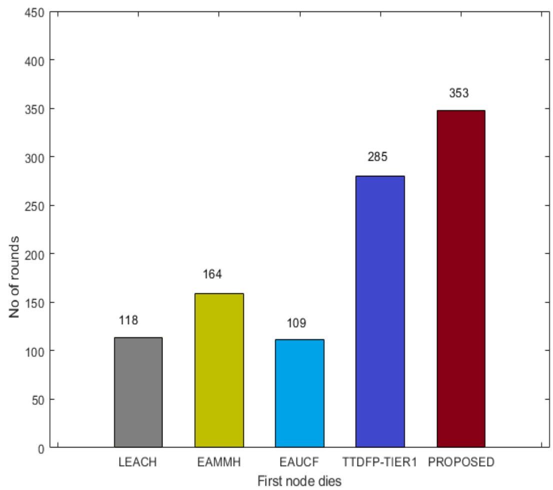


FIGURE 11. No. of round vs FND.

If energy-consumption between the nodes varies, some nodes will finish their energy earlier than others, hence making the network unstable. Fig. 10 shows the measured stability of the WSN. The measurement is achieved by comparing the average energy consumed in the network in each round. Therefore, the suggested algorithm consumes less energy compared to the older algorithms, such as EAMMH, EAUCF, LEACH, and TTDFP Tier-1 algorithms.

Several calculations have previously been utilized in other literature to explain the network duration of WSNs. The Half Node Die (HND) and First Node Die (FND) metrics are some of the commonly utilized calculations in EAUCF [13]. HND and FND include many rounds. The genesis of the network operation proceeds with the initial node until it runs out of battery. The other half of the rest of the nodes also run out of battery, respectively. Fig. 11 and fig. 12 demonstrate the simulation results of the network duration (HND and FND). Therefore, the suggested algorithm will perform better than previously considered algorithms (EAMMH, LEACH, TTDFP Tier-1, and EAUCF) for HND and FND calculations. Among the previously utilized algorithms, LEACH has the lowest performance. This is because LEACH utilizes a probabilistic method to choose CHs. For 500 rounds of cluster functions, nodes in LEACH start to run out of battery at 118 rounds. On the other hand, nodes in the EAMMH protocol start to run out of battery at 164 rounds, while the first node in the EAUCF protocol starts to run out of battery at 109 rounds, and the TTDFP Tier-1 protocol starts to run out of battery at 285 rounds. However, our suggested algorithm includes the first node running out of battery at 353 rounds.

The FND suggested algorithm has more outstanding performance than the TTDFP Tier-1 algorithm by 123.85%, EAUCF algorithm by 323.85, LEACH algorithm by 299.15%, and EAMMH algorithm by 215.24%. In fig. 11, half node died at 372 in LEACH. In EAMMH, half node died at 416, in EAUCF, half of the node died at 515, in TTDFP Tier-1 HND at 593, and in the proposed algorithm, half node died at 610, which is better than comparing to all these algorithms. The HND suggested algorithm has greater performance than the TTDFP Tier-1 by 102.86%, EAUCF algorithm by 118.44%, LEACH algorithm by 163.97%, and EAMMH algorithm by 146.63%.

Fig. 12 presents the number of sensor nodes that ran out of battery versus their respective number of rounds. In the suggested algorithm, the nodes that have run out of battery are less. The proposed algorithm considers all the possibilities in the selection of CHs. Therefore, energy usage by the WSNs is less, resulting in the recorded lower number of nodes running out of battery.

Fig. 13 and fig. 14 expresses that the first node died, and the Last Node died in the different network areas vs. the round number. The proposed algorithm performance is better than LEACH, EAMMH, EAUCF, and TTDFP Tier-1. The purpose of taking different network sizes is to establish the effect of the density of the node on the suggested algorithm. Equal clustering is used to determine a low-energy adaptive

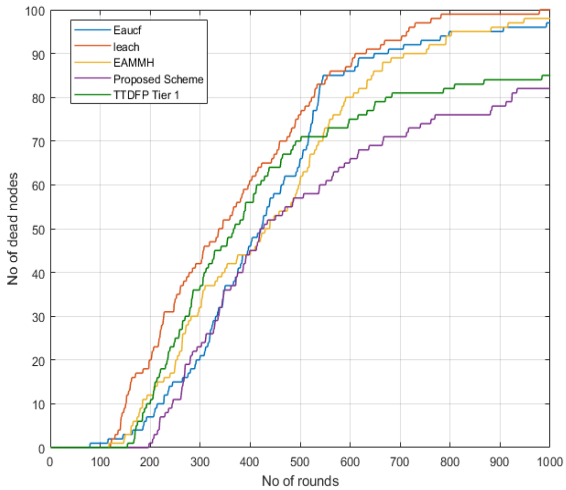


FIGURE 13. Round vs dead nodes.

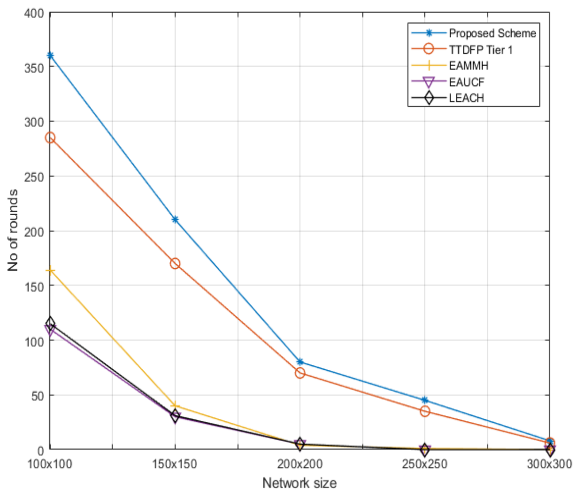


FIGURE 14. Round vs network area (FND).

hierarchy. Therefore, balancing of workload between adjacent nodes is not performed in this suggested algorithm. EAMMH (which is an energy-aware unequal clustering fuzzy protocol) balances the workload. However, its CH choice is determined by one parameter. This makes energy consumption to be high. The suggested protocol balances energy usage across the network. Forming unequal clusters achieves this. Besides, CH selection is achieved using the fuzzy method. In conclusion, the suggested algorithm performs better in all metrics than the previously used algorithms.

G. ENERGY DISSIPATION

The above table shows the energy dissipation of the proposed protocol with other algorithms at different network sizes. It can be seen that the energy dissipation of the proposed protocol is less with respect to other protocols as LEACH, EAMMH, and EAUCF, which leads to prolonging network lifetime. Also, the smaller cluster size near the sink in the proposed protocol balances the load among the nodes as well as solves the energy hole problem.

TABLE 6. Energy dissipation.

Network Size	Algorithm	FND energy dissipation	HND energy dissipation
100*100	LEACH	0.3032	0.0871
	EAMMH	0.2983	0.0738
	EAUCF	0.3587	0.0422
	TTDFP	0.2573	0.0671
	PROPOSED	0.2345	0.0551
150*150	LEACH	0.3515	0.1362
	EAMMH	0.3576	0.1222
	EAUCF	0.4077	0.1187
	TTDFP	0.2963	0.0852
	PROPOSED	0.2548	0.0637
200*200	LEACH	0.3683	0.1237
	EAMMH	0.3934	0.1333
	EAUCF	0.4758	0.1371
	TTDFP	0.3581	0.0.0760
	PROPOSED	0.3202	
250*250	LEACH	0.4189	0.1246
	EAMMH	0.4380	0.1416
	EAUCF	0.4996	0.1424
	TTDFP	0.4037	0.1269
	PROPOSED	0.3733	0.1013
300*300	LEACH	0.3481	0.1468
	EAMMH	0.4362	0.1501
	EAUCF	0.4698	0.1584
	TTDFP	0.3911	0.1395
	PROPOSED	0.3830	0.1006

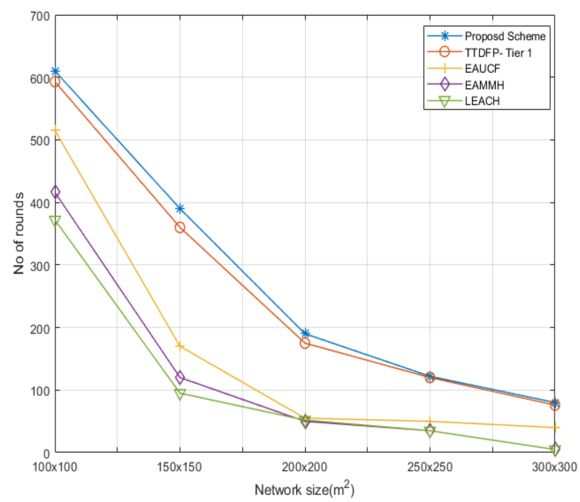


FIGURE 15. Round vs network area (HND).

H. SCENARIO 2

In this scenario, we try to assess the performance of clustering independently. The distribution of a total of 1000 sensor nodes and BS in a 1000m*1000m monitoring area. We assume the initial energy is 0.5J. The simulation frameworks utilized in the proposed system are shown in table 7.

In this scenario, fig. 16 shows the average energy of the nodes when the network executes 50, 100, and 150 rounds, which reflect the energy consumption of the network. In the graph, the proposed algorithm is always higher than the other algorithms and performs approximately 99.99% better than LEACH, nearly 83.4% better than EAMMH, 46.37% better than EAUCF, and 19.5% better than TTDFP Tier-1. This study shows that the proposed algorithm has lower energy

TABLE 7. Simulation parameters.

Area	1000m*1000m
Nodes	1000
Packets size	4000 bits
ϵ_{mp}	0.0013 pj/bit/m4
ϵ_{fs}	10 pJ/bit/m2
E_{elec}	50 nJ/bit
Initial Energy	0.5j
E_{DA}	5nj/bit/signal
Control Pcaket Size	200 bits

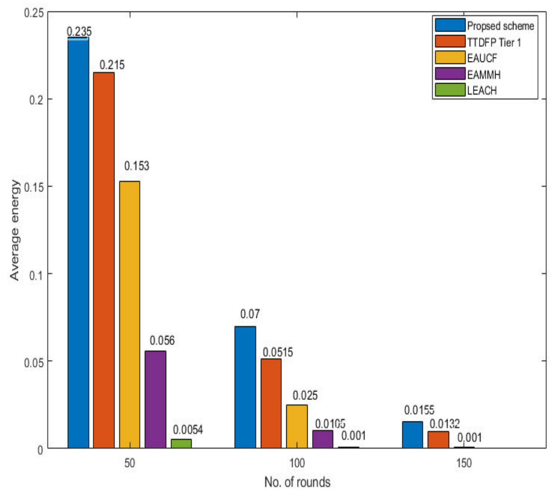


FIGURE 16. No. of round vs average energy.

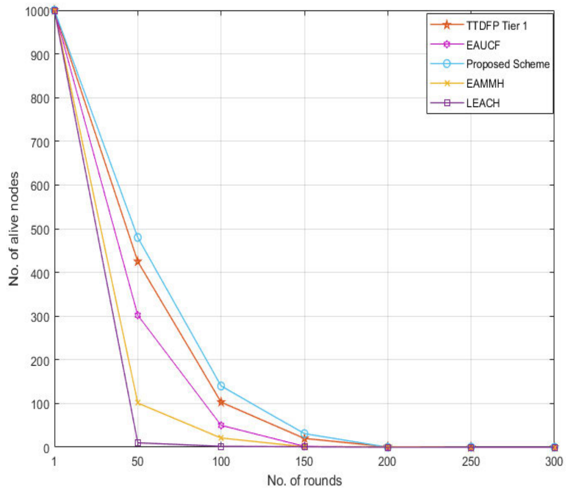


FIGURE 17. No. of rounds vs alive nodes.

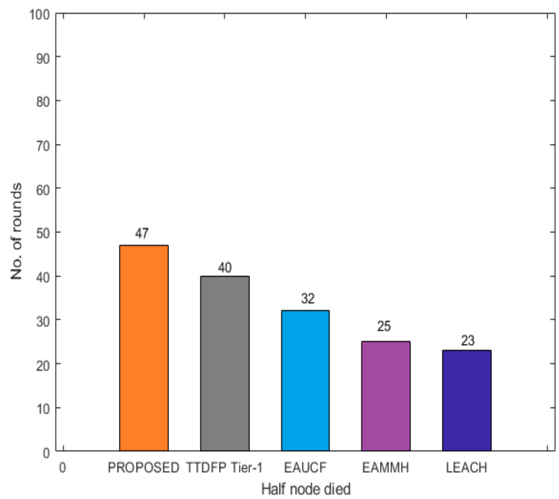


FIGURE 18. No. of rounds vs HND.

consumption that means its network lifetime is better and stable than other these comparing algorithms.

Fig. 17 shows the number of alive nodes in this scenario, and the proposed algorithm performance is better than comparing algorithms. Considering 300 rounds in this result and get LEACH algorithm nodes died quickly in the large scale wsn because LEACH sends data directly from CHs to BS. Other EAUCF, EAMMH, and TTDFP Tier-1 algorithm nodes also low survival time. Fig. 18 shows the number of rounds vs. half node died in scenario 2. The proposed algorithm has better performance than other comparing algorithms. The proposed algorithm performs 204.34% better than LEACH, 188% better than EAMMH, 146.87% better than EAUCF, and 117.5% better than TTDFP Tier-1.

I. DISCUSSION

The proposed algorithm's performance accumulations in a large area, i.e., scenario 2, were smaller than those in a smaller area, i.e., scenario 1. The use of fuzzy rules in different scenarios is an important reason for the difference in performance gains, which is the current algorithms' limitations. Because EAUCF, TTDFP Tier-1, and Proposed algorithm all adopt unequal clustering, which ensures the load balance of relay nodes in the cluster, also it can effectively avoid the hotspot problem. Compared with LEACH, these methods have better load balance and lower network energy consumption. In EAUCF and TTDFP, the algorithm is employed to calculate the CH chance and cluster radius by including the different parameters. Compared with EAUCF and TTDFP Tier-1, the proposed algorithm has better load balancing and longer network lifetime. The proposed algorithm uses one variable node concentration that handles better uncertainties in WSN. Therefore, the proposed algorithm has less network energy consumption and a longer network lifetime than other comparing algorithms in scenario 1 and scenario 2.

J. TIME COMPEXITY OF PROPOSED ALGORITHM

In the clustering, each node calculates its competition radius and CH chance independently. Accordingly, for this phase, the time complexity is O(1) for the entire network. At the cluster formation phase, each ordinary nodes selects from its competition range. Each ordinary node may need to process (n-1) number of comparisons in the worst case. Consequently, the time complexity of proposed for n nodes in the network is O(n). In clustering, the rule base is stored in a memory. The space complexity of memory is proportional to 2^N, where N is the number of fuzzy inputs in the fuzzy system.

IV. CONCLUSION

We proposed a fuzzy logic-based protocol because it performs better than other comparing algorithms. Some of the assumptions made include equally significant stationary networks of the existing nodes. Regarding this assumption, we introduced the new algorithm in three subsequent steps. The initial step is to apply multi-hop communication to reduce energy consumption. The step is followed by an offline phase, where an unequal clustering algorithm solves the energy hole issue by reducing the sizes of clusters near the BS and determining the competition radius through the fuzzy logic protocols. The final step utilizes fuzzy logic. After the distance to a BS, node residual energy and concentration have been used to select CHs. This final step helps in the distribution of workload among the CHs. Simulation results demonstrated that our process is useful for implementations that need minimization of energy consumption, load balancing, and prolonged network duration. Overall, the proposed algorithm is a better protocol compared to TTDFP Tier-1, EAMMH, EAUCF, and LEACH clustering algorithms. In our future work, we will use the interval type-2 fuzzy logic theory to solve the secure clustering protocol for mobile ad-hoc networks and the light weight secure mechanism will be our research focus.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[2] H. Taheri, P. Neamatollahi, O. M. Younis, S. Naghibzadeh, and M. H. Yaghmaee, "An energy-aware distributed clustering protocol in wireless sensor networks using fuzzy logic," *Ad Hoc Netw.*, vol. 10, no. 7, pp. 1469–1481, Sep. 2012.

[3] T. Kaur and J. Baek, "A strategic deployment and cluster-header selection for wireless sensor networks," *IEEE Trans. Consum. Electron.*, vol. 55, no. 4, pp. 1890–1897, Nov. 2009.

[4] G. Ran, H. Zhang, and S. Gong, "Improving on LEACH protocol of wireless sensor networks using fuzzy logic," *J. Inf. Comput. Sci.*, vol. 7, no. 3, pp. 767–775, 2010.

[5] N. A. Torghabeh, M. R. A. Totonchi, and M. H. Y. Moghaddam, "Cluster head selection using a two-level fuzzy logic in wireless sensor networks," in *Proc. 2nd Int. Conf. Comput. Eng. Technol.*, Apr. 2010, pp. V2-357–V2-361.

[6] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proc. 33rd Annu. Hawaii Int. Conf. Syst. Sci.*, Jan. 2010, pp. 357–361.

[7] O. Younis and S. Fahmy, "HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks," *IEEE Trans. Mob Comput.*, vol. 3, no. 4, pp. 660–669, Oct. 2004.

[8] J.-M. Kim, S.-H. Park, Y.-J. Han, and T.-M. Chung, "CHEF: Cluster head election mechanism using fuzzy logic in wireless sensor networks," in *Proc. 10th Int. Conf. Adv. Commun. Technol.*, Feb. 2008, pp. 654–659.

[9] M. C. M. Thein and T. Thein, "An energy efficient cluster-head selection for wireless sensor networks," in *Proc. Int. Conf. Intell. Syst., Modeling Simulation*, Jan. 2010, pp. 287–291.

[10] S. Bandyopadhyay and E. J. Coyle, "An energy efficient hierarchical clustering algorithm for wireless sensor networks," in *Proc. IEEE INFOCOM 22nd Annu. Joint Conf. IEEE Comput. Commun. Societies*, vol. 3, Apr. 2003, pp. 1713–1723.

[11] I. Gupta, D. Riordan, and S. Sampalli, "Cluster-head election using fuzzy logic for wireless sensor networks," in *Proc. 3rd Annu. Commun. Netw. Services Res. Conf. (CNSR)*, May 2005, pp. 255–260.

[12] C. Li, M. Ye, G. Chen, and J. Wu, "An energy-efficient unequal clustering mechanism for wireless sensor networks," in *Proc. IEEE Int. Conf. Mobile Adhoc Sensor Syst. Conf.*, Nov. 2005, p. 8.

[13] R. V. Kulkarni, A. Förster, and G. Kumar Venayagamoorthy, "Computational intelligence in wireless sensor networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 1, pp. 68–96, 1st Quart., 2011.

[14] Z. Ye and H. Mohamadian, "Adaptive clustering based dynamic routing of wireless sensor networks via generalized ant colony optimization," *IERI Procedia*, vol. 10, pp. 2–10, Jan. 2014.

[15] B. Singh and D. Lobiyal, "A novel energy-aware cluster head selection based on particle swarm optimization for wireless sensor networks," *Hum.-Centric Comput. Inf. Sci.*, vol. 2, no. 1, p. 13, 2012.

[16] B. A. Attea and E. A. Khalil, "A new evolutionary based routing protocol for clustered heterogeneous wireless sensor networks," *Appl. Soft Comput.*, vol. 12, no. 7, pp. 1950–1957, Jul. 2012.

[17] C. V. Negoita, "Fuzzy sets," *Fuzzy Sets Syst.*, vol. 133, no. 2, p. 275, Jan. 2003.

[18] M. M. Afsar and M.-H. Tayarani-N, "Clustering in sensor networks: A literature survey," *J. Netw. Comput. Appl.*, vol. 46, pp. 198–226, Nov. 2014.

[19] J.-F. Jian, G.-J. Han, L. Liu, X. Jiang, and J.-F. Huang, "An unequal clusterbased routing protocol for wireless heterogeneous sensor networks," *J. Internet Technol.*, vol. 16, no. 6, pp. 945–955, 2015.

[20] G. Chen, C. Li, M. Ye, and J. Wu, "An unequal cluster-based routing protocol in wireless sensor networks," *Wireless Netw.*, vol. 15, no. 2, pp. 193–207, Feb. 2009.

[21] A. Ali, Y. Ming, T. Si, S. Iram, and S. Chakraborty, "Enhancement of RWSN lifetime via firework clustering algorithm validated by ANN," *Information*, vol. 9, no. 3, p. 60, Mar. 2018.

[22] J. A. Stankovic, "Research directions for the Internet of Things," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 3–9, Feb. 2014.

[23] S. Jerusha, K. Kulothungan, and A. Kannan, "Location aware cluster based routing in wireless sensor networks," *Int. J. Comput. Commun. Technol.*, vol. 3, pp. 36–41, Jan. 2015.

[24] K. Kulothungan, S. Ganapathy, S. I. Gandhi, and P. Yogesh., "Intelligent secured fault tolerant routing in wireless sensor networks using clustering approach," *Int. J. Soft Comput.*, vol. 6, no. 5, pp. 210–215, May 2011.

[25] S. Lindsey and C. S. Raghavendra, "PEGASIS: Power-efficient gathering in sensor information systems," in *Proc. IEEE Aerosp. Conf.*, Mar. 2001, pp. 149–155.

[26] M. R. Mundada, V. CyrilRaj, and T. Bhuvaneswari, "Energy aware multi-hop multi-path hierarchical (EAMMH) routing protocol for wireless sensor networks," *Eur. J. Sci. Res.*, vol. 88, no. 4, Oct. 2012.

[27] H. Mostafaei, "Energy-efficient algorithm for reliable routing of wireless sensor networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5567–5575, Jul. 2019, doi: 10.1109/TIE.2018.2869345.

[28] H. Mostafaei and M. S. Obaidat, "Learning automaton-based self-protection algorithm for wireless sensor networks," *IET Netw.*, vol. 7, no. 5, pp. 353–361, Sep. 2018, doi: 10.1049/iet-net.2018.0005.

[29] H. El Alami and A. Najid, "ECH: An enhanced clustering hierarchy approach to maximize lifetime of wireless sensor networks," *IEEE Access*, vol. 7, pp. 107142–107153, 2019.

[30] H. El Alami and A. Najid, "MS-routing-G i: Routing technique to minimise energy consumption and packet loss in WSNs with mobile sink," *IET Netw.*, vol. 7, no. 6, pp. 422–428, Nov. 2018.

[31] J.-S. Lee and C.-L. Teng, "An enhanced hierarchical clustering approach for mobile sensor networks using fuzzy inference systems," *IEEE Internet Things J.*, vol. 4, no. 4, pp. 1095–1103, Aug. 2017.

[32] Y. K. Tamandani and M. U. Bokhari, "SEPFL routing protocol based on fuzzy logic control to extend the lifetime and throughput of the wireless sensor network," *Wireless Netw.*, vol. 22, no. 2, pp. 647–653, Feb. 2016.

[33] H. Bagci and A. Yazici, "An energy aware fuzzy approach to unequal clustering in wireless sensor networks," *Appl. Soft Comput.*, vol. 13, no. 4, pp. 1741–1749, Apr. 2013.

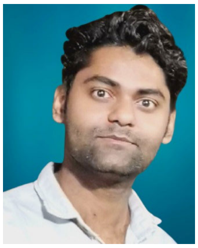
[34] S. A. Sert, A. Alchihabi, and A. Yazici, "A two-tier distributed fuzzy logic based protocol for efficient data aggregation in multihop wireless sensor networks," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 6, pp. 3615–3629, Dec. 2018, doi: 10.1109/TFUZZ.2018.2841369.

[35] S. A. Sert, H. Bagci, and A. Yazici, "MOFCA: Multi-objective fuzzy clustering algorithm for wireless sensor networks," *Appl. Soft Comput.*, vol. 30, pp. 151–165, May 2015.

[36] R. Logambigai and A. Kannan, "Fuzzy logic based unequal clustering for wireless sensor networks," *Wireless Netw.*, vol. 22, no. 3, pp. 945–957, 2016.

[37] S. A. Sert and A. Yazici, "Optimizing the performance of rule-based fuzzy routing algorithms in wireless sensor networks," in *Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE)*, Jun. 2019, pp. 1–6, doi: 10.1109/FUZZ-IEEE.2019.8858920.

[38] H. El Alami and A. Najid, "Energy-efficient fuzzy logic cluster head selection in wireless sensor networks," in *Proc. Int. Conf. Inf. Technol. Org. Develop. (IT4OD)*, Mar. 2016, pp. 1–7.
[39] J.-S. Lee and W.-L. Cheng, "Fuzzy-logic-based clustering approach for wireless sensor networks using energy predication," *IEEE Sensors J.*, vol. 12, no. 9, pp. 2891–2897, Sep. 2012.
[40] M. Mirsadeghi, A. Mahani, and M. Shojaee, "A novel distributed clustering protocol using fuzzy logic," *Procedia Technol.*, vol. 17, pp. 742–748, Jan. 2014.



MOHD ADNAN received the B.Tech. degree in electrical engineering from the Sam Higginbottom Institute of Agriculture, Technology and Sciences, Allahabad, India, in 2016. He is currently pursuing the master's degree in information and communication engineering with the School of Communication and Information Engineering, Chongqing University of Posts and Telecommunication, Chongqing, China. His current research interests include wireless sensor networks and software define networks.

LIU YANG received the B.S. degree in electronic information science and technology from the Qingdao University of Technology, Shandong, China, in 2010, and the Ph.D. degree in communication and information systems from the School of Communication Engineering, Chongqing University, Chongqing, China, in 2016. He is currently a Lecturer with the Chongqing University of Posts and Telecommunications. His current research interests include the Internet of Things, data analysis, and artificial intelligence.

TAZEEM AHMAD received the B.Tech. degree in electronics and communication engineering from the University Institute of Engineering and Technology, CSJMU, Kanpur, India, in 2017. He is currently pursuing the master's degree in information and communication engineering with the School of Communication and Information Engineering, Chongqing University of Post and Telecommunication, Chongqing, China. His current research interests include the Internet of Things, wireless sensor networks, and software define networks.

YANG TAO graduated from the National University of Defense Technology. He received the master's and Ph.D. degrees from Chongqing University. He was a Professor and a Ph.D. Supervisor. He was a Postdoctoral Fellow with the Institute of Computing Technology, Chinese Academy of Sciences. He was a Visiting Scholar with the University of Missouri. He is currently the Deputy Dean of the School of Communication, Chongqing University of Posts and Telecommunications, and the Director of the Chongqing Communication Software Engineering Technology Center. He has five provincial and above individual titles, including one hundred high-end engineering and technical talents in Chongqing and scientific and technological talents in the national three districts. He has undertaken more than ten national, provincial, and ministerial key major projects. He concurrently serves as the municipal government, several district, county, and municipal department informatization expert consultant, and the Director of the China Communications Industry Association. He has published more than 140 professional academic articles, 13 monographs, obtained 25 authorized national invention patents, and successively directed more than 200 Ph.D. and master's graduate students. He has successively received nine military, provincial, and national science and technology awards.