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# UNEQUAL CLUSTERING AND ROUTING PROTOCOL FOR A SUSTAINABLE WSN-BASED INTERNET OF THINGS BASED ON GREY WOLF OPTIMIZATION AND FUZZY LOGIC

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## ABSTRACT:

***With the ever-growing application of Wireless Sensor Networks (WSN)-based Internet of Things (IoT), it has gained enormous attention in the public and research domains. The energy constraint of WSN limits its applicability. In the paper, we have proposed a hybrid of Grey Wolf Optimisation along with Fuzzy Logic (FL) for energy-efficient Cluster Head (CH) selection, cluster formation, and cost-effective routing which improves Quality of Service (QoS) that can enhance the applicability of WSN in the diverse domains of IoT. The proposed work is simulated, and performance assessment is done on the basis of QoS metrics namely FND, HND, throughput, average energy, average node load and latency. The obtained results exhibit significant enhancement in the network lifetime with an enhanced stability period, higher throughput, reduced latency, and lessen traffic load and load-balanced network towards its comparative making it suitable for wide applicability in WSN based IoT.***

**Keywords:** Grey Wolf Optimisation, Fuzzy Logic, Unequal Clustering, Routing, Energy Efficiency, WSN, IoT

## 1.INTRODUCTION

WSN is one of the well-known and well-established technologies that, in terms of the network layer and sensor layer, may be readily integrated in IoT systems due to several innovations and improvements. With the aid of WSN, the sensor-generated network develops IoT devices. WSN has reached our province through a number of smart applications, including remote control systems, smart homes, smart health monitoring, etc. [1–3]. The design of low-power WSNs for the smart cities, transportation industries, etc. has recently been the subject of studies [4, 5].

Most of the time, WSN is installed in an unattended area of interest where it is strenuous to recharge or replacing the power supply once it has been fully depleted. WSN is predicted to have a prolonged lifespan because of efficient energy use, which has drawn academicians' and researchers' interests from many different fields. IoT networks also resemble adhoc networks, which can handle WiFi-Direct and device-to-device communication. The large scale deployment of nodes and the maintenance of the topology are important in such Adhoc IoT networks. Clustering in ad-hoc networks, such as WSN, is traditionally among the most popular approaches to topology maintenance. For the purpose of data collection, data forwarding, assuring service quality, and resource management, the clustering approach divides the network into groups or clusters. Data transfer must be done hop by hop in Adhoc IoT networks and WSNs due to several design similarities in their topology management. It is extremely desired to use routing approaches that are efficient and can reduce energy consumption [6–8].

The information is passed from the cluster members to the CH, who gathers it and forwards it to the Base Station (BS) for processing [9]. In order to improve a network's lifespan, effective CH selection, cluster creation, and information routing are necessary. Therefore, it can be believed that Adhoc IoTs can manage the topology without having to create it from scratch using WSN's clustering and routing algorithms [10].

In this work, a simplified architecture for WSN based IoT is considered that is depicted in Figure 1.

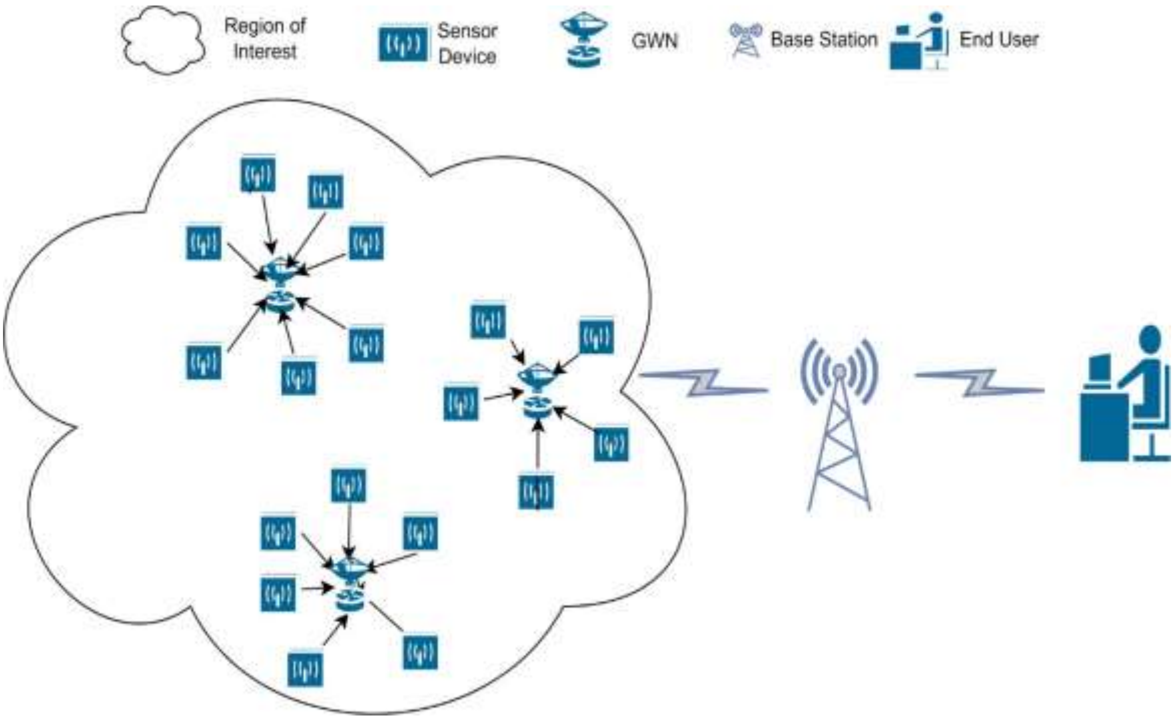


**Fig. 1 A simplified architecture for WSN based IoT.**

### 1.1 Contribution of paper

The contributions of the propound GWO-EFUCA protocol are

1. The GWO-EFUCA protocol balances the load of the network protracting the network lifetime.
2. Fuzzy extended grey wolf optimized algorithm is designed with dominant variables for the selection of CH nodes.
3. For clustering process, another fuzzy extended grey wolf optimized algorithm is designed for efficient unequal cluster formation.
4. For unequal clustering, fuzzy inference system is used for efficient routing.
5. For preventing long-distance communication during data dissemination from CH to BS, a fuzzy extended grey wolf optimized algorithm is designed for multi hop routing.
6. GWO-EFUCA is simulated and contrasted with LEACH [11], GWO-C[12] and E-FUCA[13] protocols and obtained simulation results support justify the sustained stability period, better average energy with load balancing, minimum delay and low overhead on sensor nodes.

The remnants of this paper are classified as follows: the literature work is discussed in Section 2. In Section 3 the network model, system model, GWO algorithm, and FL preliminaries are explained. Section 4 elaborates the working of proposed GWO-EFUCA protocol. Simulation experimental setup and performance assessment is covered in section 5. The concluding remarks of the proposed work is given in Section 6.

## 2. RELATED WORK

The challenging aspect for WSN is energy efficiency, which can be achieved through clustering algorithms. This section discusses a few relevant unequal clustering techniques. Any cluster-based proposed work's literature review would be lacking without a consideration of the LEACH [11], Heinzelman et al. introduced LEACH in 2000, which uses a non-deterministic approach to choose the CH and makes local judgments. CHs are cycled in each round to balance the strain on the network because static CHs prematurely age out in contrast to nodes without CHs. To cut down on communication costs, data fusion is executed at the CH level. The CH selection in this technique is completely random, and important characteristics like remnant power and remoteness from BS, which effect energy level, are not examined.

The distributed algorithm EDUC[14] protocol avoids the energy loss and hot spot issues in heterogeneous WSN. It makes use of clusters rotating under the influence of energy. In this protocol, the position of CH is available to every node at some point. Multi-hop networks cannot benefit from this technique. The hotspot problem is prevented by LUCA [15], which is based on likelihood. Cluster sizes vary according to how far away from BS they are. GPS, which is location-aware, is included with SN. There is a backoff timer with a random initial value. The CH sends the message to SN then only it will join; otherwise, it announces its candidacy. The EADUC [16] algorithm is made to continually collect information in the network. The candidates for CHs are given more weight based on leftover energy and node degree since they perform better over the course of a lifespan. The fuzzy-based protocol CHEF[17] considers remnant energy and neighbourhood distance as two inputs for FIS with nine IF- THEN rules which determine how the inputs should be evaluated and how likely it is that a node will be selected as the cluster coordinator. A distributed protocol called CHFL [18] uses reachability, distance to the BS, and residual energy as fuzzy inputs. For cluster formation, the non-CHs pick the adjoining CHs.

In EAUCF [19] a clustering algorithm is developed that is based on FL. The algorithm elects the CH using remnant energy and remoteness from the BS. The provisional CH is chosen using nine IF-THEN fuzzy criteria. Each prospective CH determines its candidacy's competitive radius. However, this proposed effort does not account for energy depletion brought on by extensive intra-communication that deteriorates protocol performance. FBUC [20], in which the potential CHs are chosen using a probabilistic technique, is an improvement on EAUCF. During the election of the CH, the chance and competition radius are calculated. The non-CH nodes estimate each CH's likelihood of forming a Cluster based on its density and distance from other CHs. Comparing the protocol's longevity to that of LEACH Head and EAUCF, it is more durable. The proposed IFUC [21]protocol has the potential to minimize energy use. Their protocol also extend network lifetime. The CH nominations and the cluster's range are determined based on FL The last CH is chosen from among the SNs with a higher chance. The DUCF [22] protocol ensures load balancing by the establishment of clusters utilising FL. Node density Aloofness to BS, and residue energy are the fuzzifier's inputs. Size and chance are the two output variables. The cluster's size is determined by the chance attained. For inference, the Mamdani method is employed.

Unequal clustering that considers remnant energy, computed density, and distance from BS is proposed in MOFCA[23], which is independent of distribution. To reduce intra-cluster relay, the cluster radius is modified according to how far it is from the BS. Hotspot and energy hole problems have been successfully resolved. There are numerous clustering algorithms mentioned in MCFL [24]. The best candidates are chosen as CHs, and re- clustering is temporarily delayed in order to reduce the amount of messaging needed to establish clusters. Experiment results demonstrate that the proposed work outperforms its competitors.

The E-FUCA [13] used Fuzzy-based methods for improved cluster formation and efficient routing for WSN. The protocol focuses on unequal clustering and uses FL to determine the competition radius and rank. Some important factors such as remaining energy and distance to BS and average distance are discussed. Rank of CH, proximity to CH, and the number of SNs inside the CH radius are taken into account while calculating CH probability. Rank of next-hop, reduced distance to BS, and closeness to next-hop are used as input factors to the FIS for estimating cost during the data dissemination stage. The network's lifespan is greatly increased by the proposed effort. A multi-level smart city design and a number of IoT-based application domains were presented by Gaur et al. [25]. It addresses the uncertainty issue in the context of the smart city. The customised services in the environment which are utilising semantic modelling and Dempster-Shafer theory are taken into account. A review on the investigation and application of WSN clustering strategies was published by Shahraki et al. in [10].It offers extensive analysis into IoT clustering and routing that give the reader a more comprehensive interpretation of the design issues and throw light on potential future uses of cutting-edge technology combined with IoT. A survey of IoT smart city technologies, practises, and difficulties was given by Syed et al. [26] The paper offers comprehensive treatment of IoT-based Smart automation and in detail analysis of enabling technologies. The implementation of IoT systems is reviewed along with a review of common methods and applications, obstacles, and potential solutions. WSN is described along with their benefits and drawbacks in [27].Their work provides comprehensive overview on the clustering and routing strategies.

GWO algorithm has been extended in [28] based on threshold based energy-efficient clustering to elongate the network stability. Their approach perform significantly better as compare to other clustering algorithms. The energy consumption is low with increase in system lifetime. In GWO-C [12], authors proposed an algorithm for election of CH. Their algorithm is efficient to enhance the lifetime of network in WSN. GWO is modified to achieve the goal of CH selection. Authors proclaim that their approach outperform its comparatives in terms of lifespan, energy consumption, and network's throughput. Average intra cluster distance has been formulated to minimise the energy expenditure in the network. Average BS distance is also determined as the ratio of BS and CH distance and alive SN in network. Remnant energy is applied to compute the utilisation of energy in WSN. A CH selection approach has been proposed in [29] which is based upon Grey wolf optimization technique for WSN. Authors consider many distinct factors such as node degree, energy level, intra cluster distance, sink distance and priority factor. The proposed approach is used to solve the routing problem for reliable and effective inter cluster routing from CHs to BS through QoS aware relay node selection. The network performance is claimed that it has enhanced by 23.75%, 10.00%, and 54.54% as compared to GECR ESO, and LEACH approach.

Kaushik et. al in [30] propound DBSCDS-GWO which is stable connected dominated set approach using a meta-heuristic technique. To enhance the functionality of cluster-based WSN, authors also offer the DBSC-GWO method, which uses distance-based stable clustering. In terms of energy efficiency and network stability. DBSCDS-

GWO outperforms its comparatives. For comparison and verification of proposed approach, authors used MATLAB simulation and Netsim Emulator. Lipare et. al in [31]used the GWO method for clustering and routing in energy efficient WSN. Two more fresh fitness functions are also presented for resolving the clustering and routing problem in WSN. It minimise the hop count to formulate the fitness function for routing. In this function according to distance from BS to gateway the overall load is distributed among clusters.

## 3. PRELIMINARIES AND SYSTEM MODEL

This section elaborates the energy model, network model, grey wolf optimization algorithm and fuzzy model which is incorporated in the proposed GWO-EFUCA protocol.

### 3.1 Energy Model

In the proposed GWO-EFUCA protocol, we have adopted the energy model as discussed in [11] and depicted in Figure 2.

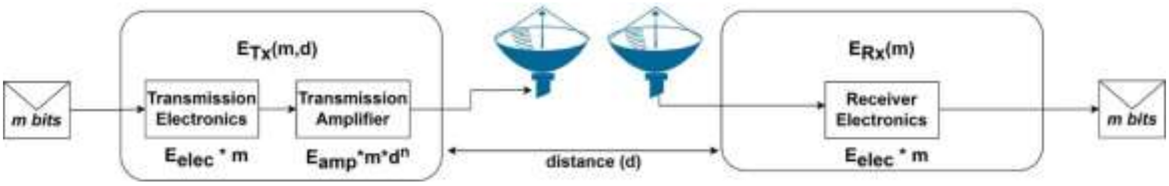


**Fig. 2 Energy model.**

There are several operations that depletes the energy of the SNs like sensing, transmission, amplification and reception. The amount of energy which dissipates while transmitting ($ETx$) as well as receiving ($ERx$) for $m$ bits over $d$ distance is computed by Eq.(1) and Eq.(2).

$$E_T(m,d) = \begin{cases} m * E_{elec} + m * \varepsilon\varepsilon_{fs} * d^2, d < d_o \\ m * E_{elec} + m * \varepsilon\varepsilon_{mp} * d^4, d \geq d_o \end{cases} \quad (1)$$

$$E_{Rx}(m) = E_{Rx-elec}(m) = m.E_{ele}, \quad (2)$$

The variables like $\mathcal{E}fs$, $Eelec$ , and $\mathcal{E}mp$ are the energy exhausted in free space, the energy dissipated in electrical ciruitary, energy exhausted in multipath fading respectively.

For amplying the received signal, the amount of energy required ($Eamp$) is computed by Eq. (3).

$$E_{amp} = \begin{cases} \varepsilon\varepsilon_{fs} * d^2, if d < d_o \\ \varepsilon\varepsilon_{mp} * d^4, if d \geq d_o \end{cases} \quad (3)$$

*Where* $d_O$ represents the threshold determining whether multipath or free space model is being implemented. This is computed using Eq. (4)

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

The cost of communication which is being borne by each CH for one round is evaluated by Eq. (5)

$$E_{CH} = n * m\ (E_{DA} + E_{Rx}(m,(CH,CM)) + E_{amp}) + E_{sens} + E_{Tx}(m,d(BS)) \quad (5)$$

wherein *m* signifies the number of bits, *n* denotes the total members of cluster, *d(CH, CM)* represents the distance from CH to cluster member, $EDA$ denotes the energy for data aggregation, *Esens* signifies the amount of energy required for sensing and *d(BS)* symbolizes the distance from the SN to BS.

Since cluster members will also dissipate energy during the processing of each round and thus it can be computed by Eq.(6).

$$E_{CM} = m * (E_{elec} + \varepsilon\varepsilon_{fs} * d_C) \quad (6)$$

Where $dCH$ denotes the distance of a cluster member from its CH.

### 3.2 Energy Model

In proposed GWO-EFUCA protocol, we have considered four different regions as considered in the EFUCA protocol[13]. All four regions are depicted in Figure 3. In region 1, The size of the field is 200×200 with one hundred SNs possessing one joule of energy level, and the BS is held in reserve at a faraway location as of the network specifically (100,300). In region 2, the region's size is same as region 1 and BS is positioned at the center of the regions i.e. (100,100) with two hundred SNs possessing half joule of energy level. For region 3, there are three hundred SNs possessing half joule of energy level and the size of the network as 300×300, and BS is set aside at the bottom center i.e. (150,0). In region 4, with five hundred SNs possessing half joule of energy level, and the network size with BS is 500×500 situated at the top-left place of the network i.e at (0,500). The reason for these four regions is to increase the applicability of the proposed work irrespective of BS position.

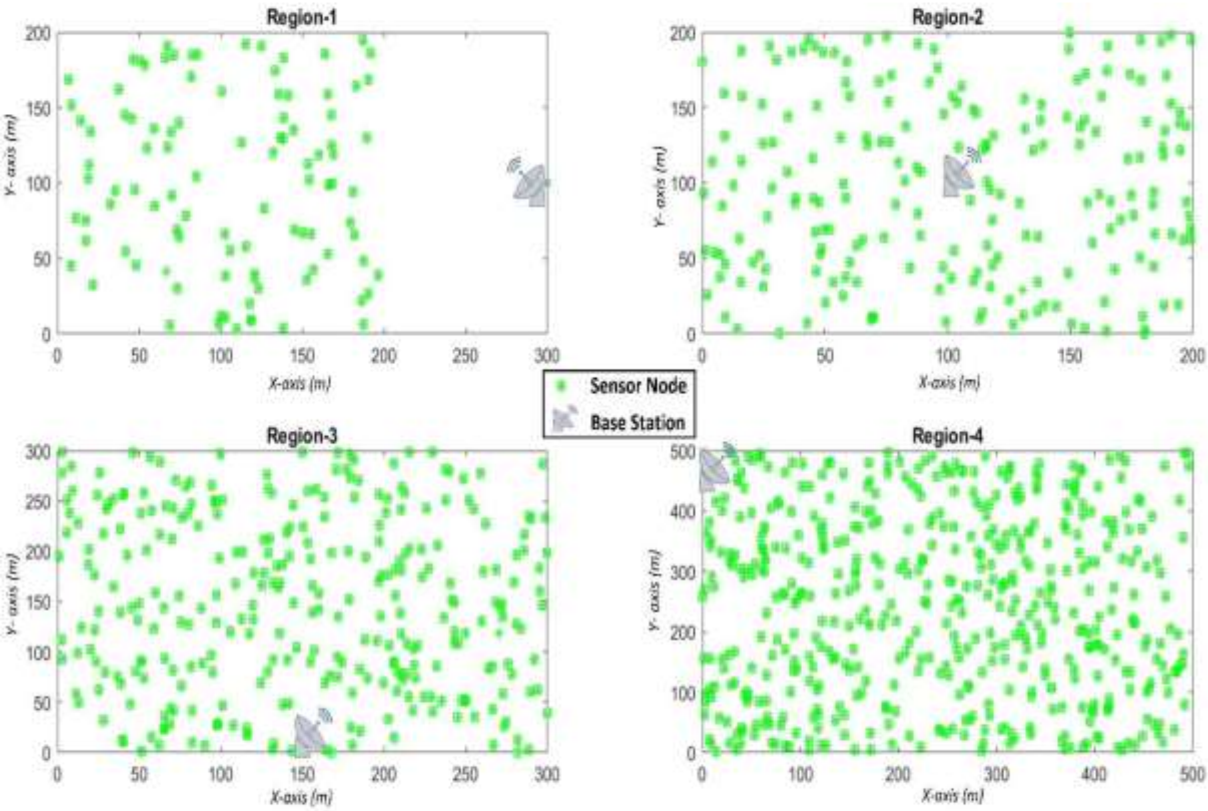


**Fig. 3 Regions considered for proposed GWO-EFUCA protocol.**

There are some assumptions considered for the network as mentioned below:

1. The BS has a constant supply of energy whereas SNs are bundled with the irreplaceable power source.
2. The deployment of SNs is random and immovable once deployed.
3. Every SNs will possess a unique identifier which is associated with its memory.
4. The network consists of homogeneous SNs in terms of processing power, memory, and energy.
5. Symmetric communication link is established between two SNs for simplicity.
6. Every cluster will have one CH and every node will have one CH in each round.
7. RSSI (Received Signal Strength Index) may be used for approximating the distance. GPS can also be used for the accurate position of nodes as required by the application.
8. Once the nodes deplete all its energy, they will be deemed as dead.

### 3.3 GWO

GWO [32] is a bio-inspired algorithm that imitates the grey wolf's intelligent behavior that includes the leadership as well as hunting behavior of grey wolf. These animals live in groups that generally consist of 5-12 members that strictly follow a social hierarchy. The group is split into four level hierarchies as shown in Figure 4. each individual level named as alpha (α), beta (β), delta (δ) and omega(ω).

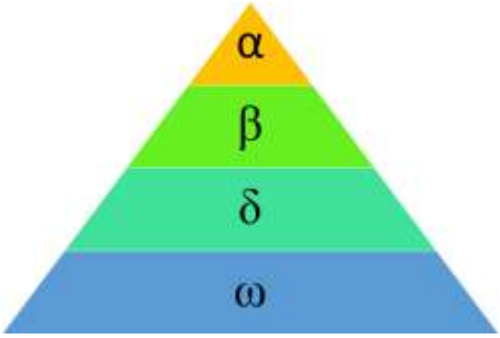


**Fig. 4 Hierarchy of wolves in GWO algorithm**

Alpha wolves (α) belong to the first level in the hierarchy and are measured as the first leader of the pack. Every decision-making process like approaching, hunting, and instructing other wolves in the entire pack is the responsibility of Alpha wolves. Beta wolves (β) resides at the second level in the hierarchy which guides alpha wolves in decision making and take over the responsibility of alpha wolves after they pass away. They are sometimes called the subordinate wolves. The third level in the hierarchy is the Delta which is also called caretaker. The last level in the hierarchy is represented by Omega which follows the instructions of the leaders above in the hierarchy. They are also responsible for maintaining safety as well as integrity in the wolf pack. The working of GWO algorithm can be mathematically modelled as follows:

#### 3.3.1 Initializing

The GWO process starts with the exploration process by scattering arbitrarily some of the wolves in the search space to find the prey (optimal solution). The grey wolves' positions are represented by the vectors as per Eq. (7).

$$\vec{X} = \{[1], x[2], \dots \dots \dots, x[m]\} \tag{7}$$

where *m* denotes the search space size.

During the chasing process of GWO i.e., optimization, with the help of objective function, the fitness of each wolf can be determined. There are three best fitness values for wolves which are ranked as α, β, and δ. α, β, and δ describe the best solution, the second-best solution and the third best solution respectively. As per the values of the α, β and δ, rest of the wolves i.e. (ω) update their position. The working of GWO can be broken down into two stages, such as, hunting and encircling i.e., the optimum solution.

### 3.3.2 Encircling the prey

To inhibit the activities of the prey, the wolves surround the prey. This encircling process can be represented mathematically as

$$\vec{D} = |\vec{C}\cdot\vec{X}_p(t) - \vec{X}(t)| \quad (8)$$

$$\vec{X}(t+1) = |\vec{X}_p(t) - \vec{A}.\vec{D}|, \quad (9)$$

Where $t$ denotes the current iteration, the vector $\vec{X}_p(t)$ represents the prey's position and $\vec{X}$ denotes the wolf's position. The coefficient vectors $\vec{A}$ and $\vec{C}$ calculated from Eqs. (10) and (11) respectively.

$$\vec{A} = 2\,\vec{a}\cdot\vec{r}_1 - \vec{a} \quad (10)$$

$$\vec{C} = 2.\vec{r}_2, \quad (11)$$

where, $\vec{a}$ is accustomed linearly with the iterations ranging from 2 to 0, $\vec{r}_1$ and $\vec{r}_2$ are the random vectors in the [0,1] interval.
To see the effects of Eq. (8) and Eq. (9), Figure 5 illustrate the 2D position vector with some possible neighbors.

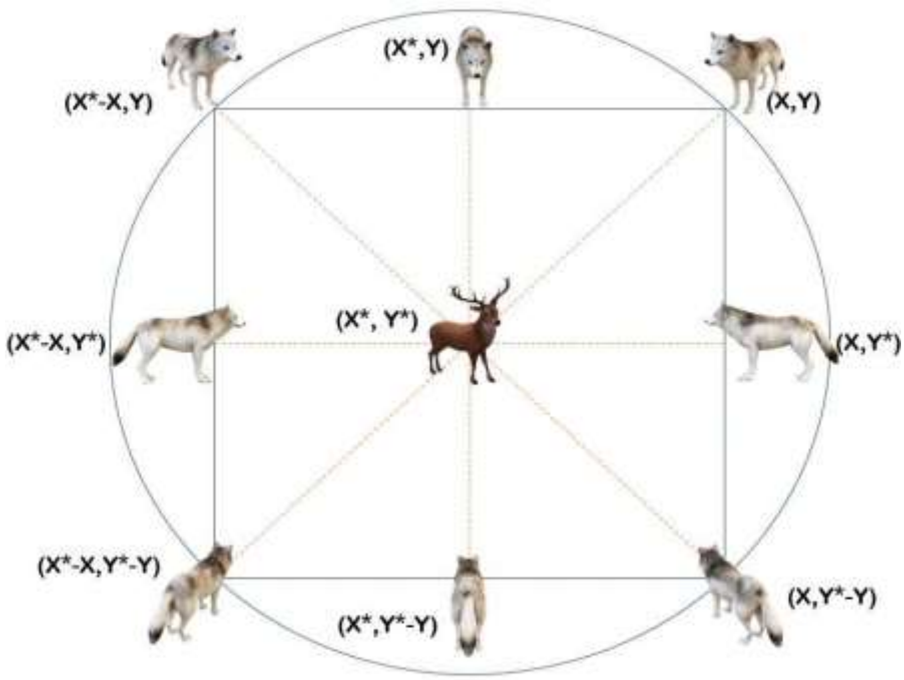


**Fig. 5 2D position vector of wolf with possible next locations**

As we can see, a grey wolf update its position from current position at (X, Y) to the position of the prey (X*, Y*). Different positions about the best agent can be moved w.r.t the present position by altering the value of $\vec{A}$ and $\vec{C}$ vectors. For example, (X*–X, Y*) can be reached by adjusting $\vec{A}$ = (1,0) and $\vec{C}$ = (1,1).

### 3.3.3 Hunting

The best and optimal location of the prey is given using the variables $\alpha$, $\beta$ and $\delta\delta$. The location of $\alpha$, $\beta$ and $\delta\delta$ is always discovered, preserved and updated as given in equation 12. For example, with Eqs. 14, $X_{WWi}$ indicates the location of the wolf $WW$ ,$\alpha$ is α wolf's location and $D_\alpha$ is updated α location. Similarly, $X_\beta$ is β wolf's location and $D_\beta$ is the updated β location.$X_{\delta\delta}$ is δ wolf's location and $D_{\delta\delta}$ denote the updated $\delta\delta$ location. $C_1$ , $C_2$, and $C_3$ are calculated using Eq. 11. Equation 13 are used for the current iterations to calculate the final locations ($X_1$,$X_2$,$X_3$) of a wolf as per Eq.(12) and Eq. (13).

$$\vec{D}_\alpha = |C_1 . X_\alpha - X_{Wi}|, \vec{D}_\beta = |C_2 . X_\beta - X_{Wi}|, \vec{D}_{\delta\delta} = |C_3 . X_{\delta\delta} - X_{Wi}| \quad (12)$$

$$X_1 = X_\alpha - A_1 . D_\alpha, X_2 = X_\beta - A_2 . D, X_3 = X_{\delta\delta} - A_3 . D_\delta \quad (13)$$

We calculate $A_1$, $A_2$, $A_3$ utilizing Eq.10. Utilizing Eq. (14) the wolf in the end updates its location as per the best solutions $\alpha$, $\beta$ and $\delta\delta$.

$$\vec{X}(t+1) = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \quad (14)$$

### 3.3.4 Attacking

Grey wolves wander while searching for prey (exploration) where we make use of $\vec{A}$ as a mathematical model wherein |A|>1 compel the grey wolves to diverge away from the prey and converge while attacking the prey (exploitation) where as |A|<1 compel the grey wolves to converge and attack the prey. In the next step, each $\omega$ wolf is again updated as per present $\alpha$, $\beta$ and $\delta\delta$, which is known as updating of population. There are three terminating condition i) if the predecided iteration count completed, ii) if the algorithm converge to an optimal solution in case the optimal value is unknown, and iii) if there is no progress after a certain number of reiterations.

### 3.4 Fuzzy Model

For resolving any uncertainties that are involved in a system, Fuzzy Logic is used as an alternative. There are several overall overlapping factors like energy, centrality, aloofness etc. while striving for energy efficient network. These overlapping factors create uncertainty which can be solved by Fuzzy Logic. Membership functions (MF) like Trapezoidal and Triangular are used in proposed work. They are used for boundary and intermediate variables, respectively, as they are capable of providing speedy calculation and easy to implement. The MF lies between 0 to 1, which is to be satisfied. Although, there are other MF that could have been used but proposed work exhibited promising results with triangular and trapezoidal MFs which are given by Eq. (15) and (16) respectively.

$$(y; p, q, r) = max\,(min\,(\frac{y-p}{q-p}, \frac{r-y}{r-q}), 0) \quad (15)$$

Where p and r denotes the base and q represents the peak of the triangle

$$(y; p, q, r, s) = max\,(min\,(\frac{y-p}{q-p}, 1, \frac{s-y}{s-r}), 0) \quad (16)$$

Where p,s denotes the feet and q,r represents the shoulders of the trapezoid.

The proposed work incorporates Mamdani Inference method[33] since it is simple and efficiently interpret and draw conclusions on the basis of specified IF-THEN rules quickly. For defuzzification, the Centre of Area (COA) method is used that is mostly used [20, 34, 35] . It is computed by Eq. (17).

# 4.PROPOSED GWO-EFUCA PROTOCOL

The proposed GWO-EFUCA protocol focuses on improving the stability as well as the prolonged network. To the best of our knowledge, the proposed GWO and Fuzzy logic is the first application for Unequal Clustering and routing in WSN. It is an improvement over E-FUCA [13] protocol which considers only fuzzy logic but the proposed work contemplates the GWO-Fuzzy Logic for efficient selection of CH, cluster formation, and data routing towards BS. The working of the proposed GWO-EFUCA is split into rounds. In the proposed work, for each round, there are two phases namely setup and steady. In setup phases, CH selection and cluster formation is done and in the steady phase, data forwarding takes place from the source i.e. SNs to the destination i.e. BS.

## 4.1 Setup Phase

This section discusses the CH selection and clustering process in the proposed GWO-EFUCA protocol. We consider a WSN consisting of $N$ SNs. These SNs are randomly distributed in the regions where the network is to be established. All the SNs are having unique IDs to differentiate among themselves and this information is available with the BS. In next subsection, the process of CH selection is discussed.

### 4.1.1 Selection of CH

Once the network becomes operational, The BS needs to collect information from the SNs in the network. It sends a broadcast requesting information like remnant energy which will help to compute factors like average distance, location estimation, and distance to BS. Since BS is having significant power in terms of computation, processing and energy, therefore the resource-intensive task will be carried out at BS. In the course of CH selection, The BS carries out the CH selection process using GWO and Fuzzy Logic as described in flow chart in Figure 6. During the CH selection process, the BS incorporates fuzzy logic for computing the fitness value(rank) of the search agents i.e. SNs. The FIS for the same is depicted in Figure 7. Three input variables are considered for *competition radius* and *Rank* : average distance, residual energy, and closeness to BS. *Rank* denotes the fitness value of a node and *Competition radius* decides the transmission range for each node up to which the communication will take place. It is adjusted as per the value of rank computed for SN. It is influential factor because a low powered energy node need not to communicate to longer distance as it long distance transmission deplete a quicker energy. The MF plots shown in Figure 8 and Figure 9 represent the graph for the input and output variable.

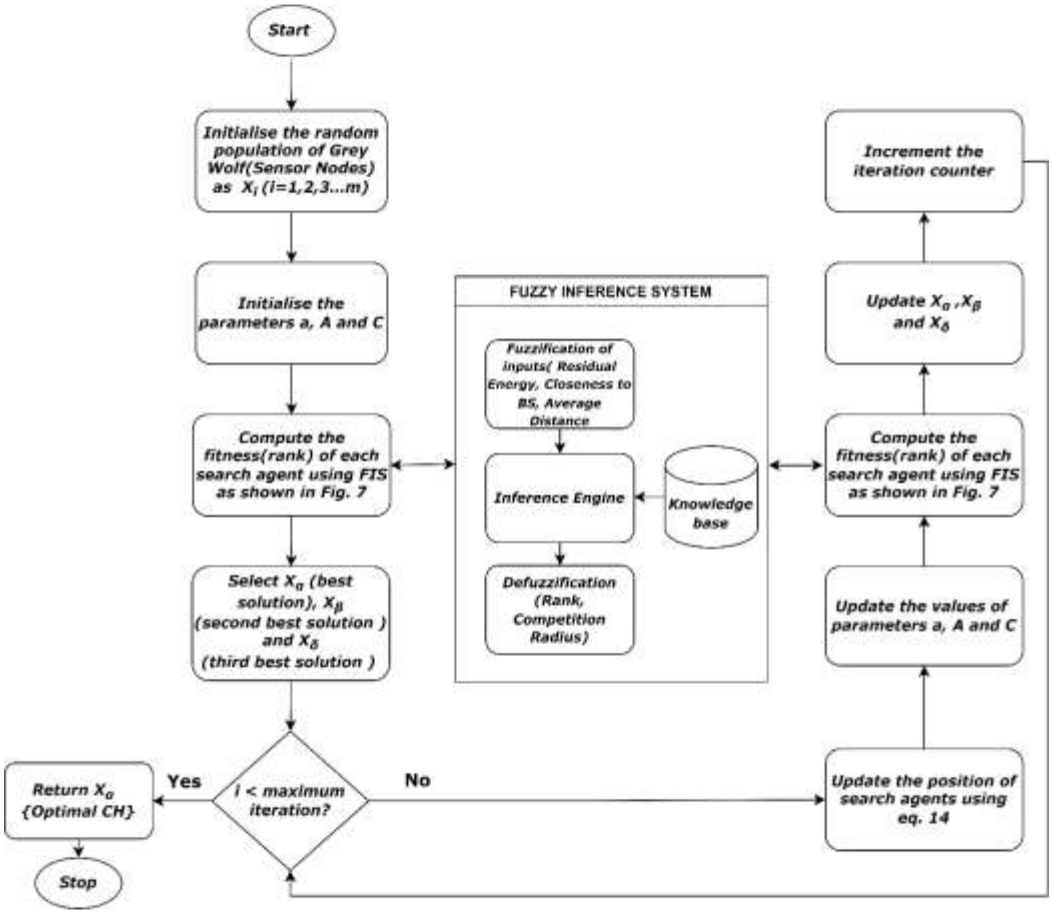


**Fig. 6 Flowchart for CH selection in GWO-EFUCA**

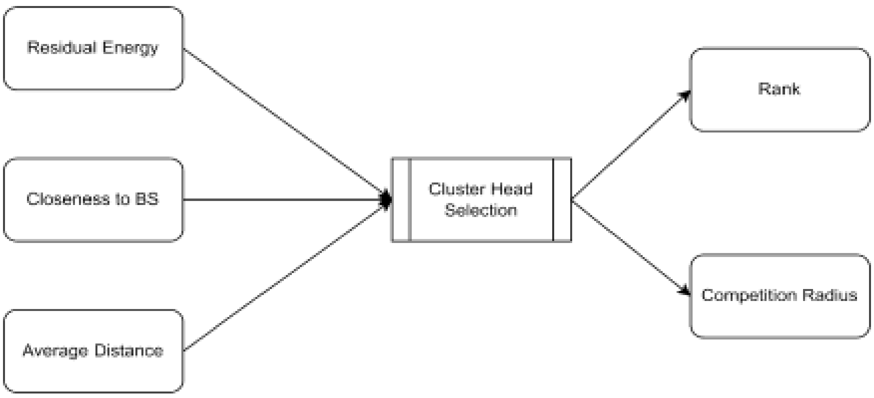


**Fig. 7 FIS for CH selection**

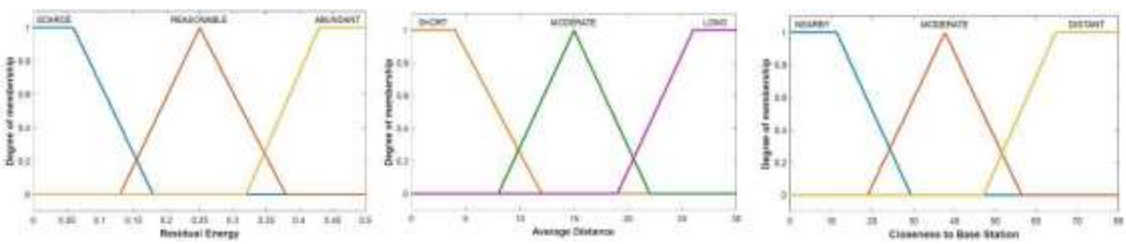

**Fig. 8 MF for input variables in CH selection**

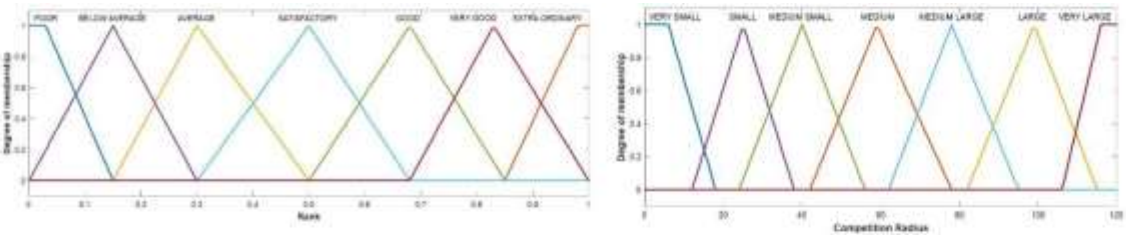


**Fig. 9 MF for output variables in CH selection**

The inputs have their own linguistic variables. Residual energy has Scarce(Sc), Reasonable(Rs) and Abundant(Ab); Closeness to BS has Nearby(Ny), Moderate(Mte) and Distant(Dt); Average distance has Long (Lg), Moderate (Mte) and Short (St). The output variables also have their linguistic variables. Rank has Poor(Pr), Below Average(BA), Average(Ag), Satisfactory(Sf), Good(Gd), Very Good(Vg), Extra Ordinary(EO); Very Large (VL), Large (Lg), Medium (Mm), Medium Large (MmL), Medium Small (MmS), Small (Sm), and Very Small (VSm) are the sizes of the competition radius .Fuzzy rules defined to compute rank and competition radius are represented in Table 1.

| Residual Energy | Closeness to BS | Average Distance | Rank | Competition Radius |
|---|---|---|---|---|
| Sc | Ny | Lg | Ag | MmS |
| Sc | Ny | Mte | Ag | MmS |
| Sc | Ny | St | Sf | Mm |
| Rs | Ny | Lg | Sf | Mm |
| Rs | Ny | Mte | Sf | Mm |
| Rs | Ny | St | Gd | MmL |
| Ab | Ny | Lg | Vg | Lg |
| Ab | Ny | Mte | EO | VL |
| Ab | Ny | St | EO | VL |
| Sc | Mte | Lg | BA | Sm |
| Sc | Mte | Mte | BA | Sm |
| Sc | Mte | St | Ag | MmS |
| Rs | Mte | Lg | Sf | Mm |
| Rs | Mte | Mte | Sf | Mm |
| Rs | Mte | St | Gd | MmL |

| | | | | |
|---|---|---|---|---|
| Ab | Mte | Lg | Gd | MmL |
| Ab | Mte | Mte | Vg | Lg |
| Ab | Mte | St | Vg | Lg |
| Sc | Dt | Lg | Pr | VSm |
| Sc | Dt | Mte | Pr | VSm |
| Sc | Dt | St | BA | Sm |
| Rs | Dt | Lg | BA | Sm |
| Rs | Dt | Mte | BA | Sm |
| Rs | Dt | St | Sf | Mm |
| Ab | Dt | Lg | Gd | MmL |
| Ab | Dt | Mte | Gd | MmL |
| Ab | Dt | St | Vg | Lg |

### 4.1.2 Cluster formation

Once the process of CH selection is completed, cluster formation needs to be completed. Since, the competition radius has been calculated in CH selection process, the selected CHs information need to be notified within the competition radius. All the non-CH nodes need to be assigned their CHs. This decision of choosing the CH is done using GWO-Fuzzy-based method which is described as Flow chart in Figure 10.

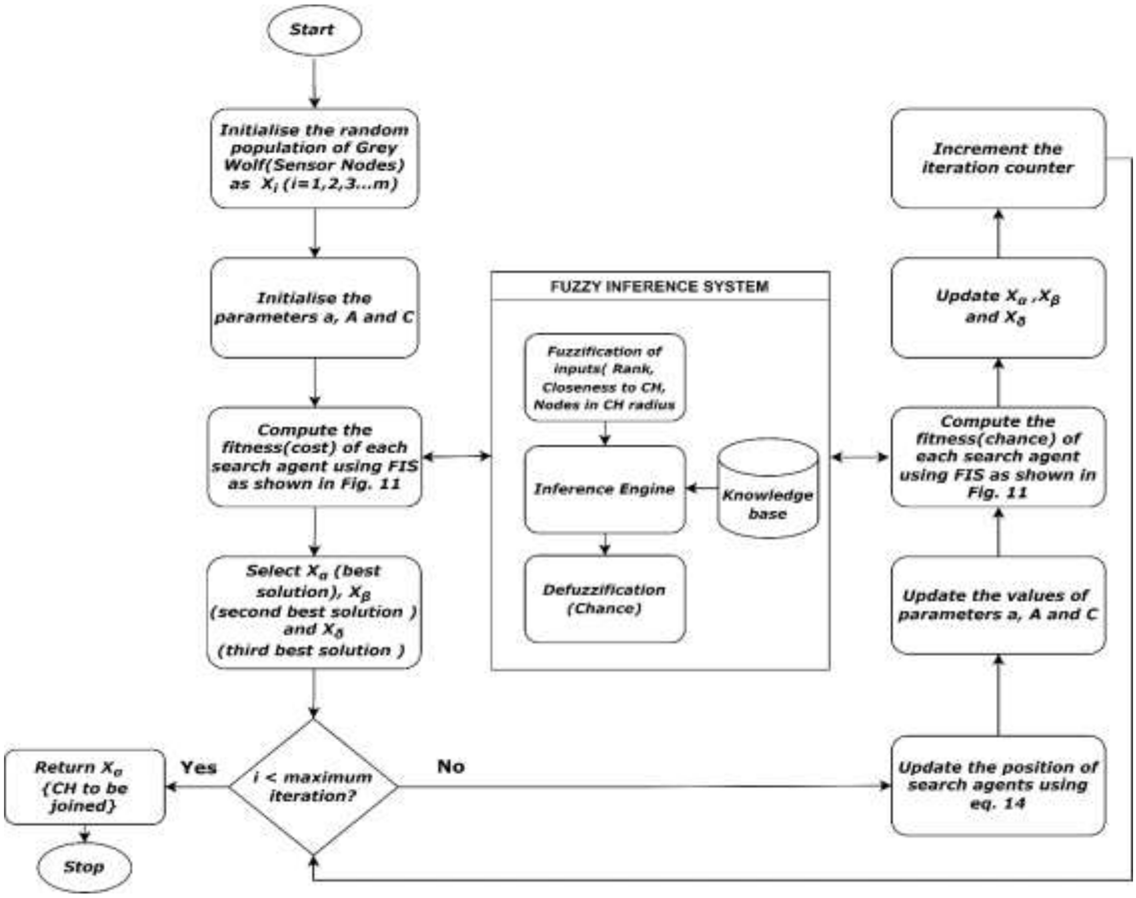


**Fig. 10 Flow chart for clustering in GWO-EFUCA**

The non-CH nodes are considered at input to the GWO-Fuzzy based algorithm. Every CH notifies its candidature within its radius. The non-CH nodes receives these notifications. All the CHs will act as search agent and their fitness value in each iteration is determined by the FIS as shown in Figure 11.

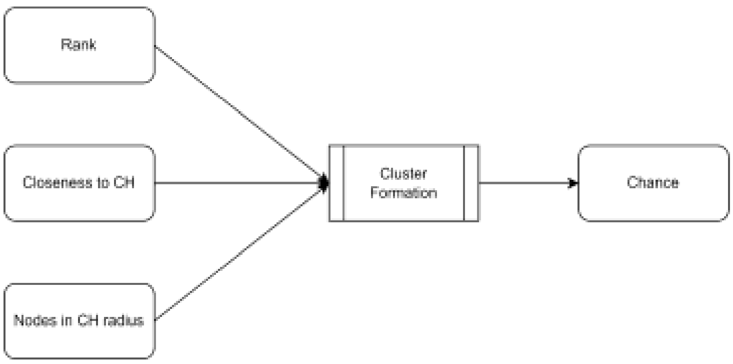


**Fig. 11 FIS for cluster formation in GWO-EFUCA**

The MF functions considered in input and output variables are depicted in Figure 12 and Figure 13 respectively.

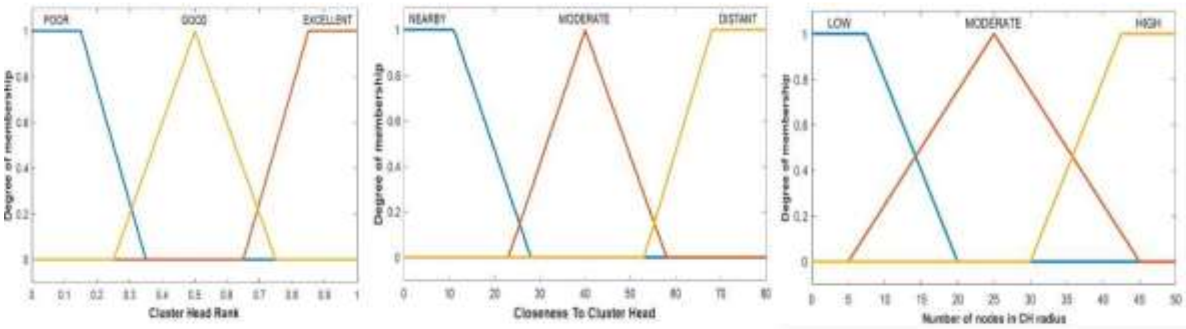


**Fig. 12 MF for input variables in clustering**

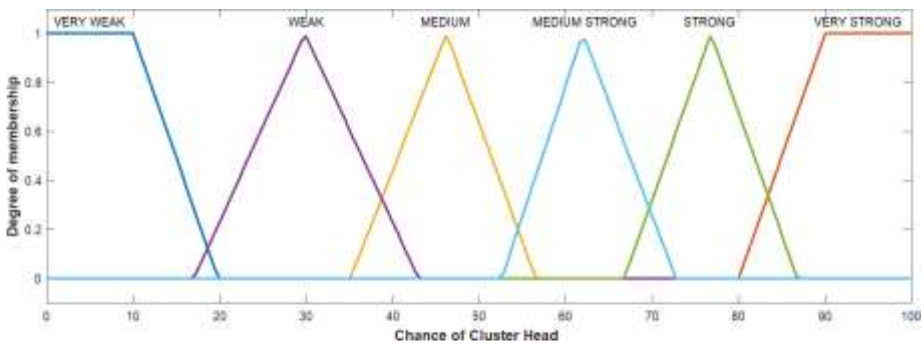


**Fig. 13 MF for output variables in clustering**

The inputs have their own linguistic variables. Rank has Poor(Pr), Good(Gd), and Excellent(Ex); Closeness to BS has Nearby(Ny), Moderate(Mte) and Distant(Dt); Nodes in CH radius has Low (Lw), Moderate (Mte) and High(Hg). The output variable Chance has Very Weak(VWk), Weak(Wk), Medium(Mm), Medium Strong (MSt), Strong(St), Very Strong (VSt). The chance of every CH is computed by applying IF-THEN rules to the inputs depicted in Table.

2. The algorithm returns the best CH to be chosen by each Non-CH node.

**Table 2** Fuzzy rules for computing chance of CH

| Rank | Closeness to CH | Nodes in CH radius | CH's Chance |
|---|---|---|---|
| Pr | Dt | Hg | VWk |
| Pr | Dt | Mte | VWk |
| Pr | Dt | Lw | VWk |
| Pr | Mte | Hg | Wk |
| Pr | Mte | Mte | Wk |
| Pr | Mte | Lw | Wk |
| Pr | Ny | Hg | Mm |
| Pr | Ny | Mte | Mm |
| Pr | Ny | Lw | Mm |
| Gd | Dt | Hg | VWk |
| Gd | Dt | Mte | Wk |
| Gd | Dt | Lw | Wk |
| Gd | Mte | Hg | Mm |
| Gd | Mte | Mte | MSt |
| Gd | Mte | Lw | MSt |
| Gd | Ny | Hg | MSt |
| Gd | Ny | Mte | St |
| Gd | Ny | Lw | VSt |
| Ex | Dt | Hg | Mm |
| Ex | Dt | Mte | Mm |
| Ex | Dt | Lw | Mm |
| Ex | Mte | Hg | MSt |
| Ex | Mte | Mte | St |
| Ex | Mte | Lw | St |
| Ex | Ny | Hg | St |
| Ex | Ny | Mte | VSt |
| Ex | Ny | Lw | VSt |

### 4.2 Steady Phase

Once the clustering process is completed for a round, the data transmission will take place from the source to destination i.e. SNs to BS. The data routing process is discussed hereafter.

#### 4.2.1 Routing

Significant energy dissipation can be reduced with efficient routing in WSN. The steady phase begins with sensing of information from the surroundings and generated data is forwarded on a periodic basis until and unless some emergency situation occurs. As per the TDMA schedule, SNs transmit, and respective CHs receive the data for avoiding data collision. Once the TDMA schedule is completed, every CH compresses the data before further transmission. Direct transmission of data to BS occurs. Such transmission significantly reduces the energy level of SNs as in most of the protocols. Even if multi-hop communication is incorporated, it must not trap in a loop else a large amount of energy loss will occur. In the propound GWO-EFUCA protocol, the GWO-Fuzzy logic-based algorithm is used which is depicted as flow chart in Figure 14 which considers multi-hop transmission towards BS.

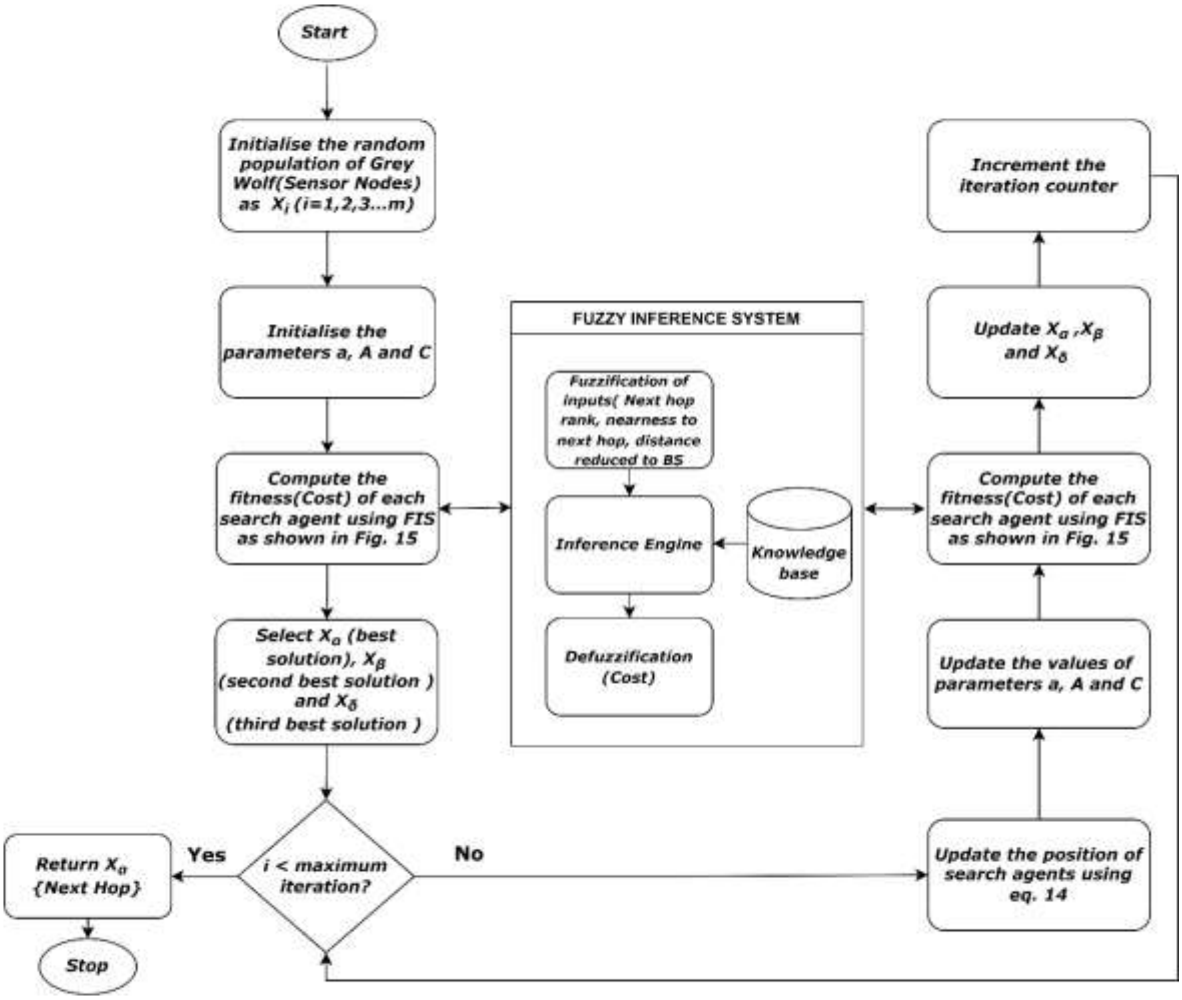


**Fig. 14 Flow chart for routing in GWO-EFUCA**

The CHs are considered as search agents and the next hop is determined. The algorithm computes the fitness value of the search agents by making use of FIS as shown in Figure 15.

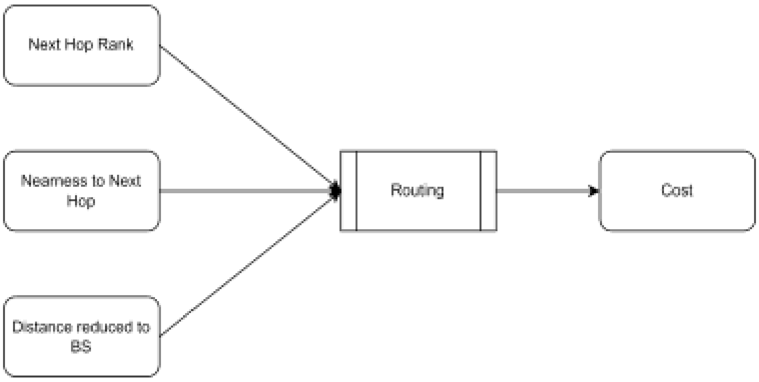


**Fig. 15 FIS for routing in GWO-EFUCA**

The FIS considers three input values, namely, nearness to the next hop, next-hop rank, and distance reduced to BS for calculating the cost of the next hop. The next hop in the process can either be CH or BS. The inputs have their own linguistic variables. *Next hop Rank* has Low(Lw), Average(Ag), and High(Hg); *Nearness to Next Hop* has Nearby(Ny), Moderate(Mte) and Distant(Dt); Distance reduced to BS has Significant(Sf), Average(Ag), and Negligible(Ng). The output variable *Cost* has Very Large (VL), Large(Lg), Medium Large(MmL), Medium(Mm), Medium Small (MmS), Small (Sm), Very Small (VSm). The MF for input and output variables are depicted in Figure 16 and Figure 17.

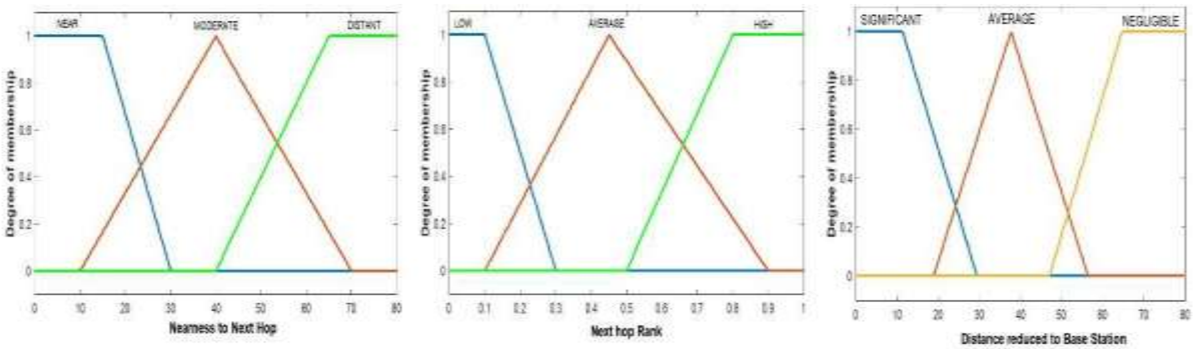


**Fig. 16 MF for input variables in routing**

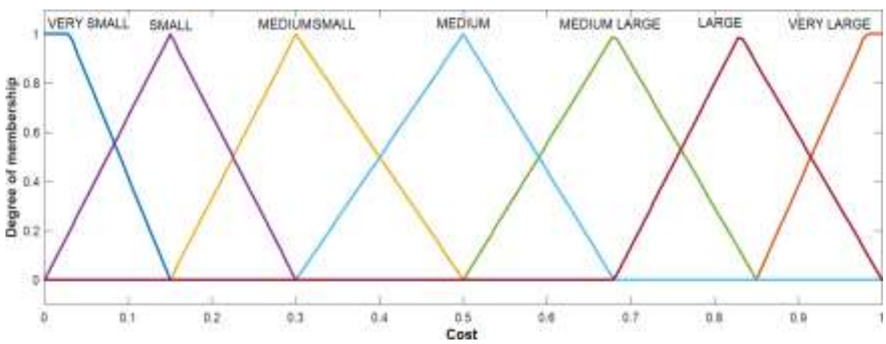

**Fig. 17 MF for output variables in routing**

The *cost* of every other next hop in the direction of BS, is computed using the IF-THEN rules designed for mapping inputs to output which are shown in Table 3.

**Table 3** Fuzzy rules for computing cost of next-hop

| Next Hop rank | Nearness to next-hop | Distance reduced to BS | Cost |
|---|---|---|---|
| Lw | Dt | Ng | VL |
| Lw | Dt | Ag | VL |
| Lw | Dt | Sf | Lg |
| Lw | Mte | Ng | VL |
| Lw | Mte | Ag | VL |
| Lw | Mte | Sf | MmL |
| Lw | Ny | Ng | Lg |
| Lw | Ny | Ag | Lg |
| Lw | Ny | Sf | MmL |
| Ag | Dt | Ng | Lg |
| Ag | Dt | Ag | MmL |
| Ag | Dt | Sf | Mm |
| Ag | Mte | Ng | MmL |
| Ag | Mte | Ag | MmS |
| Ag | Mte | Sf | Sm |
| Ag | Ny | Ng | Mm |
| Ag | Ny | Ag | MmS |
| Ag | Ny | Sf | Sm |
| Hg | Dt | Ng | Mm |
| Hg | Dt | Ag | MmS |
| Hg | Dt | Sf | MmS |
| Hg | Mte | Ng | Sm |
| Hg | Mte | Ag | VSm |
| Hg | Mte | Sf | VSm |
| Hg | Ny | Ng | Sm |
| Hg | Ny | Ag | VSm |
| Hg | Ny | Sf | VSm |

If the distance of the next hop is larger as compared to BS, then the node will transmit data directly to BS otherwise next hop will be considered. Following algorithm 3, the proposed GWO-EFUCA protocol completes one round as the data is communicated to BS for further processing. The proposed GWO-EFUCA protocol can be understood from the flow chart depicted in Figure 18 illustrating the steps followed in the setup and steady phase.

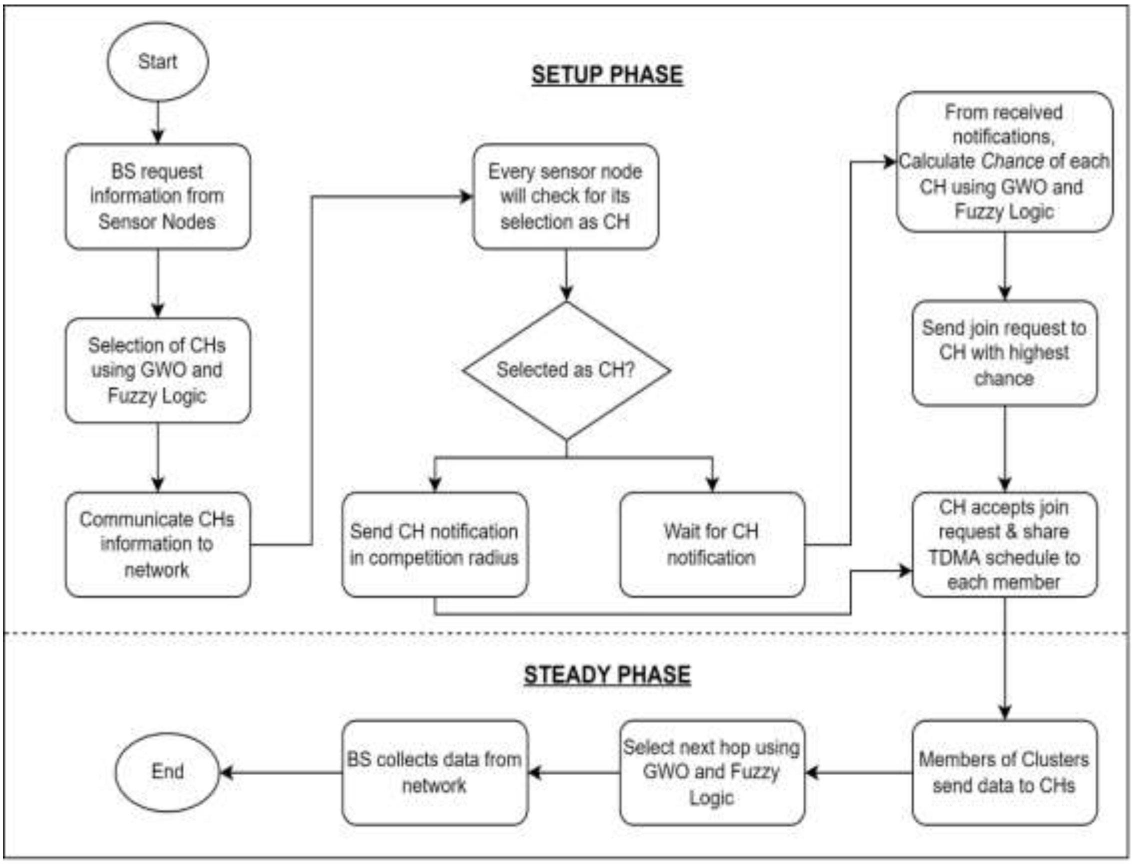


**Fig. 18 Flow chart of GWO-EFUCA protocol**

## 5. SIMULATION EXPERIMENT AND RESULT ANALYSIS

This section describes the simulation experiment conducted along with their parameter which are considered for different region of interests. Performance metrics are also discussed, and analysis of result is provided.

### 5.1 Simulation experiment

As already mentioned in section 3.2, we have considered, four different regions of interest or test beds where the simulation experiment was carried out. The experiment is conducted in MATLAB 2016 with i7 processor and 16GB RAM. The proposed GWO-EFUCA protocol is compared extensively LEACH [11], GWO-C[12] and E-FUCA[13] and results are obtained. The protocols are evaluated based on rounds. One round begin with clustering, sensing of data, forwarding of data and finally completed when data is received at BS. The death of node is confirmed if its energy level is zero. The simulation parameters used are shown in Table 4.

| **Parameter** | **Symbol** | **Values** |
|---|---|---|
| Communication Channel | - | Wireless |
| Radio Model | - | First Order |
| Type of MAC | - | IEEE-802.11 |
| Antenna | - | Directional/Adjustable |
| Energy for Transmission | $E_{Tx}$ | 50nJ/bit |
| Amplifier energy for multipath | $\varepsilon_{mp}$ | 0.0013pJ/bit/m $^4$ |
| Reception Energy | $E_{Rx}$ | 50nJ/bit |
| Energy for data fusion | $E_{DA}$ | 5nJ/bit/report |
| Data packet size | $M$ | 4000bits |
| Electronic circuitry | $E_{elec}$ | 50nJ/bit |
| Energy Expenditure in idle mode | $E_{idle}$ | 0.80mJ/s |

## 1.1 Assessment metrics

Following metrics are considered for comparative study of experimental results obtained for LEACH, GWO-C, EFUCA and proposed GWO-EFUCA protocol.

*First node death (FND):* It depicts the round number up to which all the SNs in the network were alive. With this metric, one can be assured of the reliability of the network up to that span.

*Half node death (HND):* It depicts number of rounds up to which more than half of the SNs in the network were alive.

*Lifetime:* It depicts the quantum of nodes (i.e.10%) dead w.r.t the round.

*The network's average energy:* The higher the average energy level of network, better the load balancing in the network. This metric shows the energy level of network w.r.t the rounds.

*Packet Delivery to BS:* It depicts the information delivered in form packets to BS during the life time.

*Average Latency:* It is the time span between the transmitted packets reaching the destination for each round.

*Average Traffic Load per node:* It describes the average number of packets in the network lifetime transmitted/received/processed by the nodes.

## 5.3 Experimental Result analysis

### 5.3.1 FND

Figure 19 represents the rounds where the first node of the protocols under consideration i.e.

LEACH, GWO-C, E- FUCA and proposed GWO-EFUCA protocol becomes dead for all four regions of interest. We can observe from the obtained results that for region 1, the improvement of GWO-EFUCA is 73.45% over LEACH, 55.50% over GWO-C and 31.51% over E-FUCA. For region-2, the enhancement made by the proposed GWO-EFUCA is 71% over LEACH, 39.45% over GWO-C and 28.65% over E-FUCA protocol.

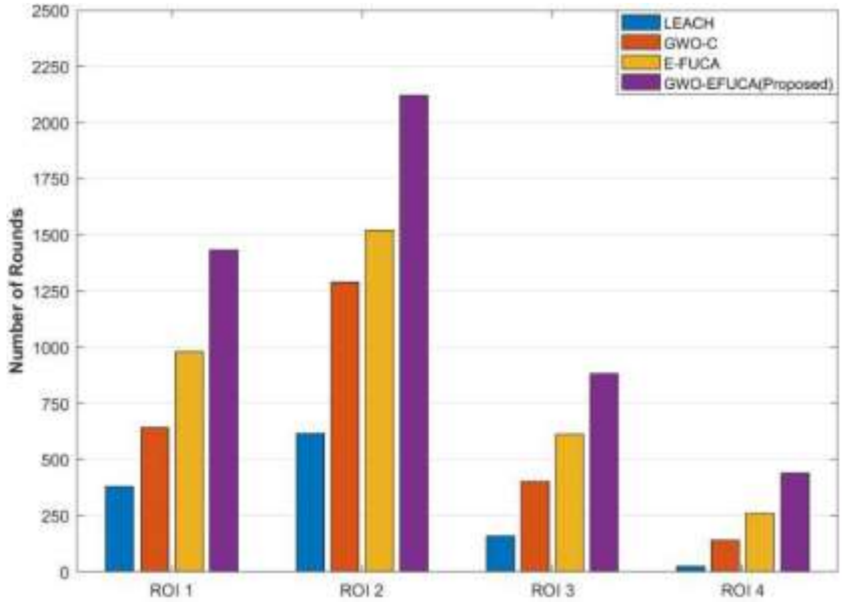


**Fig.19 FND for ROI 1, ROI 2, ROI 3 and ROI 4.**

For region 3, the proposed GWO-EFUCA protocol has performed 81.91%, 54.10% and 30.45% better than LEACH, GWO-C and E-FUCA protocol respectively and for region 4, the improvement of 95%, 69.55% and 41.10% can be seen over LEACH, GWO-C and E-FUCA protocol respectively.

### 5.3.2 HND

Figure 20 displays the HND of the protocols under observation. It is clearly visible that the HND is increased by 47.65%, 35.20% and 30.85% as compared to LEACH, GWO-C and E-FUCA protocol respectively for region 1. For region 2, increments of 54.95%, 39.10% and 31.43% can be seen over to LEACH, GWO-C and E-FUCA protocol respectively. For region 3, GWO-EFUCA's advancement of 67.23%, 47.88% and 33.22% can be observed for HND over LEACH, GWO-C and E-FUCA protocol respectively. At the same time, for region 4, GWO-EFUCA has 77.87%, 49.91% and 38.59% better results in terms of HND over LEACH, GWO-C and E-FUCA protocol respectively.

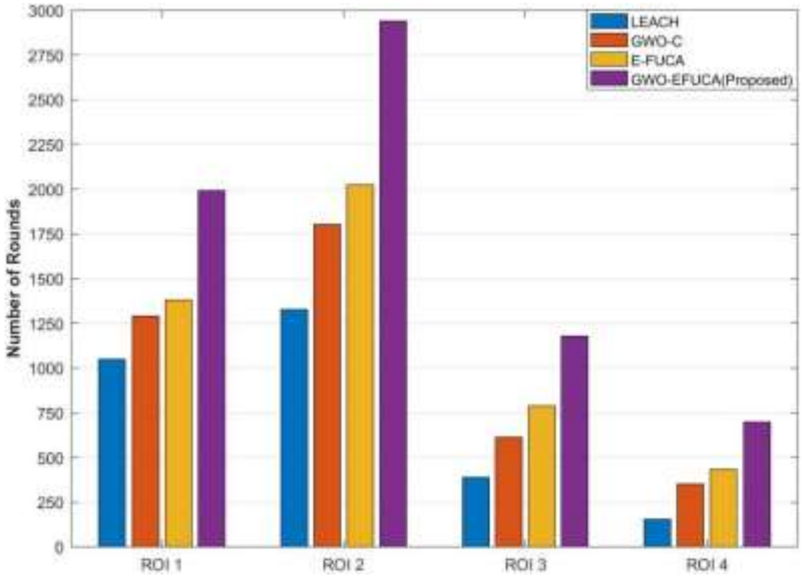


**Fig. 20 HND for ROI 1, ROI 2, ROI 3, and ROI 4.**

### 5.3.3 Lifetime

While deploying the WSN in any region of interest, it is expected to operate for as long time as possible. We have depicted the lifetime of protocols under consideration in Figure 21 for all four regions.

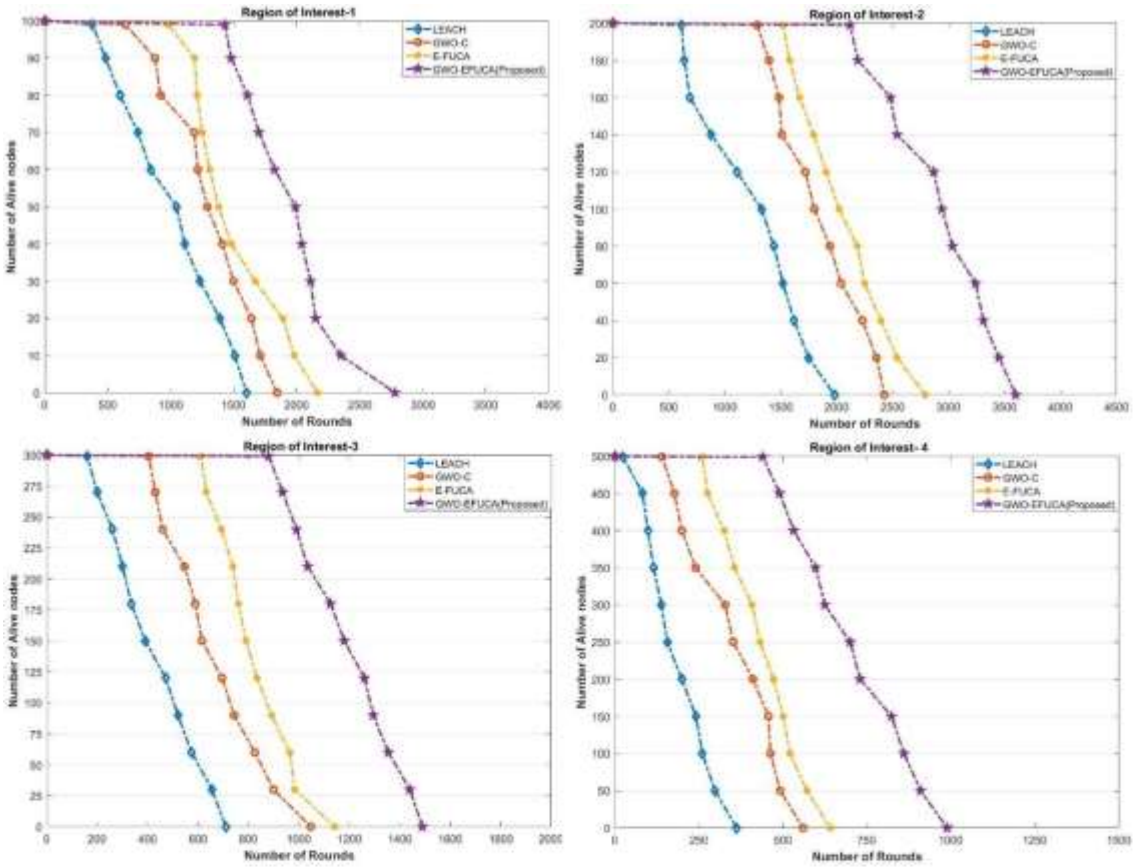

**Fig. 21 The lifetime for ROI 1, ROI 2, ROI 3, and ROI 4.**

In all the regions, we can observe that the proposed GWO-EFUCA outperforms its comparatives i.e. LEACH, GWO-C, and E-FUCA. It can be easily analyzed that up to the stability period of GWO-EFUCA almost fifty percent of the nodes of LEACH, GWO-C, and E-FUCA are expired. The reason for the prolonged lifetime is that the network load is comparatively balanced which is delaying the death of SNs.

### 5.3.4 Network's average energy

Figure 22 exhibits the network's average energy for all four regions under consideration. It can be observed that the GWO-EFUCA protocol has higher average energy as compared to the LEACH, GWO-C, and EFUCA protocols. The higher the average energy of the network, the better the load balancing. As per Figure 22, The proposed GWO- EFUCA protocol has been successful in balancing the load of the network. The reason behind this achievement is that the efficient CHs and clustering are done at the setup phase and cost-effective routing is ensured at the steady phase which somehow does not deplete the energy level of the node drastically.

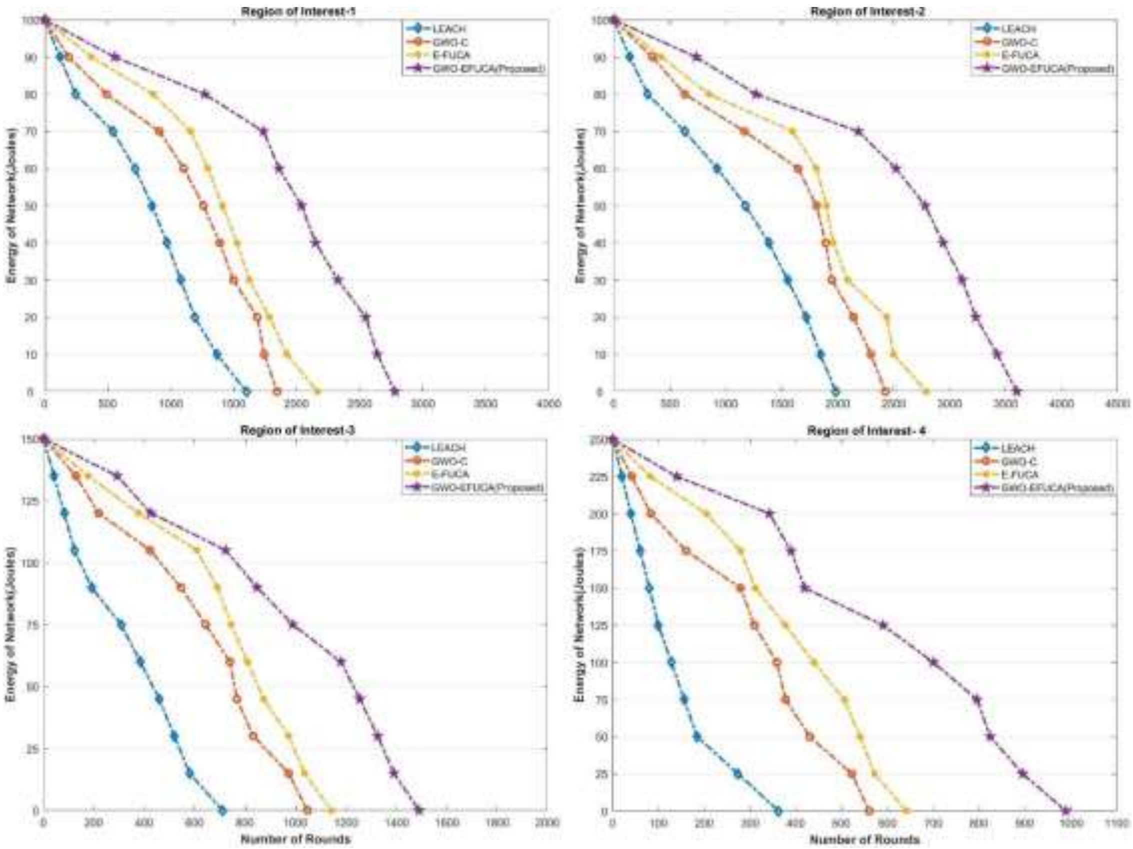


**Fig. 22 The network's average energy for ROI 1, ROI 2, ROI 3, and ROI 4**

### 5.3.5 Packet Delivery to BS

When deploying any network, the objective is to fetch as much information as possible to satisfy the requirement of the application. Figure 23 shows the graph for information received in terms of the packet by the BS for all four regions. It is also considered the throughput of the deployed network. We can observe that the proposed GWO-EUCA has delivered many packets to the BS in comparison with other protocols such as LEACH, GWO-C, and E- FUCA. It is due to the fact that if more nodes are alive then more information can be fetched from the regions of interest and the proposed GWO-EFUCA has a prolonged lifetime than its comparatives.

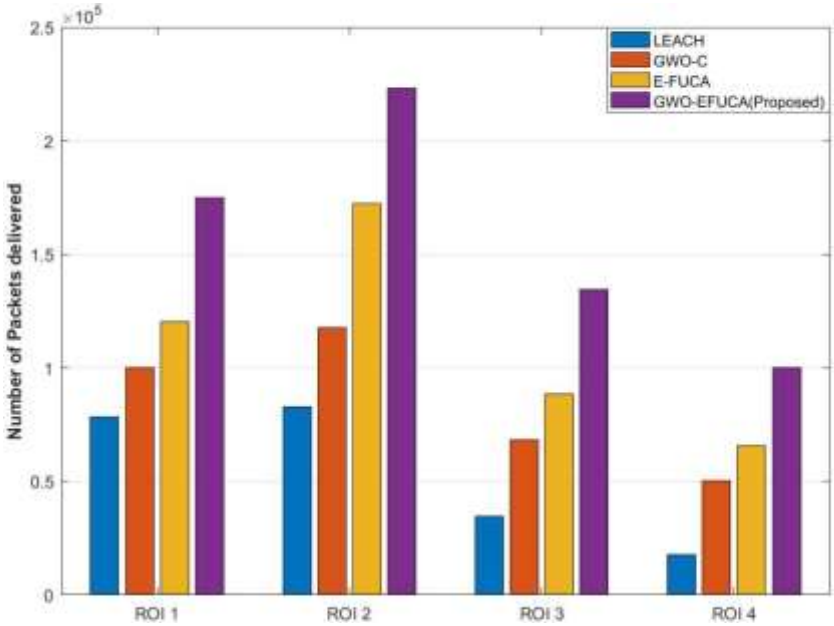


**Fig. 23 Packet delivery to BS for ROI 1, ROI 2, ROI 3 and ROI 4.**

### 5.3.6 Average Latency

Latency in a network degrades its performance, especially in the case of time-critical applications. Figure 24 display the average latency of the protocols under consideration for all four regions. Our proposed protocol GWO-EFUCA has substantially lower latency than LEACH, GWO-C and E-FUCA protocols as can be noticed from Figure 24.

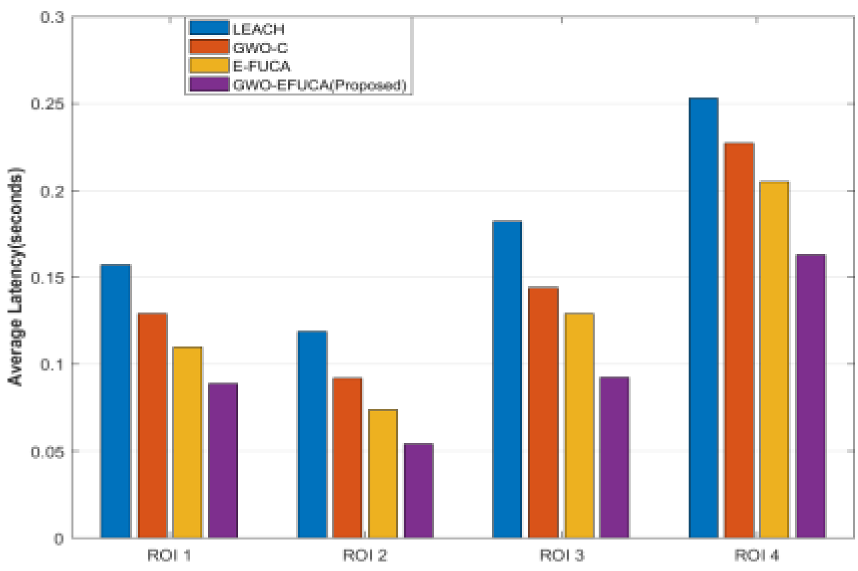


Fig. 24 The average latency for ROI 1, ROI 2, ROI 3 and ROI 4.

### 5.3.7 Average Traffic Load per node

To determine the average traffic load per node, the amount of information in terms of bits being transmitted, received and processed by the node during its life span is computed and represented in Figure 25. From the obtained results we can observe that proposed GWO-EFUCA protocol has comparatively lower traffic load than LEACH, GWO-C and E-FUCA protocols which results in less burden in SNs thereby saving their energy. The justification for reduction of average traffic load is the selection of appropriate CHs, efficient cluster formation and cost-effective routing.

### 5.3.8 Average Traffic Load per node

To determine the average traffic load per node, the amount of information in terms of bits being transmitted, received and processed by the node during its life span is computed and represented in Figure 25. From the obtained results we can observe that proposed GWO-EFUCA protocol has comparatively lower traffic load than LEACH, GWO-C and E-FUCA protocols which results in less burden in SNs thereby saving their energy. The justification for reduction of average traffic load is the selection of appropriate CHs, efficient cluster formation and cost-effective routing.

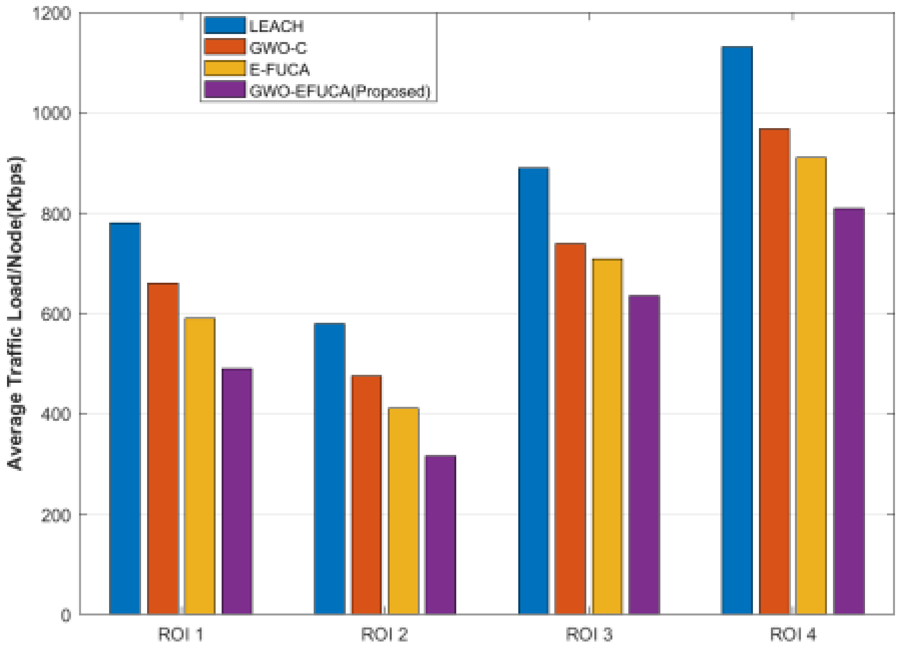


**Fig. 25 Average traffic load per node for ROI 1, ROI 2, ROI 3 and ROI 4.**

### 5.4 Convergence rate

The convergence rate is the number of iterations taken by the evolutionary optimisation method to obtain the best solution. We have two evolutionary optimization methods in this paper and their convergence rate comparison is shown in Table 5. The proposed GWO-EFUCA protocol achieves better solution in less number of iterations as compared to GWO-C while avoiding local optima. The reason for the same is that the fitness function value is obtained using FIS which reduces the search space.

**Table 5** Comparison of convergence rate

| Protocols | Mean | Standard Deviation |
|---|---|---|
| GWO-C | 80.34 | 25.65 |
| GWO-EFUCA(Proposed) | 77.98 | 22.25 |

## 6. CONCLUSION

In this work, GWO-EFUCA protocol is proposed for efficient CH selection, Clustering and routing for WSN- assisted IoT. The proposed work incorporates Grey wolf optimization along with FL to improve the E-FUCA protocol. The proposed GWO-EFUCA protocol rigorously experimented for different regions making the protocol suitable for the diverse domain applicability in IoT. The hybrid approach significantly improves the stability period along with a prolonged lifetime. The network's average energy, throughput and the lifetime is at a higher end than its comparatives. The average load of the SNs is minimal with reduced latency which results in better reliability of the protocol. The information retrieval from the network is significantly higher than LEACH, GWO-C, and E- FUCA. For future work, we can incorporate the mobility of nodes and experimentation on real sensors-based test beds for a vivid picture of the proposed work.

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