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# Admission Allotment Scheme Base Load Balancing Techniques for Clustering Routing in Wireless Sensor Network

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The Wireless Sensor Network, often known as WSN, has a wide range of applications spanning the commercial, indus-trial, and social spheres. WSN clustering is an efficient and low-cost way to extend the lifespan of a network while simultaneously improving its scalability, reliability and throughput. The performance of the WSN is hindered by lim-ited-power battery-driven sensor nodes and inaccurate cluster head (CH) location during the process of cluster crea-tion. This paper presents the Fuzzy C-mean algorithm (FCM) for clustering as well as the Artificial Bee Colony Algo-rithm (ABC) for CH selection and optimization. Both of these algorithms can be found here. A number of different clustering parameters are taken into consideration by the proposed ABC. These considerations include CH energy balancing, CH load balancing, the energy GINI coefficient, connectivity, as well as intra-cluster and inter-cluster distance. Afterward, an Ant Colony Optimization (ACO) that is more energy efficient is developed to transfer the data from CH to the base station (BS). Further, the novel Admission Allotment Scheme (AAS) it utilized for energy efficient intra-cluster communication to enhance the load balancing of the network. In relationship to the conventional state of the art, the newly suggested method delivers optimum cluster selection, which results in improved network lifespan, packet delivery ratio, and throughput.
**Keywords:** Ant Colony Optimization, Artificial Bee Colony, Data Aggregation, Fuzzy C-Mean Routing, , Intra-cluster communica-tion, , Wireless Sensor Network.

## 1. Introduction

Industry 4.0 and 5G communication technologies are making WSNs more desirable for military scouting, agriculture monitoring, disaster management, landslide monitoring, security surveillance, habitat tracking, medical and health, transportation, logistics, robotics, automation, and more [1, 2]. Therefore, WSNs have been effective in establishing a connection between the realm of computers, the physical world, and the human community. A WSN encompasses huge count of very smaller sensor nodes that are dispersed out over a very large area, together with one or multiple BSs that collect the information from distributed sensor nodes [3, 4].

Each sensor has limited access to power supply, in addition to the capabilities of physical data sensing, information processing, and wireless communication. In WSNs, routing is one of the utmost important technologies that may be used. The routing in WSNs is complicated because of the basic differences between them and conventional ad-hoc networks. To begin, the available electricity, processing capability, and bandwidth for transmission are all grossly insufficient. Second, it is difficult to develop a global addressing system comparable to the Internet Protocol (IP). In addition, IP implementation is difficult in WSNs since the high cost of changing addresses in a denser and dynamic WSN prevents its use in these networks. Finally, due of limitations on the available resources, routing is unable to accommodate both unpredictable and consistent changes in network topology [5]. This is especially true in mobile environments.

The collection of data from a high number of sensors usually results in data redundancy, which raises the overheads associated with routing. Load balancing is essential for increasing the network's lifespan since the communication mechanism in WSN is many-to-one. Lastly, in time-sensitive WSN applications, the completion of data transfers must occur within a pre-determined amount of time. As a direct consequence of this, it is necessary for these kinds of applications to take into consideration a limited latency for the transfer of data. Given that all sensors are restricted by energy that is directly proportional to network lifespan, energy preservation is more critical than quality of service (QoS) in the majority of applications. It is necessary for a WSN that is dispersed across a greater region to cluster its nodes in order to offer effective routing and data aggregation. The CH selection is very important given its role in accepting data from sensors and transmitting it to BS. There are lots of instances in which the CH is chosen based on its location within the cluster, and permissions are frequently granted to nodes that are centrally positioned regardless of their energy, load-balancing ability, connection, or distance from the BS [6] [7].

In the past, a variety of different clustering strategies for WSN information gathering and routing have been reported. Janaki et al. [8] evaluated the influence of a parallel ACO and a k-means clustering strategy for assembling sensors in WSN routing to discover the finest route. This was done in order to determine the optimum path. It revealed a network capable of lasting a long time and having a more effective routing system. Liu et al. [9] presented an issue of unsupervised clustering that was based on the ACO methodology. They used ACO while maintaining the optimum stochastic solution. Researchers in [10] created an upgraded adaptation of the ACO based LEACH clustering algorithm in order to facilitate efficient CH selection. During the course of their research, the data were first transmitted from the node to the CH, then moved on to be transmitted from the CH to the cluster manager, and ultimately transmitted from the cluster manager to the BS. As a direct consequence of this, the typical amount of energy used has decreased. They have given less concentration on data redundancy, which has an effect on the data aggregation process. Adil et al. [11] investigated Clustering based ACO for VANETs for clustering. During algorithm testing, they took into account a number of parameters, including the size of the network, the count of nodes it included, the area the network covered, the communication range of the sensor nodes, the speed of the VANETs nodes, and their orientation. In WSN, the chief goal was to lengthen the lifetime of sensor networks while simultaneously cutting down on the amount of energy that was consumed by the networks. The MRP algorithm was used to choose the CHs, and the ACO was used to select several paths that connect the sensor node and each CH. It led to improvements in data aggregation efficiency, enhanced load balancing, longer lifetimes for sensor networks, and decreased energy consumption for WSNs. The authors came to the conclusion that it was challenging to pick the parameters for the algorithm, and that changing those values led in slower speed [12].

Maheshwari et al. [13] proposed butterfly optimization enabled ACO for developing cluster based routing. The Butterfly algorithm facilitates the effective node clustering, whilst the ACO ensures the finest routing of information towards the CH and BS. When compared with LEECH and DEEC, it has shown better performance. The Genetic Tabu Search [14] and Cuckoo search algorithms [15] have shown significant improvement in load as well as energy balancing of WSN. Clustering routing in WSN was reported by Selvi et al. [16], and it was based on cluster selection by a gravitational method, and clustered gravitational routing technique was used for the routing. It improved the longevity of the network while simultaneously reducing the amount of delay in data transfer. In order to find the CHs and the total count of CHs for WSN clustering routing, Rodrguez et al. [17] devised the Locust Search (LS) technique. Reddy et al. [18] have researched the results of ACO based routing in conjunction with the Glowwarm swam optimization (GSO) method in order to address the issues of energy exhaustion and WSN breakdown. In [19] authors demonstrated zonal clustering in a diverse network with movable CH for the purpose of CH balancing. It delivered superior outcomes compared to DEEC and LEACH. However, since mobile sensors need greater energy consumption, this system can only be used in very dynamic settings for a limited amount of time. A wide variety of clustering and routing strategies have been given in order to increase the longevity, security, scalability, load balancing, and enhance the catastrophe handling capability under harsh environmental circumstances [20-23]. Even though there are a lot of different optimization algorithms being used for the clustered routing in WSN, the outcomes are still not optimum. It is necessary to concentrate on a number of performance factors all at the same time, including network longevity, latency, network overheads, energy depletion, load balancing, network stability, scalability and many more.

The purpose of this study is to show the optimal clustering-routing protocol utilizing the ABC and the ACO algorithm. The following is a condensed summary of the most important contributions made by this paper:

- Energy efficient and load balanced CH selection optimization using FCM-ABC algorithm based on

CH energy balancing, energy GINI coefficient, CH load balancing, intra-inter cluster distance, and connectivity of CH.

• ACO based energy efficient routing mechanism to enhance network lifespan, throughput, scalability, stability and overall performance.

• Energy efficient load balanced intra-cluster communication using proposed admission allotment scheme (AAS) algorithm

The remaining parts of paper are ordered as seen below: In Section II, the details of the proposed clustering routing protocol that is based on FCM-ABC-ACO-AAS are presented. In Section III, the simulation details and comments about the experimental results of the recommended strategy are presented. In the last section of the article, known as Part III, a succinct conclusion is presented, along with a potential path forward for the enhancement of the suggested system.

## 2. Proposed Methodology

The suggested technique consists of five stages, which are the establishment of the network, the clustering of the nodes, the selection and optimization of the CH using the FCM-ABC algorithm, use of the ACO algorithm to achieve energy efficiency in the routing and proposed AAS algorithm for intra-cluster communication as shown in Fig. 1. During the initialization phase, you will initialize the network parameters, as well as the radio model, node count, the network area, the starting energy, the location of the BS, and the position of the nodes. The radio model constraint initialization comprises things like energy required for transmission and reception of message bits, free space and multipath amplification factors, traffic scenario, network homogeneity, MAC protocol etc.

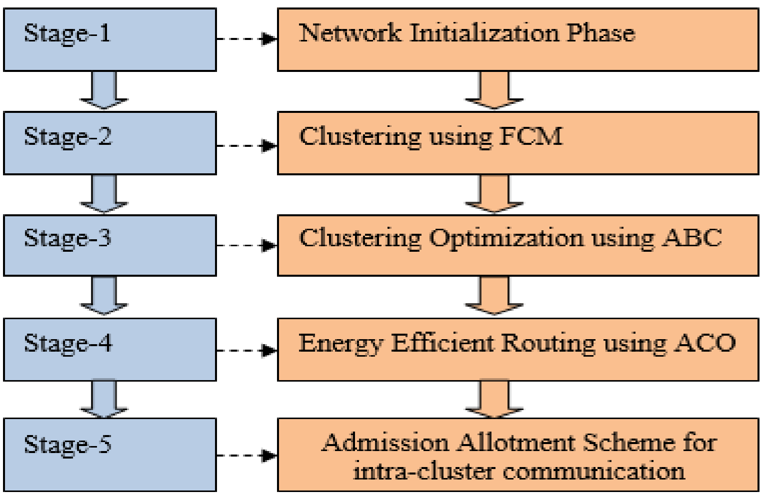



Fig. 1 Flow diagram of proposed system

### 2.1. FCM Clustering

The FCM divides the nodes into clusters based on the node positions in the region that is being simulated. It takes into account the case of a uniform network, in which every node has the same beginning energy. The FCM offers the percentage of members present in each cluster that originates from the cluster that is deemed centralized. The value of nodes that are farther from the centered node is lower, while the degree of nodes that are closer to the centered node is greater [24-25]. The nodes are gathered into clusters that have a higher membership function.

The group of n nodes is considered as X = {x1, x2, x3 ..., xn} and randomly selected ‘k’ cluster heads are represented by V = {v1, v2, v3 ..., vk}. The fuzzy membership ($\mu_{ij}$) of each sensor node is estimated based on the distance between two nodes and distance between node and CH as given by equation 1.

$$\mu_{ij} = 1 \Big/ \sum_{k=1}^{k} (d_{ij}/d_{ik})^{(2/m-1)} \quad (1)$$

Further, the fuzzy clusters ($V_j$) are estimated using fuzzy membership function ( $\mu_{ij}$) of each node is computed using equation 2.

$$V_j = \left(\sum_{i=1}^{n} (\mu_{ij})^m x_i\right) \Big/ \left(\sum_{i=1}^{n} (\mu_{ij})^m\right), \forall j = 1,2, \ldots \ldots k \quad (2)$$

The membership function and fuzzy clusters are repeatedly computed until ||U(z+1) - U(z)|| < β  or minimum value for 'j' is achieved. Here, z indicates iteration count, β depicts the termination condition, j signifies the objective function.

### 2.2. Cluster Selection and Optimization using ABC

The initial FCM clusters are produced using FCM, and the proposed technique employs the ABC algorithm to perform optimum CH selection from those clusters. The clusters formed by utilizing the FCM method are employed for the selection of optimum CHs with the help of the suggested ANC that he uses. For the purpose of cluster head selection, the upgraded ABC takes into account the CH load balancing factor, energy GINI coefficient, CH energy balancing, intra-cluster and inter-cluster distance.

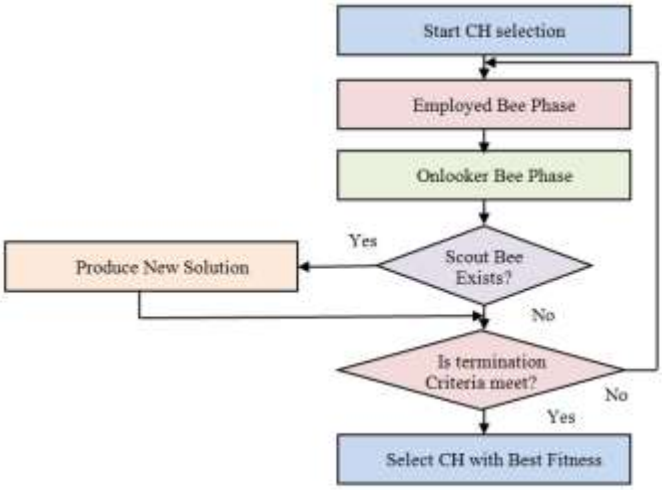



Fig.2 Flowchart of CH selection and optimization using ABC algorithm

Karaboga first conceptualized the bio-inspired phenomena known as ABC in 2005. There are three categories of bees involved in this process: employed, bystanders, and scouts [26-27]. The worker bees are the ones who find the food sources, the spectator bees are the ones that determine which food source to use, and the scout bees are the ones that hunt for food in random directions after the worker bees are discarded. The count of worker bees is always equal to the count of food sources in the area around the hive. When an employed bee's food supply runs exhausted, it transitions into a scout bee role. Fig. 2 provided an explanation of how the CH selection process works inside the ABC algorithm.

The ABC algorithm provides possible SN solutions via random sampling, which is comparable to food sources. Let $SN = \{S_1, S_2, S_3, \dots\dots S_C\}$ be the initial bee population. The onlooker uses probability function for CH selection as given in equation 3.

$$p_i = \frac{F_i}{\sum_{n=1}^{SN} F_n} \qquad (3)$$

Here,

$P_i$ is the probability fitness estimated by onlooker bees

$F_i$ is fitness of $i^{th}$ solution that is relative to nectar amount of the food source at position i.

The $F_i$ value is determined by the CH load balancing factor, the CH energy balancing factor, the energy GINI coefficient, inter-cluster and intra-cluster distances for CH selection, as well as the coverage/connectivity of node. Equation 4 provides the fitness function, which specifies that the criterion outlined in equation 5 must be met for weight factors to be considered fit.

$$F_i = \omega_1 * f_1 + \omega_2 * f_2 + \omega_3 * f_3 + \omega_4 * f_4 + \omega_5 * f_5 \qquad (4)$$

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1. \qquad (5)$$

2.2.1. Fitness for Energy GINI Coefficient

As seen in equation 6, the $f_1$ variable helps to maintain a stable level of energy at the cluster's head by using the GINI coefficient, which results in an unequal distribution of energy across the nodes. In its simplest form, the GINI may be understood to be a representation of the income division of the population [28].

$$E_{s(G)} = \frac{1}{2num^2(s)E_{ave}(s)} \sum_{i=1}^{num(s)} \sum_{j=1}^{num(s)} |E(i) - E(j)| \quad (6)$$

Where, $E_{s(G)}$ is energy Gini coefficient of the $s^{th}$ cluster, $E_{ave}(s)$ is the average outstanding energy of the $s^{th}$ cluster, $num(s)$ depicts count of nodes in the $s^{th}$ cluster and E(i) describes outstanding energy of node i.

Equation 7 is used to calculate the GINI coefficient's standard deviation. The lesser value of E s indicates that the energy balance in the cluster is similar and that it may be leveraged to create an efficient cluster.

$$E_\sigma = \sqrt{\frac{\sum_{s=1}^{k}(E(s) - E_{ave}0)^2}{k}} \quad (7)$$

Where, $E_\sigma$ depicts degree of division of $E_{s(G)}$ of k clusters, E(s) is the outstanding energy of the $s^{th}$ cluster, k symbolizes count of CHs of the existing network, and $E_{ave}$ defines the average remaining energy of every cluster. The GINI coefficient based fitness function is given in equation 8.

$$f_1 = \frac{e^k}{K} . E_\sigma \quad (8)$$

2.2.2. Fitness for Cluster Head Energy Balancing

The fitness $f_2$ describes the CH energy balancing ($f_{21}$) and CH energy proportion ($f_{22}$) as described in equation 9 and 10. Equation 11 provides the energy ratio of CHs and energy balance degree.

$$f_{21} = 1 - [\frac{1}{k} \sum_{s=1}^{k} (\frac{E_{CH}(s)}{E_{ave}(CH)})^{1-\varepsilon}]^{1/1-\varepsilon} \quad (9)$$

Where, $E_{CH}(s)$ represents the outstanding energy of the s-th CH, $E_{ave}(CH)$ depicts the average outstanding energy of the CH, and $\varepsilon$ signifies the disparity repugnance parameter ($\varepsilon = 0.5$). The lower value of $f_{21}$ describe superior energy balancing between CHs.

$$f_{22} = \frac{\sum_{i=1}^{n} E(i)}{\sum_{s=1}^{k} E_{CH}(s)} \quad (10)$$

n represents live nodes, $E(i)$ provides overall energy of the network, and $E_{CH}(s)$ defines residual energy of all CHs.

$$f_2 = \omega_1 f_{21} + \omega_2 f_{22} \quad (11)$$

2.2.3. Fitness for Inter and Inter Cluster Distance

The fitness $f_3$ gives the relation between sum of distance between all CHs ($f_{31}$) and overall distance between node to its consequent CH ($f_{32}$) as mentioned in equation 12 13, and 14. The larger $f_{31}$ shows the evenly distributed clusters whereas smaller $f_{32}$ indicates the compactness of cluster.

$$f_3 = \frac{f_{32}}{f_{31}} \tag{12}$$

$$f_{31} = \sum_{s=1}^{k-1} \sum_{m=s+1}^{k} D_{CH}(s, m) \tag{13}$$

$$f_{32} = \sum_{i=1}^{k} \sum_{j=1}^{num(i)} D_{CN}(i, j) \tag{14}$$

Where, $D_{CH}$ provides distance between nodes and CH and $D_{CN}$ provides inter-cluster distance.

2.2.4. Fitness for Cluster Head Load Balancing

The CH load balancing is represented by $f_4$ as given by equation 15-18 which signifies that CH must pose more energy than members and performs more operations. Therefore, minimizing CH load helps to increase the network performance. The CH load is proportional to count of cluster members.

$$N_{ave} = \frac{n - k}{k} \tag{15}$$

$$Th_{max} = N_{ave} + \frac{N_{max} - N_{min}}{k} \tag{16}$$

$$Th_{min} = N_{ave} - \frac{n_{max} - N_{min}}{k} \tag{17}$$

$$f_4 = \left(\frac{N_{max} - N_{ave}}{N_{max}}\right) \frac{N_h - N_u}{k} \tag{18}$$

Here, $N_{ave}$ represents the average nodes in every cluster, $N_{max}$ and $N_{min}$ depicts the sensors in the dense and sparse clusters, and $N_h$ symbolizes count of clusters having nodes than $Th_{max}$, $N_u$ is the count of clusters having lesser nodes than $Th_{min}$. It generates updated solution using available solution in memory using equation 19.

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{ij} - x_{kj}\right) \tag{19}$$

Where, $\phi ij$ $(xij - xkj)$ is called step size and $(i \neq k)$, k € (1,2,......SN), $j$ € (1,2,......D), and

$\phi ij$ is random value within [−1, 1]. If the location of bees stays unchanged for specified duration (limit) then the food source $x_i$ is deserted.

2.2.5 Fitness for Coverage/Connectivity

The fitness $f_5$ indicates the coverage of the sensor nodes that represents count of the nodes connected to specific node or number of nodes covered by specific node. The coverage fitness function is ratio of number nodes in cluster ($N_{CH}$) to connected nodes to specific node ($N_{cov}$) as given by equation 20.

$$f_5 = \frac{N_{CH}}{N_{cov}} \quad (20)$$

2.3 Energy Efficient Routing using ACO

The ACO algorithm is utilized to discover the energy efficient and shortest route from the node to CH and CH to BS for data transmission. The ABC algorithm consists of parameter initialization, forward ant (FANT) and backward ant system (BANT) as given in Fig. 3.

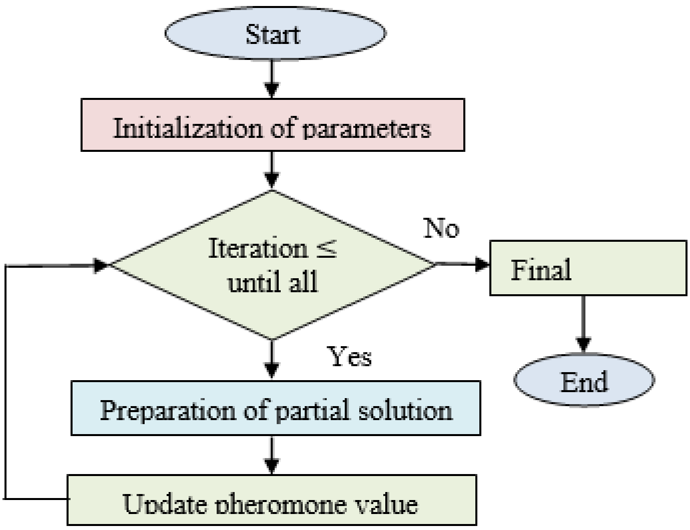



Fig.3 Generalized flowchart of ACO

The forward ants begin the journey from the shell to the location where they will go in search of food. The ID of the present sensor node, the target node, the IDs of the surrounding nodes, and the connection information that connects them are all carried by the forward ant. It contains data pertaining to the routing table of the active node. Finding the target node and remembering the trip details are the goals of the forward ant. The forward ant gets killed and transformed into the reverse ant when it reaches at the target node. The backward ant follows the forward ants' remembered path as they migrate from the target node to the source node. Along with that, it includes information on related links as well as the IDs of the present node, target node, and nearby nodes. Router tables are updated by backward ants. A synthetic pheromone is spread throughout the trail by backward ants as they return to the source node. Upon reaching the source node, backward ant modifies the routing table before killing itself. Fig. 4 illustrates the behavior of forward and reverse ants.

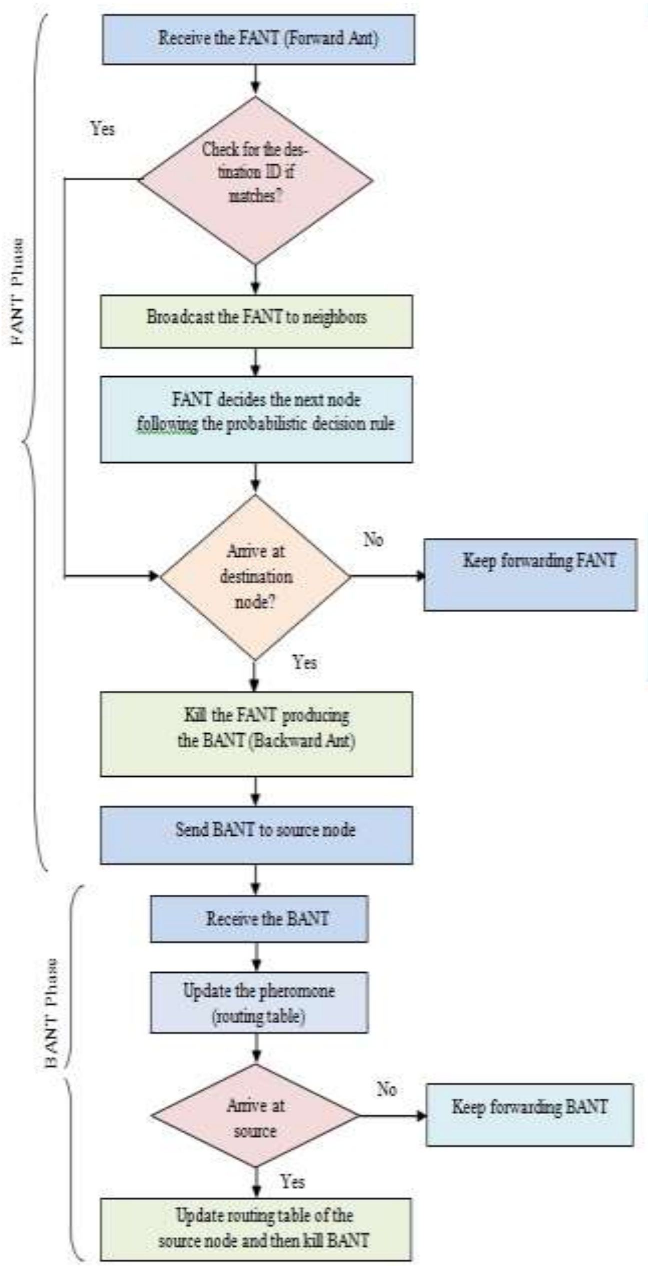



Fig. 4 Flowchart of the forward and backward ant system

### 2.3.1 ACO Algorithm

Step 1: At stable intervals, FANT k are sent from the source node to discover path until it finds destination node and all visited nodes are retained in memeory.

Step 2: The evolution probability FANT k when it travel from node "i" to ode "j" is given by equation 20

$$p_{ij}^{k} = \begin{cases} \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{l\epsilon j_i^k}\tau_{ij}^{\alpha}\eta_{ij}^{\beta}} \ldots\ldots\ldots.. j\ \epsilon j_j^k. \\ 0 \qquad \ldots\ldots\ldots\ldots \text{else.} \end{cases} \qquad (20)$$

Here FANT "k" at node "i" selects neighboring node "j" by using equation (20) based on higher values of $P_{ij}^{k}$.

Where, $j_i^k$ gives list of unvisited nodes such that FANT k can omit travelling to a node i multiple time, $\tau_{ij}$ denoted the path (i,j) pheromone level, $\eta_{ij}$ stands for the discoverability of j when position at i, ά and β are pheromone level edge and visibility of node alteration parameters ([0,1]), τ indicates the routing table that retains pheromone trail amount on the link (i, j), ŋ is the node discoverability factor represented by $\frac{1}{C - e_s}$ (Where, c is the initial node energy and $e_s$ is the actual node energy).

Step 3:When a FANT arrives to the target node, it modifies the pheromone edge amount that directs towards the target and memorize this path data. Finally, it kills FANT and convert it to BANT.

Step 4: The target node computes the pheromone trail amount placed by FANTS before start of BANT towards source node using equation 21.

$$\Delta\tau_k = \frac{1}{(N - Fd_k)} \qquad (21)$$

Where $\Delta\tau_k$ is the quantity of pheromone trail placed by FANT during FANT journey, N denotes total nodes and $F_{dk}$ distance travelled by FANT k which is retained in memory.

Step 5: The routing table is modified when BANT k from node "j" reaches to node "i" using equation 22.

$$\tau_{ij}^{k} = (1 - \rho)\tau_{ij}^{k} + \Delta\tau_k \qquad (22)$$

Where, ρ represent an evaporation coefficient that lies between $0 \leq \rho < 1$

Step 6: Once BANT arrives at source node the ant is discarded and transmission is initiated with best neighboring node.

2.4 Proposed Admission Allotment Scheme for Intra-cluster communication

Time Division Multiple Access (TDMA) is taken into account by conventional clustering routing methods for intra-cluster communication. Additionally, CH broadcasts the data via the Carrier Sense Multiple Access (CSMA) method. Once it has received the request, the nearby node connects to the CH. In proportion to the members in the cluster, the CH produces TDMA slots. Each node only sends data within the time window assigned to it. Energy is exhausted if a node does not have any data to communicate within its allotted time period. The suggested AAS is based on a merit-based admission procedure in universities and colleges, where the university seat is given to the student with the greatest merit. Once the CH (University) is chosen in the suggested AAS, the members (students) issue a request to connect with CH. The CH creates the nodes' merit tables, which include the node ID (Enrollment Number/Roll Number), merit number, and whether the node is eligible (busy) or not (free). The eligibility status is treated as 1 for the node that has data to submit and as 0 for the node that does not. There are various rounds to the admissions process. Each cycle updates each node's eligibility status. The CH awards a chance to the node with the first eligibility status and the highest merit number after creating the merit table based on remaining energy. High merit numbers are assigned to nodes with high residual energy. Once the chosen node runs out of power, it goes to sleep and gives the next sensor node in line a chance to transmit data. The algorithm for the proposed AAS scheme is given as follow:

1. Step 1: Initialize the algorithm parameters
2. Enrollment Number: Node ID
3. MeritNumber: H
4. Node eligibility: Busy/Idle
5. Step 2: The node connects send connection request to CH once it is ready for data transmission /event occurrence.
6. Step 3:while (round<= total admission round)
7. Create the merit list
8. If node is eligible && merit is maximum &&node_energy>0
9. Select node for data transmission
10. Else
11. Update the merit list

## 3. Simulation Results and Discussions

The suggested scheme is implemented using MATLAB on the personal computer system having 4GB RAM, core i5 processor and windows operating environment. The homogeneous WSN scenario is considered for the simulation. The different WSN parameters, radio model parameters are described in Table 1. The results of the anticipated scheme is evaluated based on various evaluation metrics such as packet throughput, Packet sent to BS and CH, outstanding energy, live and dead nodes per round. The energy needed for the transmission ($E_{Tx}$) and reception ($E_{Rx}$) of K for the free space and multi-path considering distance between two nodes as d is given by equation 23 and 24 respectively.

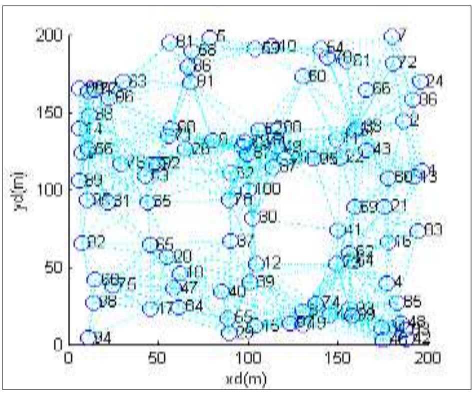
$$E_{Tx} = \begin{cases} K * E_{elec} + K * E_{fs} * d^2, & \text{if } d < d_o \\ K * E_{elec} + K * E_{mp} * d^4 & \text{if } d \geq d_o \end{cases} \quad (23)$$

$$E_{Rx} = K * E_{elec} \quad (24)$$

Table 1: Network simulation parameters and radio model parameters

| System Parameter | Specification |
|---|---|
| Network Parameters | |
| Base Station Position | Center |
| Simulation area | 200m x 200 m |
| Initial energy (Eo) | 0.1-0.5J |
| Number of Nodes | 50,100,200,300,…500 |
| Node Position | Fixed and Mobile |
| Traffic Patterns | CBR (Constant Bit Rate) |
| Radio Model Parameters | |
| Threshold Distance(do) | $\sqrt{E_{fs}/E_{mps}}$ |
| Energy consumed per bit ($E_{elec}$) | 50 nJ /bit |
| Receiver Power Consumption ($E_{RX}$) | 50 nJ/bit |
| Transmission Power Consumption ($E_{TX}$) | 50 nJ /bit |
| Multipath Amplification Factor ($E_{mp}$) | 0.0013pJ/bit/m4 |
| Free Space Amplification Factor ($E_{fs}$) | 10pJ/bit/m2 |
| Message bits (K) | 2000 bits |

The simulation outcomes of the suggested FCM-ABC-ACO are compared with conventional clustering routing techniques such as LEACH algorithm [29], LEACH-C algorithm [30], and FCM-DS-ACO algorithm [31] for the homogeneous network scenario. The original network scenario, clustering using FCM, and CH selection and optimization by means of ABC are depicted in Figure 5(a), 5(b) and 5(c) respectively. The live and dead nodes per round are illustrated in Figure 5(d) and Figure 5(e). The proposed FCM-ABC-ACO provides the superior network lifetime as the round at first and last node dead is larger. The larger value of first and last node dead shows the larger lifespan of the network. Further, Figure 5(f) and 5(g) provides the packet transmitted to the CHs and BS. The use of optimal cluster head selection, use of energy efficient routing phenomenon, load balanced intra-cluster communication strategy helps to improve the packet transmission. The proposed AAS scheme assists to improve the lifetime of the congested nodes near the CHs and BS and shown significant improvement in the packet throughput of the network.

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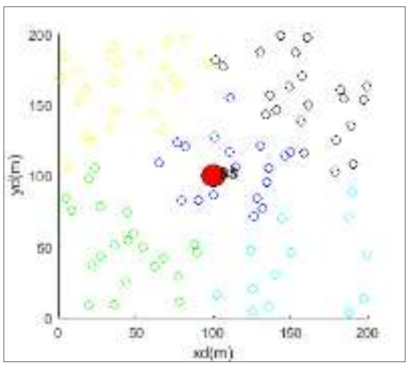


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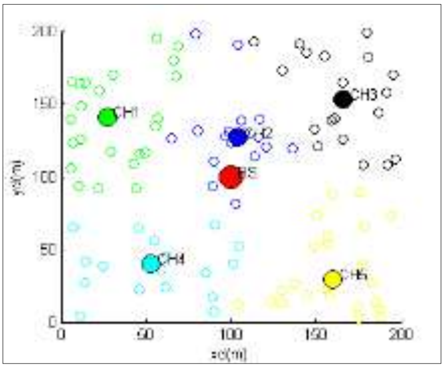


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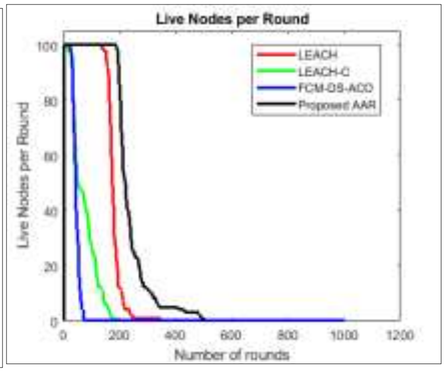


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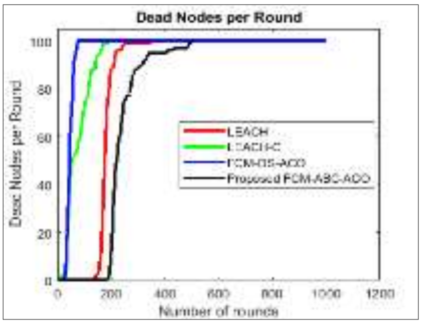


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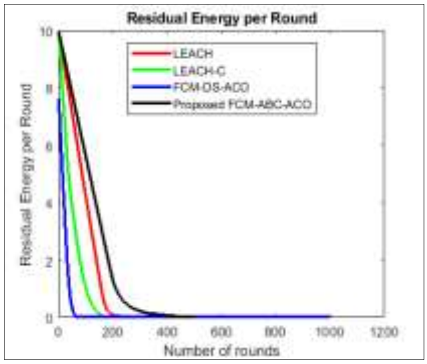


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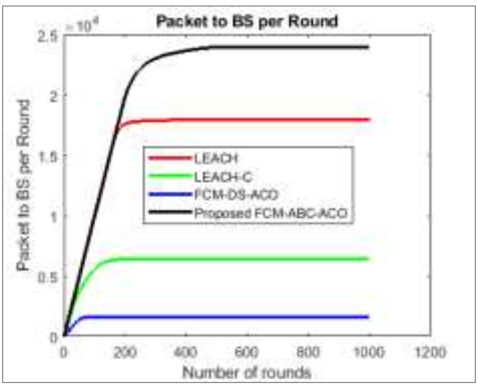


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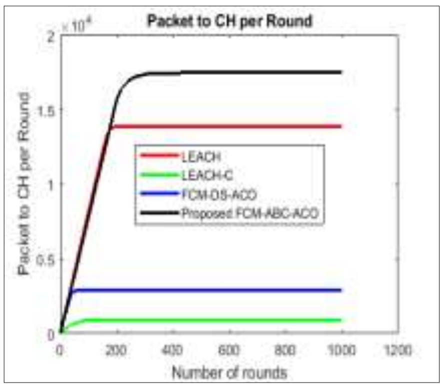
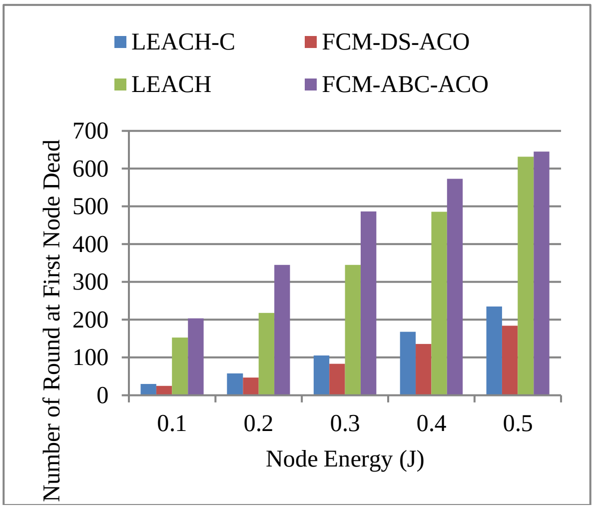



h

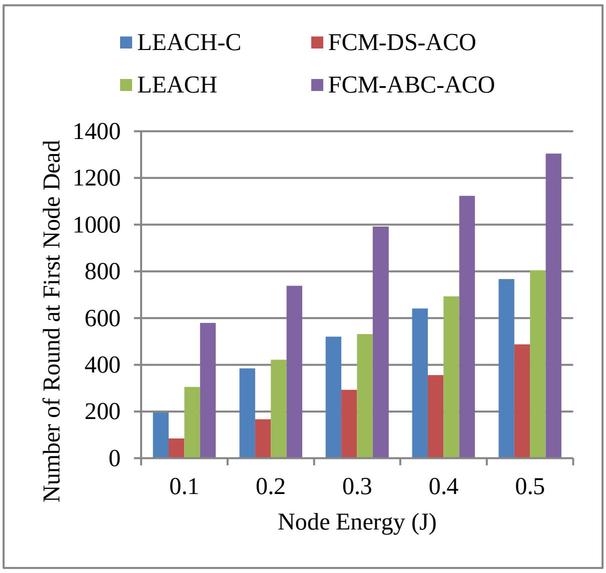
Fig. 5 Simulations results of proposed routing scheme a) Network scenario (Area =200m×200m, N=100 ) b) Clustering using FCM c) ABC based CH selection and optimization d) Live nodes per round e) Dead nodes per round f) Residual energy g) Packet delivered to BS h) Packet delivered to CHs

Figure 6 illustrates the comparative results of the FCM-ABC-ACO scheme based on round at which first and final nodes die to define network lifespan and energy efficiency.

Experimental findings reveal a considerable longevity enhancement over traditional clustering algorithms. The FCM-ABC-ACO along with AAS provides the improved network lifetime compared with exiting state of arts based on the number of round at first and last node dead.




a)




b)

Figure 6 Lifetime of the network a) First node dead b) Last node dead)

The broad use of various machine and deep learning approaches has lately benefitted a number of computer science applications, such as image processing, signal processing, voice processing, big data analytics, image processing, data mining, etc [32-35]. These schemes have shown outcomes that are encouraging for boosting system effectiveness. However given the dearth of data and the unpredictability of the environment, these solutions are essential for WSN clustering and routing. Yet, there is a chance to foresee future circumstances for WSN lifetime improvement using these schemes for autonomous learning of WSN situations [36][37].

## 4. Conclusion

This study addresses the issues of poor energy efficiency and short network lifespan in WSNs by providing optimum clustering and CH selection using Fuzzy C-Mean and an improved ABC Optimization algorithm. ACO-based energy-efficient routing helps networks last longer. The ABC takes into account factors like energy GINI coefficient, load GINI coefficient, inter-cluster and intra-cluster distance for the best CH selection. In various network density and scalability scenarios, it has proved to significantly outperform the centralized CH selection using the FCM technique. In the future, the effectiveness of the suggested strategy may be examined for the real-time situation. Future efforts to increase WSN's trustworthiness for dependable data transmission may take security into account. There is a need to concentrate on reducing the computational intricacy of the method.

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