Energy efficient clustering and routing method for Internet of Things

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ABSTRACT

The Internet of Things is crucial in monitoring environmental conditions in remote areas, but it faces significant challenges related to energy consumption, which affects network longevity and coverage. Clustering has proven effective in prolonging the life of sensor networks. Adaptive clustering in wireless sensor networks allows for more effective cluster organization via real-time rearranging of sensor nodes according to important parameters, which include energy levels and the distance between them. Fruit fly algorithm (FFA) and ant colony optimization (ACO) are emerging as encouraging techniques for creating clusters and establishing paths, respectively. This paper describes the use of the FFA to make the clustering process better by selecting the best cluster head and reducing energy consumption. This paper proposes a novel solution that integrates ACO for establishing paths with FFA for clustering. This method is tested in both homogeneous and heterogeneous settings using MATLAB, comparing its performance with two existing algorithms: low energy adaptive clustering hierarchy (LEACH) and biogeography-based optimization algorithm (BOA). According to the findings, the suggested algorithm performs noticeably better than BOA and LEACH in the context of coverage area and network service period, especially in heterogeneous settings.

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1. INTRODUCTION

The 21st century marks a period where technology is characterized by electronic information. As the scope of exploration and technological reach expands, there is an increasing need for cooperation among numerous sensors, rather than relying on each one to independently sense the environment. This cooperation enables more comprehensive and detailed monitoring tasks, with results transmitted wirelessly for further analysis and processing [1], [2]. This demand has given rise to the Internet of Things (IoT), now a focal point of information technology research. Sensor nodes in IoT often operate on energy-limited batteries and are commonly deployed in challenging or hazardous environments where replacing batteries or recharging isn't feasible [3], [4]. If these nodes exhaust their energy, it can severely disrupt the network's functionality, alter its topology, and even lead to communication breakdowns. Thus, optimizing the energy use of network nodes to prolong the network's lifespan has become a key focus in IoT research. Currently, most studies on wireless sensor network routing protocols emphasize energy-efficient utilization, creating energy-saving pathways, and establishing reliable data forwarding mechanisms [5], [6]. Balancing energy consumption across the network is a central aim in designing routing protocols.

Routing is a central technology and a key area of research in IoT. Research now focuses on reducing energy consumption to extend network life, given that sensor nodes rely on finite-capacity batteries. Clustering routing protocols are gaining popularity because they are often more practical than planar routing protocols. Figure 1 shows that the clustering routing algorithm divides the network into several clusters, each with one cluster head node and several cluster member nodes, creating a hierarchical structure. Sensing data from the gathered adjacent region and sending it to the cluster head node is the responsibility of the cluster member node. The cluster head node is in charge of gathering data from the member nodes and fusing it together before sending it to the base station.

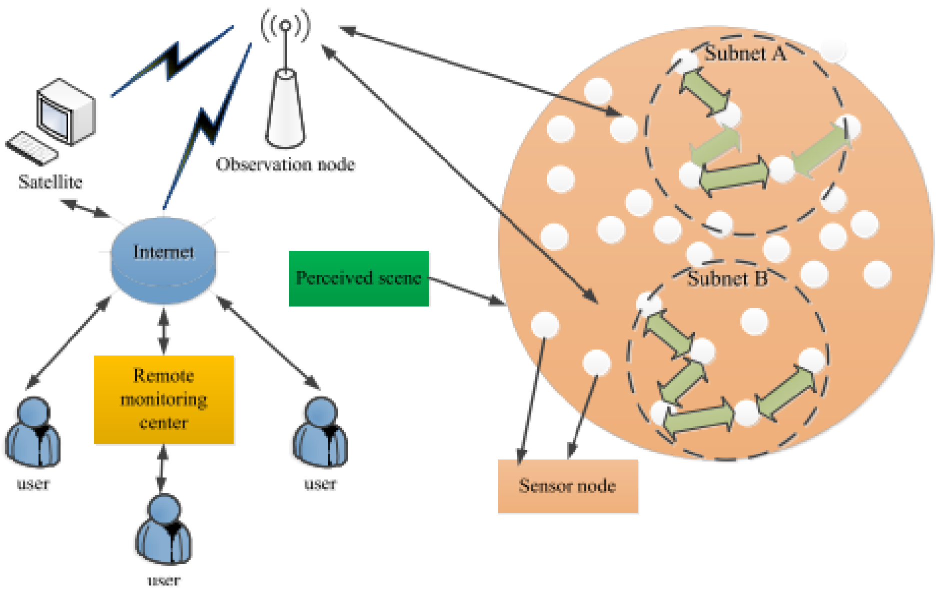

Figure 1. Clustering routing algorithm topology [4]

The clustering routing algorithm has two main phases: the cluster establishment phase and the steady transmission phase. In the cluster establishment phase, cluster heads are generated, which determines the final number and size of clusters, as well as the overall energy consumption of the network. Cluster heads are typically selected through a clustering algorithm that employs a periodic rotation method, taking into consideration factors like node energy, location, and intra-cluster communication cost. After the cluster head broadcasts information [7], [8] member nodes are chosen based on various factors such as load balancing among cluster heads, shortest distance, or lowest energy consumption within the cluster. In the data transmission phase, member nodes communicate with the cluster head, which performs data fusion within the cluster. From there, the data can be sent directly to the base station or relayed through other cluster heads that act as intermediary nodes. The clustering routing algorithm encompasses a range of clustering approaches. Options include distributed or centralized clustering, uniform or non-uniform cluster sizes, and single-layer or multi-layer cluster structures. Additionally, communication between clusters can be either single-hop or multi-hop. Regardless of the clustering method chosen, the key challenge is to balance the network's energy consumption and make efficient use of node energy to extend the network's lifespan [9], [10].

A wireless sensor network (WSN) is a cutting-edge IoT technology composed of multiple nodes with capabilities for sensing, processing, computing, and communication. However, each sensor has a limited sensing range and battery life, leading to several critical challenges in IoT, such as selecting cluster heads, localizing nodes, and designing routing protocols. Optimization methods inspired by insect foraging behavior offer efficient solutions, as these methods are flexible, robust, distributed, and scalable, aligning with IoT routing protocol requirements. Consequently, many optimization techniques have been developed for IoT routing protocols [11], [12]. The cluster routing protocol is a commonly used approach in IoT, where selecting a cluster head (CH) is a significant challenge. Specifically, choosing a CH is an NP-hard problem, meaning it is computationally complex. Swarm intelligence (SI), known for solving NP-hard problems, is a suitable approach due to its ability to work with a limited number of parameters and perform multi-objective optimization, allowing it to select CHs in multiple clusters simultaneously. While GPS is commonly used for positioning, its high energy consumption and limited coverage make it impractical for IoTs. Node localization, an issue in IoTs, is a type of error optimization problem that belongs to the category of complex optimization challenges. Optimization algorithms can be used to solve such problems effectively [13], [14].

The particle swarm optimization (PSO) algorithm, created by Kennedy and Eberhart, is a global random search method that emulates the behavior of swarms during migration and foraging. In the flock aggregation model, individuals follow certain rules: avoiding collisions with nearby individuals, aligning their speed with others in the vicinity, flying toward the flock's center, and collectively heading toward the intended destination. In PSO, each bird in the search space called a particle represents a potential solution to an optimization problem. Every particle has a velocity that dictates its direction and distance of movement, and it also has a fitness value based on the optimal function. The particles move through the solution space, adjusting their trajectory toward the particle with the best fitness, which represents the current optimal solution. Ant colony optimization (ACO) is an algorithm that uses a probabilistic approach to solve computational problems and find optimal paths in a graph [15], [16]. In ACO, each ant leaves pheromones along the path it takes. The entire ant colony can detect these pheromones. Ants tend to choose paths with higher pheromone levels, reinforcing those paths by depositing more pheromones as they travel. Over time, this process guides the ant colony toward the shortest route to food. ACO's benefits include a strong global optimization capability and flexible implementation, making it suitable for integration with other algorithms. The artificial bee colony (ABC) algorithm imitates the behavior of a swarm of bees collecting honey, with each bee exhibiting different behaviors based on its role in the division of labor. Bees communicate and share information among themselves to arrive at the optimal solution. The algorithm divides the artificial bee swarm into three categories: scouts, onlookers, and employed bees [17], [18]. In each search process, bees find the best solution by following the leading bee to a food source. If a bee scouting for food suspects is stuck at a local optimum, it randomly searches for other food sources. Each food source symbolizes a possible solution to the problem, and the quantity of nectar from a food source indicates the quality of that solution.

2. LITERATURE REVIEW

Sankar *et al.* [19] introduced a novel cluster head (CH) selection and cluster formation algorithm aimed at addressing certain limitations. The approach included two main stages: first, CH selection was conducted using the sailfish optimization algorithm (SOA), a type of swarm intelligence algorithm. Next, cluster formation was based on the Euclidean distance. The authors used the NS2 simulator for their experiments. The SOA's effectiveness was compared with three other methods: improved ant bee colony optimization-based clustering (IABCOCT), enhanced particle swarm optimization technique (EPSOCT), and hierarchical clustering-based CH Election (HCCHE). The simulation results indicated that the introduced SOA approach enhanced network longevity and reduced delays in node-to-sink communication.

Du and Gu [20] highlighted importance of low-power routing protocol design in IoT. To address the challenges related to network load and energy consumption in existing clustering methods, they presented a novel clustering routing scheme using the quantum beluga whale optimization (QBWO) algorithm. This algorithm was designed to effectively and centrally configure clusters, focusing on aspects such as cluster centroids, cluster members, cluster energy, cluster priority, and the validity period of clusters. By doing so, it shifted the computational energy consumption from individual nodes to the base station, thus optimizing the overall network operation for both the transitional and stable stages. Simulation experiments demonstrated the effectiveness of QBWO, showing its potential to deliver a more balanced network load and energy consumption compared to traditional clustering methods. This approach improved energy efficiency and a longer network lifespan.

Sharmin *et al.* [21] introduced and examined a secure bio-inspired WSN routing protocol using the ACO algorithm for the IoT. This protocol was designed to find a secure and energy-saving optimal path, aiming to establish trust in the IoT environment. The performance of this proposed routing algorithm was tested using MATLAB. The results showed that it could identify a forwarding path with relatively low cost while ensuring security. Additionally, it significantly reduced average energy consumption by about 50% even with an increase in the number of nodes, when compared with the traditional ACO algorithm, a well-known ant colony-based routing algorithm, and a contemporary IoT routing protocol.

Fan and Xin [22] introduced a clustering and routing algorithm specifically designed for fast-changing (FC-CRA) large-scale IOTs in the IoT. The FC-CRA created clusters using a cluster radius that can adjust dynamically to shifts in node energy levels and dispersion. To conserve energy and maintain balance among nodes, intra-cluster routing relied on a path energy function. Inter-cluster routing used a specific set of communication nodes to avoid premature failure of those near the base station, ensuring continued data transmission. The FC-CRA algorithm outperformed other algorithms in large-scale or sparse IOTs in terms of node lifecycle, network performance, and energy efficiency. The proposed algorithm was able to reduce the "energy hole" problem and enhance the reliability of data transmission. This was especially critical for certain IoT applications that required wide-area monitoring or operate in challenging or dangerous environments.

Zhang *et al.* [23] proposed an energy-efficient multilevel secure routing (EEMSR) protocol for IoT networks. Given that clustering is an effective way to conserve energy, the researchers used a cluster-based multihop routing protocol to minimize the high communication overhead often seen in scalable IoT networks. They implemented an analytic hierarchy process and genetic algorithms to assign weights accurately and to optimize inter-cluster routing, ensuring the protocol could support a variety of heterogeneous IoT entities and services. Additionally, by incorporating a trust factor into clustering and routing, the protocol used multiple trust levels such as data perception trust, data fusion trust, and communication trust to defend against various security threats. The proposed approach performed better than many existing algorithms in terms of network service period, throughput, packet delivery ratio, energy balance, and flexibility.

Gorikapudi and Kondaveeti [24] introduced a novice method for clustering in IoT networks. These networks faced a crucial challenge of energy-efficient routing due to the limitations of smart gadgets. Their technique employed the sandpiper optimization with cycle crossover process (SOCCP) model to select cluster heads, taking into account constraints like distance, energy, security, and cluster radius. The clustering process utilized an optimized fuzzy c-means (FCM) algorithm, while the cluster head and radius determination was optimized through the SOCCP model. The presented approach was evaluated using metrics like alive node analysis, risk analysis, and distance analysis. The findings indicated that the presented solution surpassed baseline clustering approaches, demonstrating reduced risk and enhanced energy efficiency. The distance analysis revealed that this method achieves the lowest distance at the 1500th round, whereas classic approaches showed higher distances at the same point. This new approach seems promising for advancing clustering in IoT networks.

Sun *et al.* [25] developed a network clustering approach using the K-means technique. To address the K-means algorithm's sensitivity to the initial center (IC) and its tendency to get stuck in a local optimum, they employed the PSO technique to enhance the initial clustering center, achieving optimal clustering. After clustering the network, they considered the location and energy of sensor nodes (SNs) when selecting a CH. The weights for these factors were dynamically adjusted based on the SNs' remaining energy. The proposed protocol effectively balanced energy usage across the network and extended its lifespan in test findings.

Wang *et al.* [26] introduced a data-oriented RPL method that routed data based on content, using binary gray wolf optimization to find the optimal path. This technique enhanced the effectiveness of the routing protocol for low-power and lossy networks (RPL). In the tree construction phase, they used an objective function to select the best parent node for routing, created with fuzzy logic and binary gray wolf optimization. The method was tested in the MATLAB 2022a and OMNET environments, showing improved energy efficiency while reducing end-to-end delay and instability periods. The instability period ratio of the proposed technique was significantly lower than those of other methods. Specifically, it was 57% for the proposed method, while it was 80% for ORPL and QoS RPL, and 89% for the standard RPL method. This lower instability period ratio indicated that the presented technique maintained longer stability, operating with the maximum number of nodes for an extended period.

Bajpai *et al.* [27] presented a methodology that combined advanced machine learning techniques to achieve effective clustering and data reduction. The study used a novel approach by integrating an improved version of principal component analysis (PCA) with a reinforcement learning algorithm. The main objectives were to extend a network's service life, reduce energy consumption, and improve data aggregation efficiency. The proposed method was evaluated using data from sensors installed in agricultural fields for crop monitoring. The researchers compared their suggested method, named PCA-based Q-learning (PQL), with previous approaches like regional energy-aware clustering (REAC) and adaptive Q-learning (AQL). Their findings indicated that the presented method created a fault-tolerant network and surpassed the other methods in terms of energy efficiency and network lifespan.

3. RESEARCH METHODOLOGY

This research is based on network deployment, cluster formation and data routing from cluster head to base station. The cluster formation is done using fruit fly algorithm and path will be established using ACO. The details are given as follows.

3.1. Network deployment

The random distribution of nodes is one of the basic requirements of the clustered wireless sensor network's application. The cluster heads are created due to this random distribution of sensor nodes which further creates several issues. Due to energy consumption, there is a need to avoid disposability for the cluster head. Also, the long-distance communication in the cluster head is prevented and the addition of nodes below them is also done here. The nodes which will not meet standards are not selected as the cluster head. The conditions of nodes made the nodes difficult to available in the network and almost impossible for them to be available at remote an area which further causes inappropriate nodes. When the intra-cluster energy is increased then these nodes are used as cluster heads. The genuine node consumes less amount of energy in comparisons to the receiver and the sender nodes. When the extensive spectrum is provided to the system in a synchronized manner then the battery power consumption is very less than consumed by the nodes. The parent node is selected for ever cluster head so that the actions can be separated and there is an increase in productivity. Two value functions are proposed for the competence of each sensory node which further helps the node to be chosen as the cluster head. Degree of nodes generates functions and the average power of the neighboring nodes is calculated by their distance to the base station. It is necessary to generate a higher degree of nodes so that the cluster head can be formed. If the cluster head has a higher degree can cover a large number of nodes which avoids the expensive communications.

3.2. Cluster formation

The network is deployed and the whole network will be divided into clusters. The clusters will be formed based on the distance. This work employs adaptive clustering for cluster formation. Adaptive clustering in WSNs is an approach to increase the longevity of the network by minimizing energy consumption. Wireless Sensor Networks consist of spatially distributed sensor nodes that are used to monitor the physical or environmental conditions. Efficient data transmission and energy management are the two key areas that need to be focused on for enhancing the lifespan and efficiency of the network. Adaptive clustering is one of the strategies among the efficient ones used to create clusters of sensor nodes based on dynamic criteria. In general, the operations in adaptive clustering algorithms are divided into four steps: node initialization, CH selection, cluster formation and data transmission and adaptive adjustments.

- Node initialization: Each node initializes its energy level and recognizes a list of neighboring nodes within the distance of the given transmission range. The transmission range indicates the maximum communication distance a node can cover
- Cluster head selection: Nodes decide their chances of being cluster heads according to their energy status and distances to the base station. The formula used for this is:

$$P_i = \frac{E_i}{\sum_{j=1}^{N} E_j} \tag{1}$$

where P_i is the probability of node i being a CH, and E_i is the remaining energy of node i.
- Cluster formation: Nodes broadcast their IDs to nearby nodes. Nodes with the highest probabilities become cluster heads. Other nodes join the closest cluster head based on the following criteria:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{2}$$

where d_{ij} is the distance between nodes i and j, and (x_i, y_i) and (x_j, y_j) are their coordinates.
- Data transmission: The member nodes transmit their data to a selected cluster head, which gathers the data and transmits it to the base station.
- Adaptive adjustments: After every transmission round, the nodes reassess their energy levels as well as their communication metrics. If the energy of the node goes down lower than the set threshold, it can choose to be a non-cluster head in the next round.

Adaptive clustering in WSNs provides a means of forming clusters efficiently by regrouping the sensors dynamically according to some metrics like the energy level of the node and the distance to the neighbor node. Further, this work uses the fruit fly algorithm to optimize this clustering process, so as to enhance the selection of cluster heads, hence, reducing energy consumption. In this way, WSN has better network lifetime and performance due to more optimal data aggregation and transmission. Fruit flies rely on their keen sense of smell and vision to locate food, which is superior compared to other fly species. Leveraging swarm intelligence optimization, fruit fly is adept at adjusting fitness function parameters quickly and effectively due to its optimization speed and parameter flexibility. Guided by the fitness function, which acts as an odor concentration decision function, fly optimization algorithm (FOA) aims to iteratively adjust the fruit fly population within the solution space. Figure 2 displays the cluster formation process using fruit fly algorithm. This process typically involves four steps.

– Initialization: Initialization entails determining the starting parameters for the fruit fly population, such as population size, maximum iterations, initial positions, and step length. This enables fruit flies to navigate towards their target using random flight directions and ranges.

$$X(i) = X_0 + Step \tag{3}$$

$$Y(i) = Y_0 + Step \tag{4}$$

The initial position of the fruit fly is denoted by X_0 and Y_0.

– Judgment: Compute the scent concentration (scent) of the fruit fly position using the fitness function

$$Smell\ (i) = Function\big(S(i)\big) \tag{5}$$

$$S(i) = \frac{1}{Sqrt(X(i)2+Y(i)\wedge 2)} \tag{6}$$

– Movement: Movement involves selecting the fruit fly individual with the highest concentration within the population, designating its location as the ideal position. Subsequently, instruct the remaining fruit flies to move in that direction based on their initial step length.

– Iteration: Repeat steps (2) and (3) until the scent concentration either meets the predefined threshold or reaches the maximum number of iterations. The fitness function selects the root mean square error (RMSE), described as follows:

$$min\delta_R = \sqrt{\textstyle\sum_{i=1}^{n} (y_i - \hat{y}_i)^2/n} \tag{7}$$

This indicates the projected position value as $\hat{y}_i$, the discrete position data utilized for processing denoted by y_i, the count of data represented by n, and the root mean square as δ_R

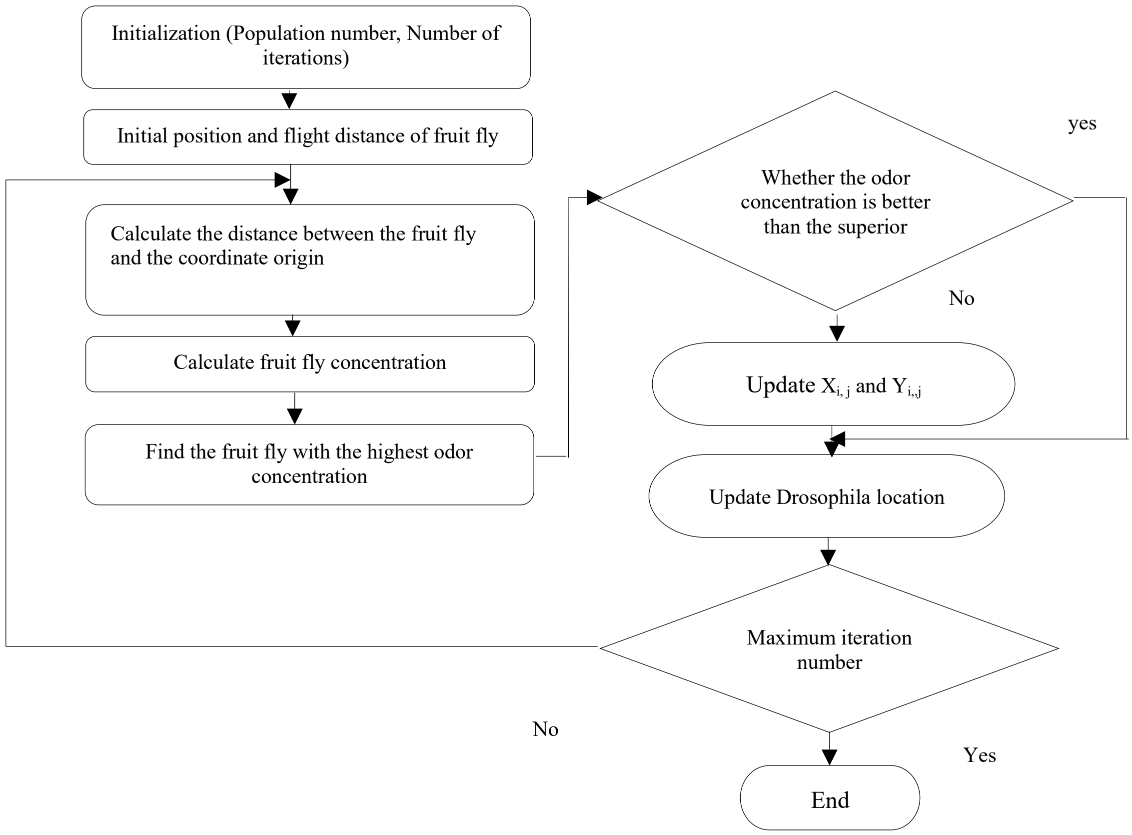

Figure 2. Fruit fly for cluster formation

3.3. Path establishment

ACO is a metaheuristic algorithm inspired by the behavior of ants. In nature, ants find the shortest paths between their nest and a food source, which has inspired the use of ACO in solving discrete optimization problems. These problems are often modeled as graphs with a specific number of nodes and links. At the start, each node has a certain number of ants, and each link has an associated weight. This weight is generally determined based on the physical distance between nodes, a generated random number, or a value derived from a mathematical formula. To improve ACO's uncertain convergence time, it can be optimized by considering factors like residual energy, distance to the base station, and node degree. The process for creating routes using ACO is detailed in this section.

- To create a route from the cluster head (CH) to the base station (BS), an ant is placed at each CH. The source CH then generates specific packets to initiate the routing process; these packets are known as forward ant packets.
- The forward ant packets are randomly sent to the next CH according to a probability matrix. This process of forwarding the packets continues from CH to CH until they reach the BS.
- As the forward ant packets are transmitted, each packet creates a local database containing information about the CHs it visits. This data includes the node ID, residual energy (E_r), distance from the CH to the base station ($d_{CH.BS}$), and the node's degree (N_D). The residual energy in each CH is largely influenced by the number of packets (l) that are transmitted through the network.
- Once the path is established with the forward ant packets, this database is used to create a backward ant packet. As the forward ant packet progresses to the BS, the backward ant packet follows the same route in reverse. It uses the information from the database to trace the exact path that the forward ant packet took to reach the BS.
- The pheromone levels for each path are updated based on factors like the residual energy, the distance from the node to the base station, and the node's degree.
- The ant chooses its next hop according to a node transition rule outlined in (8), which calculates the probability of an ant k selecting node j as the next node from node i.

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l\in N_k}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} \; if \; j \in N_k \\ 0 \qquad\qquad\qquad otherwise \end{cases} \tag{8}$$

Here, the heuristic value is denoted by η_{ij}, and the pheromone intensity by τ_{ij}. The parameters α and β control the relative importance of the heuristic value and the pheromone intensity in the transition rule. N_k indicates the set of nodes that the k^{th} ant has yet to visit. Both the heuristic value and pheromone intensity are updated based on information about the CHs stored in the routing table. The heuristic information, based on the distance between CHs, is updated as described in (9).

$$\eta_{ij} = \frac{1}{d_{CH}} \tag{9}$$

Here, the distance between the cluster heads is d_{CH}. The rule for updating the pheromone levels is described in (10).

$$\tau_{ij} = (1-\rho)\tau_{ij}^{old} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{10}$$

In this context, m represents the number of ants initialized in ACO and ρ is the pheromone decay coefficient which ranges from 0 to 1. The additional pheromone deposited on the link between nodes i and j by ant k is denoted by $\Delta\tau_{ij}^{k}$ as outlined in (11).

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{c_k} \; if \; the \; k^{th} antt \; raversed \; link \; (i,j) \\ 0 \qquad\qquad\qquad otherwise \end{cases} \tag{11}$$

In this context, Q represents a constant value, while c_k is the cost of the path detected by ant k. To convert fitness function values into a single objective, referred to as the route cost, a weight value is used. The route cost ck from (11) is incorporated into the pheromone value update. The expression for the route cost is provided in (12).

$$c_k = \varphi_1 E_r + \varphi_2 d_{CH.BS} + \varphi_3 N_D \tag{12}$$

Here, the weights for φ_1, φ_2 and φ_3 are 0.5, 0.3 and 0.2, respectively. Residual energy is given top priority to avoid using sensor nodes with insufficient energy, as these nodes are more likely to fail during communication. The distance between the CH and the BS is the second priority, ensuring shorter paths to reduce energy consumption. Lastly, the node degree is the third priority, allowing selection of the next hop CH, with fewer cluster members.

4. RESULTS AND DISCUSSION

This project aims to reduce energy requirement on IoT and extend their lifespan. Two optimization algorithms, fruit FOA and ACO, are employed for this purpose. The network is segmented into clusters, with a cluster head selected in each cluster on the basis of two parameters named distance and energy levels. The cluster head is a node with the shortest distance to the base station and the highest energy within its cluster. FOA is used to form and optimize the clusters. The cluster head relays data collected from the sensor nodes within its cluster to the base station. The ideal path for data delivery is established between two end points (i.e., cluster head to the base station). The ACO algorithm is used to optimize the route between these two points. This work uses both homogeneous and heterogeneous networks to evaluate the devised model. Table 1 presents a list of simulation metrics.

Table 1. Simulation parameters

Parameter	Description	Value
A	Area of network	(0, 0)–(200, 250)
L-BS	BS location	(150, 250)
N	Number of nodes in network	400
$E_{initial}$	Initial energy of all nodes	0.5 J
E_{fs}	Free space channel model	50 nJ/bit
E_{mp}	Multi-path fading channel model	0.0013 pJ/bit/m^4
d_0	Distance threshold	87 m
E_{DA}	Data aggregation energy	5 nJ/bit/signal
DP size	Data packet size in bit	4000
CP size	Control packet size in bit	200

Figure 3 demonstrates the setup of the entire network with a fixed number of nodes. The network is partitioned into clusters, with nodes randomly distributed across it. The figure also shows the cluster heads in each cluster, which are responsible for data aggregation.

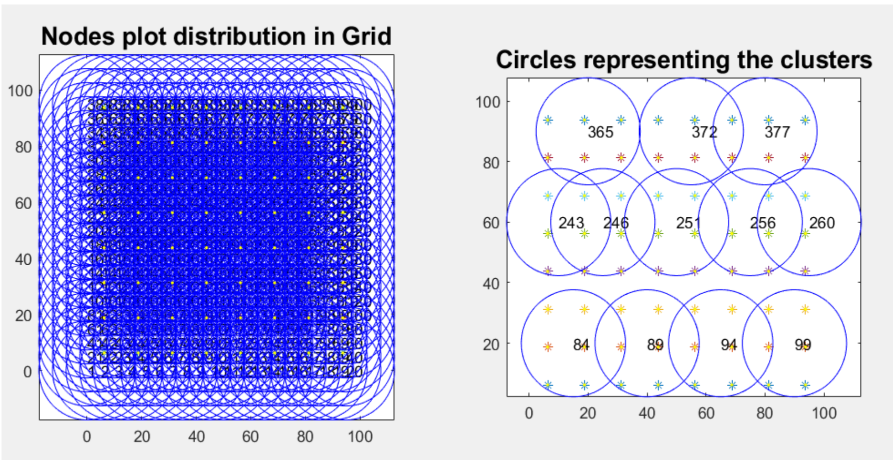

Figure 3. Node plot distribution in grid and circles representing the cluster head

Figure 4 shows how sensor coverage ratios from different algorithms are assessed for performance analysis. The proposed method and BOA are compared with the LEACH technique in homo/hetero environments. The analysis indicates that the proposed model achieves better results than the BOA and LEACH protocols in a heterogeneous setting when compared to a homogeneous one.

Figure 5 compares the percentage of dead nodes in the presented approach with the BOA and LEACH algorithms in both homogeneous and heterogeneous environments. The analysis indicates that the suggested algorithm performs best in heterogeneous settings in comparison to other approaches.

Figure 6 presents a comparison of the network service period for the presented approach, BOA, and LEACH protocols in both homogeneous and heterogeneous contexts. The results suggest that the presented approach in the heterogeneous scenario outperforms the other approaches in terms of longevity.

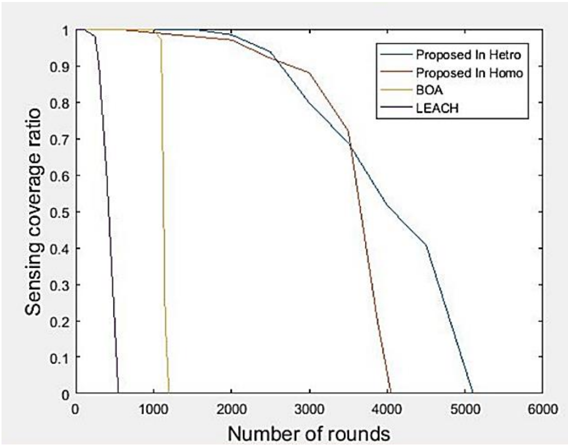

Figure 4. Sensing coverage ratio

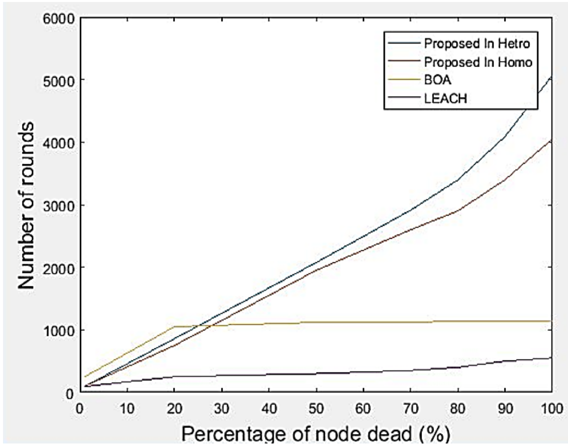

Figure 5. Percentage of dead nodes

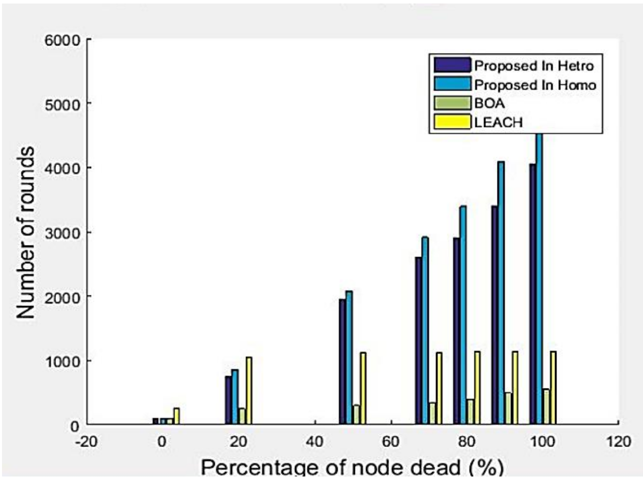

Figure 6. Network lifetime analysis

5. CONCLUSION

This work presents a novel approach for IoTs that combines the FFA with ACO for cluster creation and pathfinding, respectively. The combination of adaptive clustering with the Fruit Fly Algorithm in WSNs contributes a lot to optimizing the cluster formation process. This eco-friendly, energy-saving, and intelligence-based improvement allows for a better life span and higher performance of the network via optimized selections of cluster heads and energy balancing. The performance of the proposed algorithm is tested in both homogeneous and heterogeneous scenarios using the MATLAB tool. The proposed method is compared to two common algorithms: the biogeography-BOA and the LEACH. In the context of network longevity and coverage area, the proposed algorithm surpasses both BOA and LEACH, especially in a heterogeneous setting. This demonstrates the efficiency of this method in managing energy usage and boosting the efficiency and consistency of IoTs, especially in cases where rigorous environmental monitoring is needed.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

In this research work no dataset is used for the result generation. The generated results are based on the random data which is generated by the sensor nodes. The code can be shared based on personal request.

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