International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.3 (2025) pp. 5668-5677
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

Energy Consumption in Wireless Sensor Networks Using Fruit Fly and Ant Colony Optimization Algorithms in Heterogeneous Environments

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Article Info:

DOI: 10.22399/ijcesen.3132
Received : 15 January 2025
Accepted : 25 March 2025

Keywords

Fruit Fly
Ant Colony
BOA
LEACH
Path Optimization
Clustering

Abstract:

WSNs (Wireless sensor networks) play an important role in sensing environmental conditions in far-flung areas. However, their energy usage remains a crucial issue, affecting the network's lifetime and coverage area. Clustering has emerged as an efficient strategy to prolong sensor network lifespan, and the Fruit Fly Algorithm (FFA) and Ant Colony Optimization (ACO) are promising techniques for cluster formation and efficient path establishment, respectively. In this study, we propose an innovative approach that combines FFA for cluster formation and ACO for path establishment. This novel algorithm is implemented in MATLAB and evaluated in both homogeneous and heterogeneous environments. We compare our proposed algorithm with the Biogeography-Based Optimization Algorithm (BOA) and the LEACH (Low Energy Adaptive Clustering Hierarchy) algorithm. Our findings show that the proposed algorithm significantly outperforms both BOA and LEACH as per the network longevity and coverage area, particularly in heterogeneous environments.

1. Introduction

Advancements in modern technology has contributed to the development of small electrical sensor devices requiring minimal power. These sensors are deployed in distant places to measure various physical variables [1]. WSNs find applications across industries, including environmental monitoring, disaster management (such as detecting air pollution, landslides, and forest fires), distributed situational awareness, geographic targeted investigations, smart monitoring, defense reconnaissance, as well as wellness monitoring tasks like blood glucose monitoring, cancer detection, and managing mass casualty disasters. In contrast to conventional networking solutions, WSN innovation is advantageous in several way, like ease of installation, lower implementation costs [2], enhanced accuracy, and scalability, across various applications. Typically comprising hundreds of sensor nodes (SNs), WSNs facilitate seamless interaction among nodes to transmit high-quality data to a central base station (BS) without reliance on existing infrastructure [3]. This self-organizing feature allows WSNs to be positioned as required. As depicted in Figure 1, SNs are distributed randomly across remote locations or sensor fields, establishing connections with each other to measure physical variables.

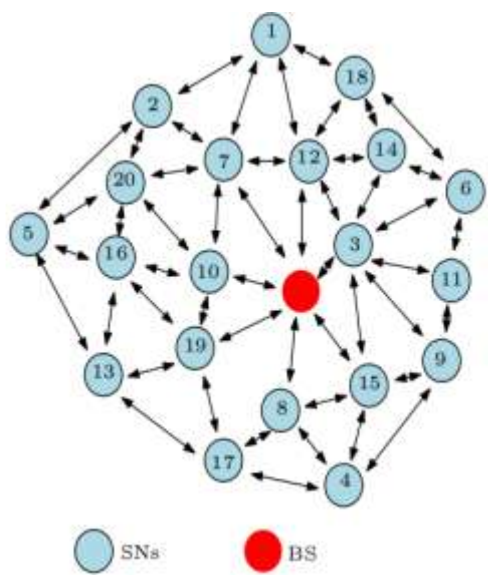

Figure 1. *Simplified diagram of a WSN.*

Additionally, replacing fully deployed sensor nodes (SNs) is highly challenging in various settings [4], especially in hostile environments like mines and battlefields. The precision and dependability of the transmitted data improve with the increased number of SNs monitoring a particular region or event. In Figure 1, each SN sends acquired info to the sink according to the selected routing protocol or algorithm. This protocol helps SNs to improve routes to reduce costs and specifies how they exchange data to send data collected to the BS [5]. The routing algorithm, often designed as a load-balanced tree routing algorithm or a clustering routing algorithm, determines the route selection. An economical routing protocol is created to strike the ideal balance between attributes such as scalability, timeliness, and resilience. Above all, the routing protocol aims to minimize energy consumption to maximize network durability significantly [6]. Balancing these service quality standards makes routing in WSNs challenging. Given that sensor nodes (SNs) are primarily battery-operated devices, energy efficiency is of utmost importance. Therefore, effective management of sensor nodes' (SNs) energy consumption is crucial to improve network endurance and maintain its usefulness for an acceptable duration [7], especially when the nodes rely entirely on energy usage.

A. Energy-efficient routing

Routing indeed imposes additional strain on energy supplies, particularly in multi-hop solutions where nodes in the vicinity of the sink bear more packet-routing responsibilities, leading to quicker battery depletion. Various routing paradigms incorporate general energy-saving mechanisms, which we'll discuss next.

Cluster architectures: According to cluster designs, the network is divided into clusters, each of which is controlled by a cluster head (CH) [8]. The cluster head's duties include coordinating tasks among cluster members and communicating with the sink or other cluster heads. By addressing a variety of factors, cluster strategies are suggested for bettering the use of energy: reducing the distance from one another within the cluster, which lowers power used for transmission usage; rotating the cluster head to balance the usage of energy among nodes; lowering the number of transfers through data fusion executed by the cluster head; cutting resource-intensive tasks, like integration and aggregation, that are entrusted to the cluster head; and facilitating some nodes within the cluster to be turned off while the cluster head deals with delivering tasks [9]. Cluster topologies increase network versatility and ecological sustainability by creating an ordered structure within the network.

Energy-centric routing criterion: To extend the lifespan of sensor networks, energy considerations are integrated into the setup path stage [10]. This makes it possible for routing algorithms to choose the next hop by taking into account both the nodes' energy reserves and the fastest routes. Researchers have presented two novel energy-conscious cost functions. ESCFR (Exponential and Sine Cost Function based Route) function is particularly noteworthy as it ensures energy balance by prioritizing sensors with larger energy stores when choosing a path [11]. Even a minor variation in nodal energy can cause a substantial shift in the cost function value, making ESCFR a robust mechanism for energy-aware routing. DCFR (Double Cost Function based Route) evaluates nodes as per on their residual energy as well as their rate of energy depletion. This is crucial because nodes in hotspots tend to deplete energy rapidly. By integrating both aspects, DCFR optimizes energy distribution in routing protocols, even in networks with physical obstructions [12].

Multipath routing: Despite being easier to use than multipath routing protocols, single-path routing methods have the potential to rapidly deplete energy along the selected path. By switching forwarding nodes, multipath routing, on the other hand, enables a more equitable allocation of energy amongst nodes [13]. For instance, to find several node-disjoint paths, the Energy Efficient Multipath Routing Protocol, or EEMRP, uses a cost function that is based on hop counts and energy availability. The traffic rate is then dispersed among these chosen routes. Between a source and a sink, the EECA (Energy-Efficient and Collision Aware) protocol creates two node-disjoint, collision-free paths. By offering numerous paths, multipath routing techniques improve network stability and allow for faster recovery from losses than single-path systems, which require recalculating a new route in the event that a node fails. [14].

Relay node placement: Energy gaps or network fragmentation may result from the early loss of nodes in a particular region. Nevertheless, through the addition of relay nodes with improved capabilities or by distributing nodes equitably, this scenario can occasionally be avoided. By doing this, sensor hotspots are avoided, coverage and k-connectivity are guaranteed, and node energy balance is enhanced. Determining the ideal number of relay nodes or where to put them in order to increase network lifetime has been the subject of numerous studies [15]. For example, researchers optimize the positioning of fixed sinks to reduce the average hop distance between each node and its nearest sink.

Sink mobility: In a WSN architecture employing a fixed sink, sensors near it tend to deplete their battery power more rapidly than other sensor nodes. This imbalance occurs because all traffic is directed toward the sink, increasing the workload on nodes closest to it. Using an inflatable base station that travels the network to gather node data can help distribute the load across nodes and extend network longevity [16]. Due to single-hop communication, sink mobility not only improves connectivity and reliability in sparse systems but also lowers message loss, contention, and collisions. Controlling the base station's mobility enables research into reducing excessive latency, memory overflow, and loss of energy.

2. Literature Review

A. S. H. Abdul-Qawy, et.al (2021) proposed a Multi-Level Stable Election Protocol (TEMSEP) that is threshold-oriented and energy-harvesting enabled in order to improve energy management in large-scale WSNs [17]. Instead of sending data all the time, the network nodes were focused on transmitting their data only according to requirement. For this, these nodes responded reactively against the changes in applicable metrics. Based on the values of heterogeneous thresholds, an innovative thresholding framework was proposed to provide the optimal system for such reactions to recognize events. In order to reduce network traffic load, maximize the energy efficiency of battery-powered nodes, and extend network lifespan, a sliding window was constructed to control the frequency of data reporting. As per findings, the new approach proved very efficient by alleviating the traffic-load around 53% and saving overall dissipated energy around 73%. Furthermore, this protocol augmented a stability period up to 69% and prolonged the duration of network up to 56% in contrast to other methods.

N. D. Tan, et.al (2023) presented EE-TLT, a two-level tree-based clustering-based energy-efficient routing protocol that stabilizes and effectively deploys sensor node (SN) energy [18]. This protocol aimed to split the regional network into clusters, having several nodes balanced in every cluster. Every cluster was responsible for dividing the nodes again into polygons. The TLT method was implemented to transmit the data only using short links. The energy residual and distance were taken in account amid candidate nodes and the BS for verifying the CH or relay CH node in every polygon or sector. Moreover, this protocol was exploited to select an optimal stage length to transmit data in every round due to which the amount of data packets transmitted to BS, were maximized. According to experiments, the introduced protocol was robust for balancing the energy used by sensors as well as increasing energy efficiency and the proportion of data packets transmitted to BS by 10% over STDC, 15% over PEGCP, and 25% over LEACH-VA.

H. Zhang, et.al (2024) presented MOALO-FCM (multi-objective antlion with fuzzy clustering) algorithm for attaining trade-off among dissimilar optimization objectives [19]. Thereafter, an adaptive membership function revision (AMFR) technique was put forward for avoiding the issue related to unbalanced energy consumed by relay nodes (RN). Two-dimensional (2D) and 3D scenes were considered with correlative algorithms in experimentation for computing the presented algorithm with respect to Pareto optimal solution sets, lifespan of network, Battery usage of sensor nodes and relay nodes (RNs), amount of living nodes, and running time of algorithms. The experimental outcomes validated the supremacy of presented algorithm over existing methods. Moreover, this algorithm was capable of mitigating energy usage, extending the duration of network, and offering several methods.

B. Saoud, et.al (2023) devised a novel method of routing protocol for reducing the amount of energy used and prolonging the WSN [20]. A novel method was presented for selecting cluster head (CH) relied on energy at every sensor node (SN). This method was deployed for alleviating the energy utilization of SNs and prolonging the life span of WSN. Choosing the CHs set and the quantity of CHs was a challenging issue. This technique was used to investigate near-optimal or ideal paths in WSN. In order to account for variations in network topology, energy levels, and traffic patterns, the Firefly optimization (FFO) algorithm was used. A comparison between the developed approach and conventional approaches was carried out. The simulation results depicted that the devised method was performed well and yielded lower energy consumption and higher PDR (packet delivery ratio) amid SNs and base station (BS). Furthermore, this method expanded the duration of WSN.

A. Hossan, et.al (2022) established CBPR (cluster based proactive routing) protocol called DE-SEP (Distance and Energy Aware Stable Election Routing Protocol) for ensuring the precise optimal energy conservation [21]. In order to choose the closest nodes from the base station (BS) as CH and to give precedence to nodes with comparatively higher energy, the energy and distance metrics were taken into account. Additionally, this protocol assisted in setting a cap on the quantity of CHs. It resulted in deploying a precise number of CHs for avoiding redundant cluster generation and diminishing the energy consumption. The experiments revealed that the established protocol had offered longer duration of network, higher stability period, greater throughput, and enhanced normalized residual energy (RE). This protocol was led to maximize the normalized RE up to 5% than P-SEP, 41% than M-SEP and 41% than SEP algorithm.

M. J. Rhesa, et.al (2024) suggested a new DBKNN (Davies-Bouldin K Nearest Neighbor) and Radial-ANFIS (Radial-Adaptive Neuro Fuzzy Interference System) framework to mitigate energy consumption in WSNs [22]. This initial task was to split the deployed nodes and extract the node features. The Laplacian Cubic Cheetah Optimizer (LCCO) was exploited for selecting cluster heads (CHs) based on features and initial method was applied for clustering the nodes. At second, the AI-GTBO (Adaptive Intensed Golden Tortoise Beetle Optimizer) method was employed to choose relay nodes (RNs) based on weight value, which were later utilized for generating routes amid node and Base Station (BS) and evaluating the shortest route. Nodes were utilized for sensing the data after developing the network and computing the association amid every data. The redundant node was detected when the second algorithm was fed with analytic output. In the end, the remaining node data was employed to transmit data to BS. The NRI-PCA (Newton Raphson Iterative Principal Component Analysis) was utilized to mitigate the first dimension. The experimental results confirmed that the suggested framework was more effective to mitigate energy usage and enhancing duration and throughput. The accuracy of this framework was found 96.49% and the EC was 3748J for 50 nodes.

S. S. Rani, et.al (2023) projected IBORSDFFNL (Improved Buffalo Optimized Route Selective Deep Feed Forward Neural Learning) method to refine energy management [23]. Various paths were generated to aggregate the data effectively in WSN. Two processes were executed for discovering the route path and selecting it. This method was utilized for generating various route paths from distributed sensor nodes (SNs). An improved buffalo optimization (IBO) algorithm was utilized to select the finest route so that the data was aggregated at lower delay and higher packet delivery ratio (PDR). Various metrics, such as EED (end-to-end delay), energy usage and PDR (packet delivery ratio) were employed for simulating the projected method. Based on simulation, the projected method was performed well in contrast to other methods for mitigating energy utilization, EED and maximizing PDR.

N. Meenakshi, et.al (2024) developed an improved EL (Engroove Leach) protocol for making the network operation longer when lower amount energy was consumed [24]. The clustering and routing protocols were implemented for prolonging the duration of network. The MIHFO (Meta Inspired Hawks Fragment Optimization) approach was adopted to cluster the data. The energy, distance to neighbors, distance to BS (base station), degree, and centrality of node, were exploited for choosing the cluster head (CH). A Heuristic Wing Antfly Optimization (HWAFO) algorithm was deployed for selecting the optimum route from CH to BS. An analysis was conducted on the overall active nodes, energy expenditure and packet count sent to BS. The developed methodology was simulated using MATLAB. The findings showed that the created protocol has offered higher throughput, greater packet delivery rate (PDR), least drop ratio, and lower energy consumption (EC).

V. Pandiyaraju, et.al (2023) designed a novel MOC (multi-objective clustering) method to group the sensor nodes (SNs) of WSNs [25]. Furthermore, an Election based Aquila Optimizer (EAO) algorithm was presented in which Aquila Optimizer (AO) was integrated with EBOA (Election-Based Optimisation Algorithm) for choosing the CH in WSNs so that the finest CH was selected. Moreover, this algorithm was employed with CNN called O-CNN (Optimized CNN) for maximizing the precision and accuracy. The outcomes of tests demonstrated the dominance of designed method over existing techniques and attained an accuracy of 99.23%, throughput of 76.92%, packet delivery ratio (PDR) of 99%, life span of network of 98.24% and energy consumption of 50%. Additionally, this method was resistible for tackling the complexity occurred in precision agriculture.

J. Reyes, et.al (2022) recommended a simple EAR (energy-aware routing) technique on the basis of GoLCA (Game of Life Cellular Automaton) to mitigate energy consumption [26]. This technique had alleviated the homogeneous energy utilization when the life span of network was expanded in regard to RE (residual energy), amount of neighbors who are active, as well as a sleep regimen. A set of rules was employed to analyze dissimilar behaviors of WSN in a discrete dynamic (DD) model. This technique was emphasized on integrating this model with a variation of the A-star algorithm. The outcomes of the simulation showed that the suggested technique was applicable for balancing the energy consumption rate, and prolonged the duration of network in comparison with existing methods. Furthermore, our approach improved energy usage in WSNs by mitigating energy use utilizing PP (path-planning) algorithms.

3. Research Methodology

This research work revolves around 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 ant colony optimization. The details are given:

A. Network Deployment

One of the fundamental prerequisites for the implementation of clustered wireless sensor networks is the random distribution of nodes. This random distribution of sensor nodes leads to the creation of cluster heads, which further causes a number of problems. The cluster head must not be disposed of because of the energy usage. Additionally, the cluster head prevents long-distance communication, and nodes below it are added here as well. The nodes, referred to as cluster heads, are not chosen according to the planned criteria and are far from ideal. Inappropriate nodes are further caused by the nodes' circumstances, which made them difficult to reach in the network and nearly impossible to reach in remote locationsThese nodes serve as cluster chiefs when the intra-cluster energy is raised. When compared to the transmitter and receiver nodes, the authentic node uses less energy. Battery power consumption is significantly lower than that of the nodes when the system is supplied with a large spectrum in a coordinated way. In order to isolate the actions and boost productivity, the parent node is chosen for each cluster head. Each sensory node's competence is given two value functions, which aids in the node's selection as the cluster head. The average power of the nearby nodes is determined by their distance from the base station, and the degree of nodes generates functions. Higher degree node generation is required in order to build the cluster head. A higher degree allows the cluster head to cover as many nodes as possible, avoiding costly connections.

B. Cluster Formation

After the network is deployed, it will be split up into clusters. The clusters will be formed based on the distance. The formed clusters will be optimized using fruit fly algorithm. 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, FOA is adept at adjusting parameters swiftly and effectively due to its optimization speed and parameter flexibility. Guided by the fitness function, which acts as an odor concentration decision function, FOA aims to iteratively adjust the fruit fly population within the solution space. This process advances in the following manner.

i. 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.

$$X(i) = X_0 + Step \quad (1)$$

$$Y(i) = Y_0 + Step \quad (2)$$

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

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

$$Smell\ (i) = Function\big(S(i)\big) \quad (3)$$

$$S(i) = \frac{1}{Sqrt(X(i)2 + Y(i) \wedge 2)} \quad (4)$$

iii. Movement: The fruit fly individual with the highest concentration among the population is chosen for movement, and its location is designated as the optimal place. Then, based on their first step length, tell the other fruit flies to follow that path.

iv. Iteration: Continue steps (2) and (3) until the fragrance concentration reaches the maximum number of iterations or reaches the predetermined threshold. The root mean square error (RMSE), which is defined as follows, is chosen by the fitness function:

$$min\delta_R = \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2/n} \quad (5)$$

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

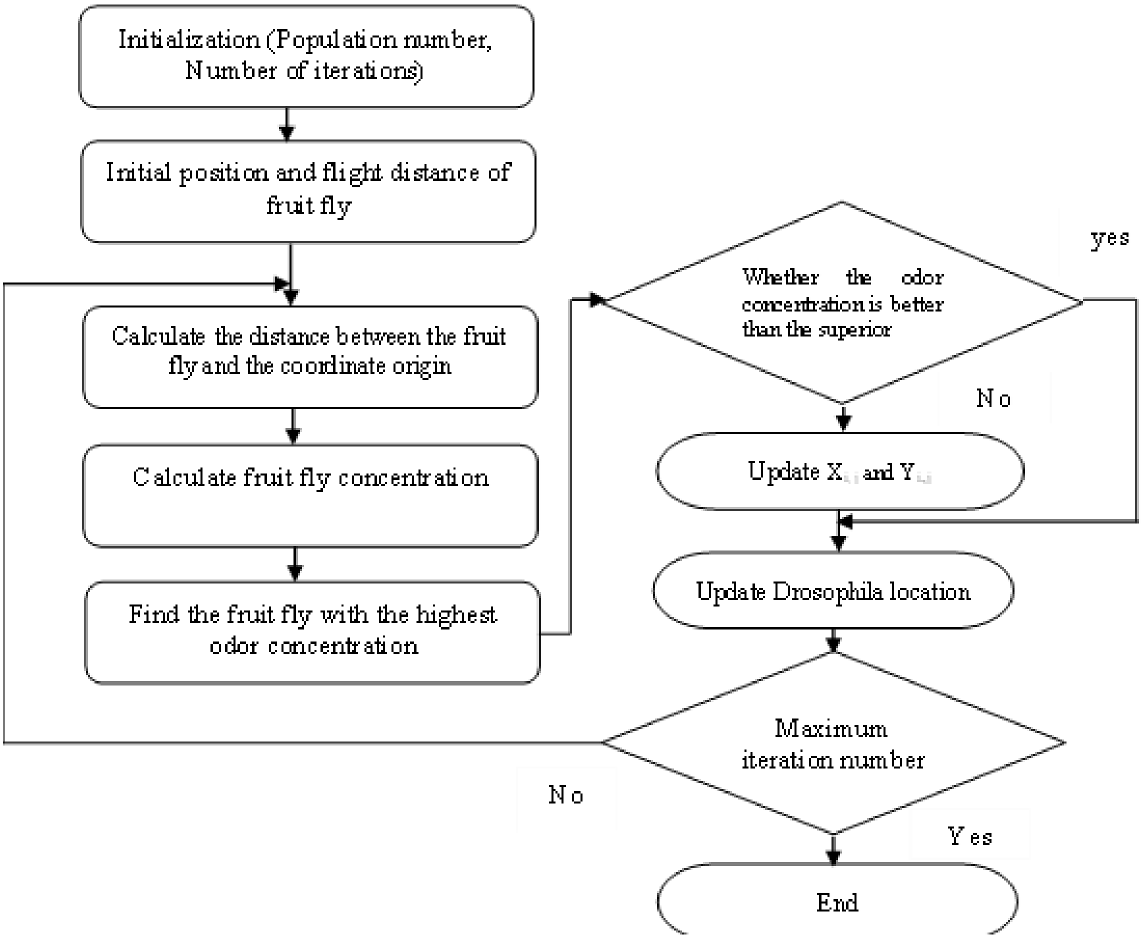

Figure 2. *Fruit fly for Cluster Formation*

C. Path Establishment

The data transmission path is set up from the cluster head to the base station. The ant colony optimization algorithm will be used to optimize the route. The ACO algorithm is a metaheuristic that looks for the quickest route to food sources by imitating the actions of real ants. Ants have the tendency to select routes labelled by the sturdiest pheromone concentrations. The ACO algorithm is an agent based crucial system that uses mechanisms of cooperation and optimization to simulate the ants' natural behavior, The ACO algorithm speedily establishes the direct route from a food source to their nest without any visual information only by emulating methods used by the actual ants. The ACO algorithm involves several iterations (iterations) of solution generation. Several ants construct a comprehensive solution in each iteration by utilizing the heuristic data and the accumulated experiences of previous ant groups. The pheromone trail that builds up on the component parts of a solution is what defines these cumulative experiences. Starting at a cluster head at random, each ant follows the transition rule to visit the other cluster heads. The pheromone information is updated repeatedly as part of the learning process.

1) The transition rule: In the path, the $k^{th}k^{th}$ant begins from city r, the selection of next city s is done amongst the remote cities memorized in J_r^k J_r^k.

$$s = \underset{u \in J_r^k}{argmax} [\tau_i(r,u)^{\alpha}.\eta(r,u)^{\beta}] if q \leq q_0 (Exploitation)$$

(6)

For vising the new city s with the probability $p_k(r,s)p_k(r,s)$,

$$p_k(r,s) = \begin{cases} \dfrac{\tau(r,s)^{\alpha}.\eta(r,s)^{\beta}}{\sum_{u \in J_r^k} \tau(r,u)^{\alpha}.\eta(r,u)^{\beta}} & if\ s \in J_r^k \\ o & otherwise\ if q > q_0 \end{cases}$$

(7)

The pheromone update rule: The solution was enhanced by updating the pheromone trails. The local and global updating is comprised in the trail update process. The local trail update formula is expressed as:

$$\tau(r,u) = (1-\rho)\tau(r,s) + \sum_{k=1}^{m} \Delta\tau_k\,(r,s)$$

(8)

Where, the rate to evaporate the pheromone trail is depicted with$\rho(0<\rho<1)\rho(0<\rho<1)$. $\Delta\tau_k(r,s)$ $\Delta\tau_k(r,s)$ denotes the amount of pheromone trail whose insertion is done to edge $(r,s)(r,s)$ using $k\ k$ ant amid in the tour. This is defined as:

$$\Delta\tau_k(r,s) = \begin{cases} \frac{Q}{L_k} & (r,s) \in \pi_k \\ 0 & otherwise \end{cases} \qquad (9)$$

In which QQ represents the constant parameter, the distance of the sequence $\pi_k\pi_k$that the ant toured is illustrated with L_kL_k.

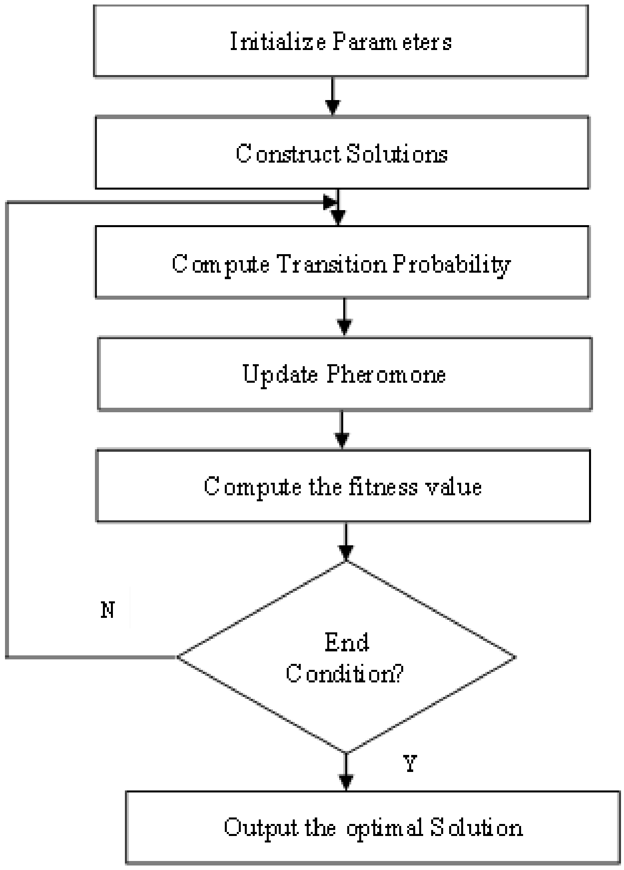

Figure 3. *Ant Colony optimization for Path Optimization*

4. Result and Discussion

This work is dedicated to reducing power usage of WSNs. To improve lifetime of WSNs two optimization algorithms are applied which are fruit fly and ant colony optimization. The entire network is separated into clusters, and the cluster head is chosen within each cluster according to energy and distance. The sensor nodes with the highest energy inside the cluster and the closest proximity to the base station will be chosen as the cluster head. Cluster creation and cluster optimization are done using the fruit fly algorithm. The cluster head compiles data from the sensor nodes in the cluster and sends it to the base station. The optimal path will be established from cluster head to base station for the data transmission. The path from the cluster head to the base station is optimized using the ant colony optimization technique. Both homogeneous and heterogeneous network types are used to test the suggested model. Table 1 provides a description of the simulation parameters.

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	100
$E_{initial}$	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

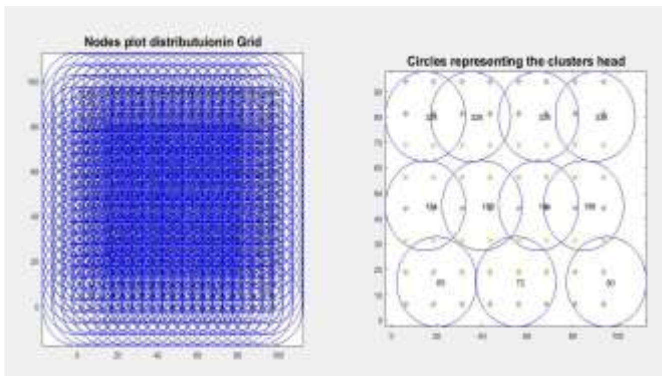

Figure 4. *Node distribution and cluster formation*

Figure 4 illustrates how the entire network is set up with a limited number of nodes. The entire network is separated into clusters, and the nodes are dispersed at random. The cluster heads are also shown in each cluster which are represented for the data aggregation.

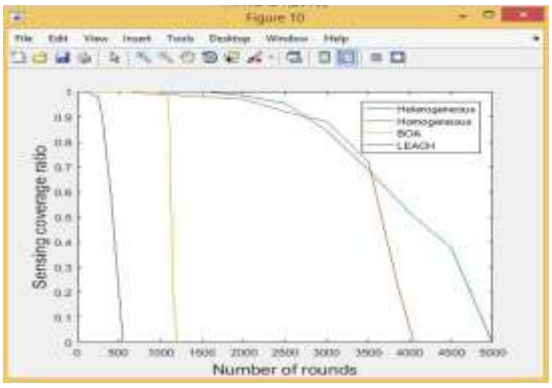

Figure 5. *Sensing coverage ratio*

Figure 5 compares the sensing coverage ratio of several algorithms for performance analysis. In both homogeneous and heterogeneous settings, the LEACH protocol is contrasted with butterfly optimization and the suggested approach. Analysis shows that the suggested model outperforms BOA and LEACH protocols in diverse scenarios compared to homogeneous scenarios.

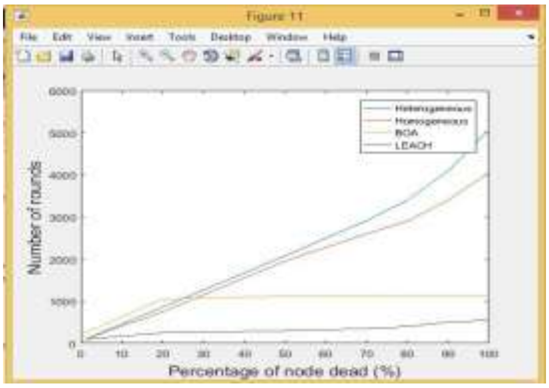

Figure 6. *Percentage of dead nodes*

Figure 6 illustrates the comparison between the suggested algorithm and BOA, LEACH algorithms under homogeneous and heterogeneous scenarios in terms of percentage of dead nodes. It is analysed that proposed algorithm under the heterogeneous scenarios has maximum performance as compared to other models. As shown in figure 7, the network longevity of proposed algorithm in homogeneous and heterogeneous scenario is compared with BOA and LEACH protocol. It is analysed from the results that proposed algorithm in heterogonous scenario has maximum lifetime as compared to other algorithms. Figure 8 compares the suggested model's throughput to that of the BOA and LEACH algorithms. It is analyzed that proposed mode under heterogeneous environment give maximum throughput as compared to homogeneous environment.

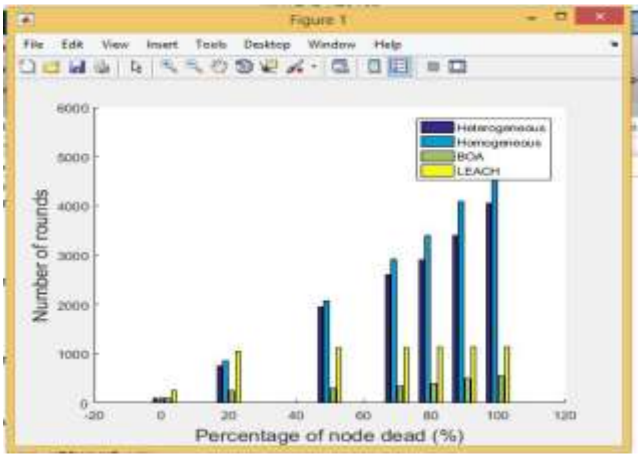

Figure 7. *Network Lifetime Analysis*

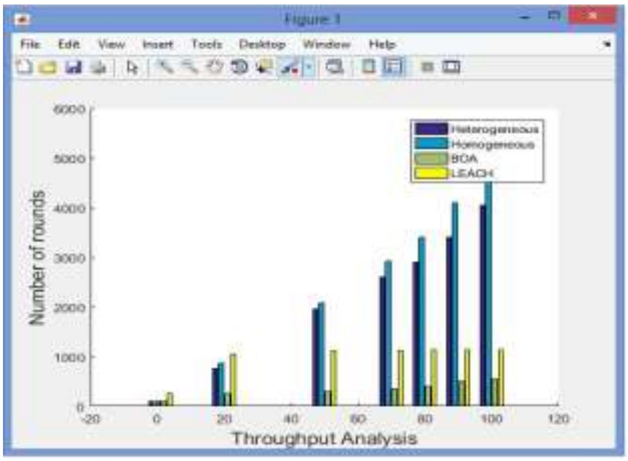

Figure 8. *Throughput Analysis*

5. Conclusion

In this work, we presented a unique method that uses Ant Colony Optimization (ACO) for path establishment in WSNs and the Fruit Fly Algorithm (FFA) for cluster creation. The suggested approach was tested in both homogeneous and heterogeneous contexts after being implemented in MATLAB. We compared its performance against two popular algorithms, the Biogeography-Based Optimization Algorithm (BOA) and the LEACH (Low Energy Adaptive Clustering Hierarchy). As the findings validate, the proposed algorithm outperforms both BOA and LEACH in relation to network durability and coverage area, especially in heterogeneous environments. This underscores the efficacy of our approach in effectively managing energy efficiency and enhancing the performance and reliability of WSNs, particularly in scenarios that demand stringent environmental monitoring.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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