Hybrid Bacteria Foraging Algorithm With PSO and DE Algorithm for Optimal Cluster Head Selection in Wireless Sensor Networks

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ABSTRACT

Network lifetime and energy constraint are the main issues for the application of wireless sensor networks. Sensor nodes spend more energy in the communication process and affect the network lifetime. Clustering is the technique for choosing the optimal cluster head from the clusters. LEACH-C is the clustering protocol in WSN. BFA is applied in the LEACH-C protocol to form the optimal clusters. This optimization obtains more steps in the tumbling process and reaches the global optimum solution very slowly. This method directly affects the network lifetime. The above limitations are overcome by introducing the hybrid approach of bacteria foraging algorithm by integrating the PSO, and DE is applied in LEACH-C algorithm for finding the optimal cluster head. The best foraging solution is utilized in the chemotactic behavior of the bacterium by using PSO and DE algorithms. The proposed methodology increases by 66% and 77% of the alive nodes when compared to FA and BFPSO.

KEYWORDS

Alive Nodes, Bacteria Foraging Algorithm, Clustering, Differential Evolution, Energy Consumption, Network Lifetime, Particle Swarm Optimization, Wireless Sensor Networks

1. INTRODUCTION

Wireless Sensor Network consists of a large number of sensor nodes that perform the sensing, communication, and data processing. This network is mostly used for various applications such as patient monitoring systems, pollution control systems, environment monitoring, forest fire detection, and surveillance system, etc. The main task of the sensor node is to collect the information from the physical environment and forward the information to the base station through the cluster head. The sensor nodes have limited energy resources for the communication process. Replacing or recharging these batteries is a critical problem for the sensor network. Energy efficiency is an essential feature to design the sensor network in data communication.

Clustering is an important technique to provide a solution for energy-efficient communication in WSN. Clustering is utilized to form the group of clusters and to identify the optimal cluster head

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selection. The whole network is classified into a group of clusters. Each cluster is managed by the cluster head. The main task for the cluster head is to collect and process the information from the sensors and forward the information to the base station. The cluster head requires more energy for handling and coordinating the activities in the cluster members. The selection of optimal cluster head is an NP-hard problem. Energy-efficient communication can be carefully designed by identifying the optimal cluster head to increase the lifetime of the network.

1.1 Background

Bacteria Foraging Algorithm (BFA) is a significant technique for biologically inspired algorithms. The biologically inspired algorithms are helpful to design the dynamic and adaptive schemes in the wireless sensor network. The complex system behavior is adapted to the new location without any failure. The group behavior of the insects uses the model to give the solution for the problem without external guidance.

LEACH-C (Heinzelman et al., 2002) is the most popular hierarchical clustering algorithm for wireless sensor networks. Bacteria Forging Algorithm is applied in the LEACH-C algorithm to find optimal cluster head. This optimization technique obtains more steps in the tumbling process and reaches the global optimum solution very slowly. This optimization method consumes more energy for calculating the fitness function and also directly affects the network's lifetime. The performance of BFA is improved by using particle swarm optimization and differential evolution to find the suitable cluster head in wireless sensor networks for improving the network lifetime and minimizing the energy consumption.

The performance of the Bacteria Foraging Algorithm is improved by using a hybrid approach of the Bacteria Foraging algorithm with Particle Swarm Optimization and Differential Evolution technique (BFPSODE) to find the optimal cluster head in wireless sensor networks. The local best and global best locations are generated by Particle Swarm Optimization and the position of bacteria is fine-tuned by Differential Evolution. These values are utilized by the tumbling process of every bacterium. The proposed methodology is utilized to update the behavior of bacteria for reaching a good position of local best and global best. The proposed method is implemented in Network Simulator (NS-2.27) and to measure the performance of the WSN. This hybrid optimization method improves the network lifetime and reduces energy consumption.

1.2 Problem Definition and Scope

Finding of an optimal cluster head selection is also NP hard problem. The selection of effective cluster head is used for improving the lifetime of the network and also minimizes the energy consumption. The effective CH is selected by using the hybrid approach of Bacteria Foraging algorithm with Particle Swarm Optimization and Differential Evolution. This methodology finds the best value of the fitness function for enhancing the network lifetime and minimizing the energy consumption.

The scope of this paper can be summarized as follows:

1. To find the optimal cluster head selection in wireless sensor networks for enhancing the network lifetime and minimizing the energy consumption.
2. To use the hybrid approach of Bacteria Foraging with Particle Swarm Optimization and Differential Evolution to find the optimal cluster head selection for considering the residual energy and distance between the cluster head and cluster members.
3. The proposed methodology presents better results when compared to other conventional algorithms by using the performance metrics such as network lifetime, residual energy, and the number of alive nodes, and the throughput of the network.

The rest of the paper is organized as follows: Section 2 discusses the clustering approaches for the sensor network and hybrid methods of biologically inspired approaches for the various applications.

Section 3 describes the overview of the bacteria foraging algorithm, particle swarm optimization, and differential evolution algorithms. Section 4 proposes the hybrid approach of Bacteria Foraging with Particle Swarm Optimization and Differential Evolution technique which identifies the efficient cluster head from each cluster. Section 5 demonstrates the simulation and performance analysis of the proposed methodology. Section 6 gives the conclusion.

2. RELATED WORKS

(Albath et al., 2013) have presented an energy-constrained minimum dominating set to form optimal cluster heads with energy constraints. This approach provides better results in terms of energy usage, node lifetime, clustering time. (Gong et al., 2013) have described a clustering algorithm for constructing the one-hop clusters in lossy wireless sensor networks with a mobile collector. This approach improves the data reception ratio, reduces the total energy consumption, and prolongs the network lifetime. (Bagci et al., 2013) have presented a fuzzy-based energy-aware unequal clustering algorithm for solving the hot spot problem where cluster heads are nearer to the base station. This method is mainly used to reduce the intracluster work of the cluster heads and low remaining battery power. This approach performs better than other algorithms in terms of first node dead and last node dead. (Li et al., 2013) have presented an algorithm for the cluster head rotation and routing for solving the energy hole problem. This methodology is used to reduce the total energy utilization of all the sensor nodes and also prolongs the network lifetime. (Liu et al., 2012) have discussed the unequal clustering method for gradient-based routing to solve the hot spot problem by using minimum hop count. This approach improves the network lifetime and balances the energy consumption between the cluster heads. (Lung et al., 2010) have presented a distributed hierarchical agglomerative clustering method to select the cluster head from each cluster. This approach prolongs the network lifetime and also maintains uniform energy dissipation with the help of cluster head rotation and re-clustering.

(Wang et al., 2009) have discussed a parallel particle swarm optimization to find the best position of the sensor nodes by using the maximum entropy clustering method. This approach maximizes the coverage metric and minimizes the energy metric by choosing the proper weight coefficient for each cluster. (Gou et al., 2010) have presented a PLEACH algorithm for selecting the cluster head in each optimal region. This method achieves better performance results in energy dissipation, network lifetime, and quality of communication. (Ren et al., 2006) have discussed some of the biologically inspired approaches for routing, clustering, and congestion control, medium access control problems in the wireless sensor networks. (Selvakennedy et al., 2007) have presented the dynamic clustering protocol to guide the optimal cluster head selection by using the collective agents. This approach is mainly used for ensuring good distribution of cluster head to achieve the highest energy efficiency. (Iyengar et al., 2007) have discussed the genetic and ant-based algorithms to find the solution in the mobile sensor networks. This approach is mainly used to reduce the computational complexity and processing delay, end to end delay. Bacteria Foraging Algorithm (BFA) is used for various applications in optimization such as the linear array of antennas (Datta et al., 2008), damping controller of the power system (Abd-Elazim et al., 2012), power flow controller (Tripathy et al., 2007), planning of complex radio frequency identification problem (Chen et al., 2010), and coefficients of proportional plus integral controllers for the active filter (Mishra, 2006). (Pitchaimanickam et al., 2013) have presented the bacteria foraging algorithm for selecting the optimal clustering in Wireless Sensor Networks. This method is mainly used to extend the network lifetime and minimize energy consumption.

(Korani, 2008) has described the hybrid bacteria foraging and particle swarm optimization to adjust the PID controller. This approach achieves better results in cost function calculation and transfer function of the systems. (Qin et al., 2008) have discussed a self-adaptive differential evolution algorithm to generate solutions from the previous experiences by using the trial vector generation strategies with control parameters. This approach provides better results in the sensitivity analysis of

LP parameters. (Karaboga et al., 2004) have discussed the differential evolution which is better than the genetic algorithms. This algorithm achieves better results in convergence speed when compared to genetic algorithms. (Vaisakh et al., 2012) have presented the hybrid method of bacteria foraging algorithm, particle swarm optimization, and differential evolution algorithm for solving the dynamic economic dispatch problem. This approach achieves good foraging strategies and eliminates the problem of stagnation of solution. (Abd-Elazim et al., 2013) have presented a hybrid method of particle swarm optimization and bacterial foraging optimization to design the optimal power system stabilizers. This methodology is mainly used to improve the power system stability with various loading conditions and disturbances. (Panda et al., 2013) have described the hybrid bacteria foraging and particle swarm optimization to improve the stability of the power system. This method is used for providing efficient damping to power system oscillations with various disturbances and operating conditions. (Azizipanah Abarghooee, 2013) has presented the hybrid bacteria foraging and simplified swarm optimization algorithm to find the best solution for the dynamic load dispatch problem. This approach is used for increasing the diversity of the solution of the search space. This algorithm achieves better results in speed of convergence and computational efficiency.

(Nayyar et al., 2018) have proposed the comprehensive details of the swarm intelligence techniques for solving the problems in the various intelligent technologies such as sensor networks, machine learning, optical fiber communications, digital signal processing, and image processing. (Sharma et al. 2014) have presented the effective solution for the classical WSN clustering and routing protocols and also compared with various approaches based on primary metrics. This approach is mainly used to improve the network lifetime and to reduce energy consumption. (Nayyar et al. 2018) have presented the foundations of the swarm intelligence techniques by considering the technical terms like collective intelligence of natural animals, the concept of self-organization in social insects, adaptability and diversity in swarm intelligence, and the various issues for swarm intelligence. (Nayyar et al. 2018) have presented the history of evolutionary computation, the concept of evolutionary algorithms, computational models, techniques and paradigms of evolutionary computation, and applications of the evolutionary computation. (Nayyar et al., 2017) have proposed the ACO-based routing in various protocols such as AODV, DSDV, and DSR. This method provides better results by using the metrics such as end-to-end delay, packet delivery rate, throughput, and routing overhead. (Nayyar et al., 2019) have proposed an energy-efficient ACO-based multipath protocol for wireless sensor networks. The performance of the protocol is measured with metrics such as throughput, routing overhead, and energy consumption. (Nayyar et al., 2015) have presented a comprehensive review for the various simulation tools in WSN and also gave the idea for selecting the suitable tool to simulate the sensor networks. (Singh et al., 2020) have proposed the energy-based heuristic Maximum Coverage Small Lifetime (MCSL) technique for solving the target coverage problem and also to ensure the Quality of Service (QoS) in a wireless sensor network. This method provides better results when compared to the greedy and HESL algorithms. (Menaria et al., 2020) have presented a node-link failure fault tolerance model for identifying any node or link failure in WSN. This method provides better results when compared to Q-MST and handoff algorithms by using end-to-end delay, throughput, and power consumption.

(El-Said et al., 2016) have presented an optimal hierarchical routing technique to minimize energy consumption and extend the network lifetime. The optimal location of the cluster heads is selected by using the Artificial Fish Swarming Algorithm (AFSA). This technique considers the remaining energy, distance from the base station, and rotates the cluster head among the cluster members. (Guleria et al., 2019) have proposed a Meta-Heuristic Ant Colony Optimization based Unequal Clustering (MHACO-UC) for the selection of optimal cluster head. By using the Ant Colony Optimization technique the location of the neighbors and link maintenance for selecting the optimal path between the nodes can be found. This algorithm performs better than other existing unequal clustering approaches such as EAUCF, CHEF, FAMACROW, and IFUC in terms of packet delivery ratio, the number of packets received by the base station, energy consumption, residual energy, and energy consumption. (Gupta et al., 2018) have presented an improved cuckoo search algorithm for forming the energy-efficient clustering and improved harmony search algorithm for efficient routing in WSN. The encoding scheme and multi-objective fitness function are utilized in the improved cuckoo search algorithm to select an efficient cluster head. The improved harmony search algorithm is used to find the effective routing path for transmitting the data packets from the cluster head to the sink node. This algorithm has better performance when compared to the LEACH, PSO-ECHS, and E-OEERP based on network lifetime, the number of alive nodes, and the number of dead nodes.

(Mittal et al., 2018) developed the Spider Monkey Optimization-based threshold-sensitive energy-efficient delay-aware routing protocol (SMOTECP) for prolonging the network lifetime and extending the stability period. This protocol is mainly utilized to identify the proper cluster head selection for balancing the workload. The dual-hop communication technique is used for distributing the load and minimizing the energy consumption of the cluster head. (Nasir et al., 2014) have presented a novel hybrid optimization of bacterial foraging algorithm and spiral dynamics algorithm to generate the dynamic model for the manipulation of robots and twin-rotor system. This approach achieves better results in fitness accuracy and convergence speed. (Rao et al., 2017) have presented the particle swarm optimization algorithm for selecting an efficient cluster head in WSN. The particle encoding scheme and fitness functions are utilized in the PSO algorithm for the selection of proper cluster head position for conserving the energy of the nodes and prolonging the network lifetime.

(Sengottuvelan et al., 2017) have proposed a Binary Fish Swarm Algorithm (BFSA) to identify the optimal cluster head selection in WSN. The fitness function mainly depends on the energy of the sensor nodes and end-to-end delay. This methodology presents better results than other popular techniques such as LEACH and GA for reducing packet loss and prolonging the network lifetime. (Panag et al., 2021) has presented a predator-prey optimization for identifying the cluster head and performs the routing. This method is mainly used to identify the optimal communication path for reducing energy consumption and delivering the number of packets to the base station. (Bhowmik et al., 2020) have proposed an improved PSO with a gravitational search algorithm for the clustering and routing in WSN. This method provides better results to other existing algorithms by using residual energy, convergence rate, and network lifetime. (Sahoo et al., 2021) have presented a hybrid approach of genetic algorithm and particle swarm optimization method for cluster head selection and sink mobility based data transmission. This method presents better results when compared to other algorithms such as PSOECSM, PSO-UFC, GADA-LEACH, and PSOBS.

(Jayalakshmi et al., 2021) have presented the hybrid Artificial Bee Colony and Harmony Search Algorithm based approach for identifying the effective cluster head. This methodology improved the dynamic search behavior for the cluster head selection. This method presents the better results for maintaining the stable energy utilization and prolonging the network lifetime. (Radhika et al., 2021) have developed the micro genetic algorithm with LEACH protocol for selecting the optimal cluster head selection in WSN. This method used to strengthen the cluster head selection and also to reduce the energy consumption. The better result is obtained by using this method for improving the network lifetime and reducing the energy consumption. (Shobana et al., 2021) have developed the cluster based systematic data aggregation model for the real time data communication. Cluster head is selected with the help of ranking of existing energy level and geographic location to the base station. This method minimizes the energy consumption and transmission delay and also prolonging the network lifetime. (Shyjith et al., 2021) have presented the hybrid approach of rider cat swarm optimization for optimal cluster head selection in wireless sensor networks. This methodology presents better results for providing alive nodes, throughput and energy utilization. (Rajput et al., 2021) have presented the fuzzy technique based clustering protocol for improving the stability and sustainability of the WSN. Fuzzy C Means technique used to select the optimal cluster head. This method used to increase the coverage and node density in different sink positions.

From the above survey, the existing algorithms are not addressed the hot spot problem for prolonging the network lifetime and reducing the energy consumption. Many of the algorithms are not considered the energy-efficient parameters for the cluster head selection process. The hybrid approach of the Bacteria Foraging algorithm with Particle Swarm Optimization and Differential Evolution algorithm has not been applied for energy-efficient optimal cluster head selection in wireless sensor networks. Hence, the author has utilized the hybrid approach of the Bacteria foraging algorithm with Particle Swarm Optimization and Differential Evolution methodology in the LEACH-C algorithm for addressing the energy-efficient cluster head selection and hot spot problem. This describes the novelty of this paper.

3. OVERVIEW OF BFA, PSO, DE ALGORITHMS

3.1 Bacteria Foraging Algorithm (BFA)

The bacteria foraging algorithm is developed by (Passino, 2002) to solve the control and distributed optimization problems. This optimization algorithm was motivated by the behavior of E.coil bacteria. This method mainly depends on the searching behavior of the food. This algorithm consists of four main processes such as chemotaxis, swarming, reproduction, elimination and dispersal process. In the chemotaxis process, bacteria movement is attained by tumbling and swimming through flagella. These two modes of operations are executed alternatively for the generation. The movement of the bacteria can be denoted by:

$$J\left(K\right) = J\left(K\right) + C\left(i\right) * \frac{\Delta\left(i\right)}{\sqrt{\Delta\left(i\right).\ \Delta\left(i\right)^{T}}} \tag{1}$$

where $J\left(K\right)$ denotes the k^{th} bacterium and $C\left(i\right)$ represents the run length vector for the random direction and $\Delta\left(i\right)$ is unit length vector in the random direction. In Eq.(1), T represents the transpose of the run length vector.

In the swarming process, bacteria reach a better location in the search period and send the attractant signal to other bacteria. This process continues to form each group of bacteria. In the reproduction process, the most healthy bacteria splits into two bacteria and the least healthy bacteria is removed from the environment. In the elimination and dispersal process, new bacteria are moved to a good nutrient environment and retain the same swarm size.

Bacteria Foraging Algorithm

```
Initialize all the variables used in BFA
Increase the elimination dispersal loop counter 'l'
If l is greater than the number of elimination dispersal then
     Stop the process
Else
Increase the reproduction loop counter 'k'

If k is greater than the number of reproduction loop then
Perform the elimination dispersal
Else
Increase the chemotactic loop

If j is greater than the number of the chemotactic loop then
Perform the Reproduction
```

```
Else

Compute the value of cost function for each bacterium

If the cost value of the current bacteria is less than the cost
value of the previous bacteria then
Apply the swimming process
Else
Apply the tumbling process

If the swim value of each bacteria is less than the number of
bacteria then
  If the current iteration is less than the number of iteration
     Perform the chemotactic loop
  Else
     Compare the cost value of current and previous bacteria
position
Else
     Apply the tumbling process
```

3.2 Particle Swarm Optimization (PSO)

The particle swarm optimization is a stochastic and population-based method developed by (Kennedy et al., 1995). This optimization technique is motivated by the group of bird's behavior. This technique initializes a random position of particles. The particles are denoted by the position vector $p_i = \left(p_{i1}, p_{i2}, .. p_{id}\right)$ and the velocity vector $v_i = \left(v_{i1}, v_{i2}, .. v_{id}\right)$. The pbest and gbest values are applied to adjust the position and velocity of every particle. The pbest value of the i^{th} particle is denoted as $Pbest_i = Pbest_{i1}, Pbest_{i2}, .. Pbest_{id}$. From the group of $Pbest_i$ particles, the best particle is denoted as $gbest_i$. Every particle is updated by using the values of $Pbest_i$ and $gbest_i$. The new velocity v_i^{k+1} is updated from its previous velocity v_i^k for the period of time K and it can be determined by:

$$v_i^{k+1} = w.v_i^k + C_1.R_1\left(pbest_i - p_i^k\right) + C_2.R_2\left(gbest_i - p_i^k\right) \tag{2}$$

The new velocity v_i^{k+1} and the earlier position p_i^k is added to obtain the new position p_i^{k+1}:

$$p_i^{k+1} = p_i^k + v_i^{k+1} \tag{3}$$

Particle Swarm Optimization Algorithm

```
Compute the initial velocity
Initialize the position and velocity
While the termination condition is not satisfied do
For each particle do
Compute the velocity
Compute the position
If the position is a feasible solution then
Evaluate the position of the particle
```

```
End
End
Compute the new velocity of the particle
End
```

3.3 Differential Evolution (DE)

The differential evolution algorithm is a population and stochastic-based optimization. This optimization method is developed by (Storn et al., 1997) for global optimization. This method is used for minimizing the cost value by using equal population vectors. The mutation, recombination, and selection operators are mainly used to apply for every population vector to form the new generation. In the mutation process, the mutant vector is calculated by finding the difference between the two population vectors, and the resultant value is added to the third population vector. The mutation factor f is generated from the range of 0.1 to 1.0 and r_1, r_2 and r_3 are the three random vectors chosen from the existing population. This can be represented by:

$$mv_{i,j}\left(G+1\right)=X_{r1,j}\left(G\right)+f*\left(X_{r2,j}\left(G\right)-X_{r3,j}\left(G\right)\right) \tag{4}$$

where $i = 1 to E$ and $j=1 to F$ and E,F are the number of generations. The recombination process incorporates better solutions from the earlier generation. The trial vector $tv_{i,j}\left(G+1\right)$ is developed by modifying the parameters of the target vector components with the parameters randomly chosen from the donor vector. The value of the crossover constant cr is taken from 0.1 to 1:

$$tv_{i,j}\left(G+1\right)=\begin{cases} tv_{i,j}\left(G+1\right) if\, rand_i \le cr \\ X_{i,j}\left(G\right) otherwise \end{cases} \tag{5}$$

In the selection process, each trial vector components $tv_{i,j}\left(G+1\right)$ is compared to the parent target vector components $X_{i,j}\left(G\right)$ and select the minimum value which is allowed to be used for the next generation. The above three processes continue until the condition is satisfied.

Differential Evolution Algorithm

```
Initialize the parameters of the differential evolution algorithm
Create the initial population
For each particle do
     Evaluate the objective function
     Measure the fitness of each individual
     Apply the mutation factor
     Apply the crossover operator and generate the new individuals
     Apply the selection by replacing the worst individuals by
previously generated one
End
```

4. PROPOSED METHOD

4.1 System Model

Clustering is an important technique to form the groups of nodes together for the collection of information. An entire network is grouped into several clusters. The cluster head is selected from the set of clusters that coordinates the data aggregation and transmission to the base station. LEACH-C (Centralized) algorithm was used as a central control method to generate the optimal clusters, which is used to identify the cluster head for the entire network. This protocol consists of 2 phases such as i) setup phase ii) steady-state phase. In the setup phase, each sensor node collects the position and energy level of the node and sends the same to the base station. The base station finds the optimal clusters by using a simulated annealing algorithm. The base station ensures the distribution of energy to all the nodes. The base station calculates the average energy of the nodes. The nodes which are having the higher energy will act as a cluster head during the current round. The base station is broadcasted the cluster head ID to the cluster nodes:

$$sn = position\left(sn_1, sn_2, sn_3 \ldots Sn_k\right) + Energy\left(sn_1, sn_2, sn_3 \ldots sn_k\right) \tag{6}$$

$$Avg\_Energy = \sum_{k=1}^{n} Energy\left(sn_1, sn_2, sn_3 \ldots sn_k\right) \tag{7}$$

$$CH = \left\{sn,\ if\, E\left(sn\right) > Avg_{Energy}\right\} \tag{8}$$

where sn are the sensor nodes. In the steady-state phase, the cluster head collects the information from the cluster members. The cluster head aggregates the information and it is transmitted to the base station:

$$CHn = \sum_{i=1}^{n} \left(cm1, cm2 \ldots .. cmi\right) \tag{9}$$

$$BS = \sum_{j=1}^{m} \left(CH1, CH2 \ldots .. CHj\right) \tag{10}$$

where cmi is the ith number of cluster members and CHj is the jth number of cluster head. A simulated annealing algorithm consumes more energy for calculating the fitness function and also directly affects the network lifetime.

4.2 Hybrid Bacteria Foraging Algorithm With Particle Swarm Optimization and Differential Evolution for Optimal Cluster Head Selection

The bacteria foraging algorithm with particle swarm optimization and differential evolution technique resolves to find the optimal cluster head. Bacteria make a move to find food resources through swim and tumble mode by using flagella in the chemotaxis process. Bacteria reach a better position, to send the attractant signal to the one in the swarming process. After receiving the signal, the relative distance is calculated by using the cost function among the bacteria. The new location of the bacteria can be denoted by:

$$J\left(i,j+1,k,l\right)=J\left(i,j,k,l\right)+C\left(i\right)*\frac{\Delta\left(i\right)}{\sqrt{\Delta\left(i\right).\Delta\left(i\right)^{T}}} \tag{11}$$

The new position of the bacteria compared with the old position and the updated new position of the bacteria. The new population of the bacteria is generated by using differential evolution. This equation is given by:

$$J\left(i,j+1,k,l\right)=J\left(i,j,r1,l\right)+f*\left(J\left(i,j,r2,l\right)-J\left(i,j,r3,l\right)\right) \tag{12}$$

The minimum cost is computed from the new population with the help of differential evolution operators such as mutation, recombination, and selection process and assigned to J_{de}. Both the cost values of J_{de} and J_{last} are compared in all the bacteria and to find the minimum cost value of the bacteria position is updated. The unit length vector value of each bacterium is substituted by the velocity value of the particles. Particle swarm optimization makes the bacteria to attain the good optimal solution at the earlier steps by using $Pbest$ and $gbest$ values. This equation can be denoted by:

$$\Delta\left(i\right)=w.v_{i}+C_{1}.R_{1}\left(\left(gbest_{i}-J\left(i,j+1,k,l\right)\right)+C_{2}.R_{2}\left(\left(Pbest_{i}-J\left(i,j+1,k,l\right)\right)\right.\right. \tag{13}$$

The above procedure is repeated for the next chemotactic steps. The swarming process is used to find the value of all bacteria that reaches a better position. Finally, the position of the bacterial colony is merged to form the best clusters and to calculate the average energy for every group of a cluster. Figure 1 illustrates the proposed BFAPSODE in the LEACH-C algorithm. The above procedure is used to construct the energy-efficient optimal clusters and select the suitable cluster head from this group.

Figure 2 shows the flow of execution of the hybrid approach of BFA, PSO and DE algorithms.

Algorithm

```
Initialize the parameters used for the BFA, PSO and DE
The initial population is randomly generated by the bacteria
Initialize the pbest and gbest values
The fitness function is evaluated by using the foraging behavior
of bacteria
for the elimination dispersal 1 to l
     for the reproduction 1 to k
          for the chemotaxis 1 to j
               for each bacterium 1 to S
                    Compute the cost value of the current position
of the bacteria
                    Apply the tumble / Swim function to find the
cost value of the next position of the bacteria
```

```
                    Compare the current and new position of the
bacteria and choose the minimum cost value of the position
                    Generate the mutation factor and random cross
over constant
                    Update the position of the bacteria by using
differential evolution
                    Compare the position of bacteria generated by
the differential evolution and bacteria foraging algorithm
                    Update the position of minimum cost value
                    for each particle in the population n
                         Update the pbest and gbest values
                         Update the velocity and position
                    end for
               end for
          end for
     end for
end for
```

Figure 1. Schematic diagram of the proposed BFAPSODE in LEACH-C algorithm

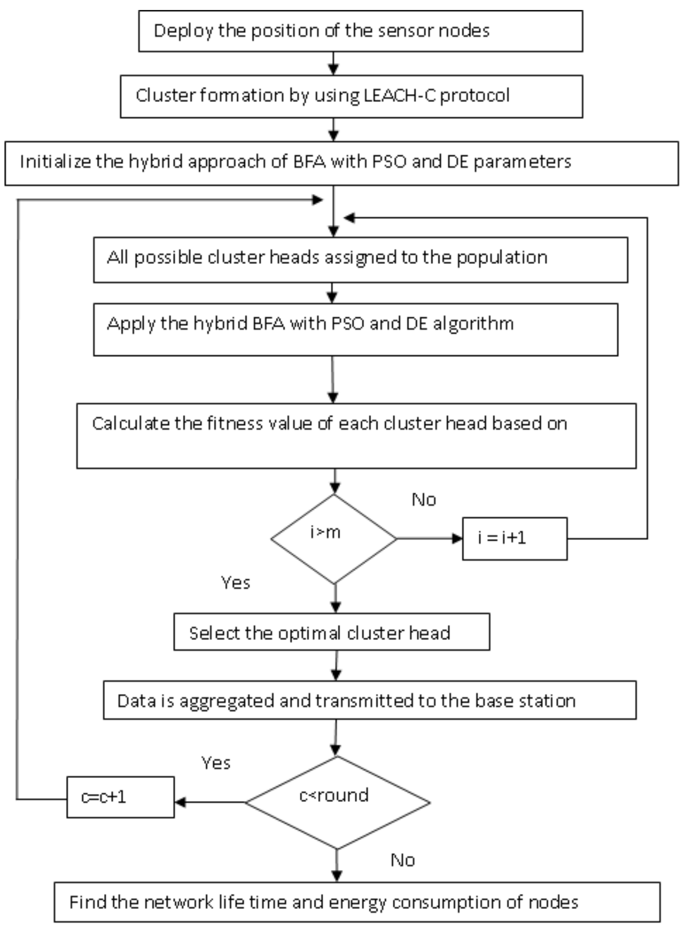
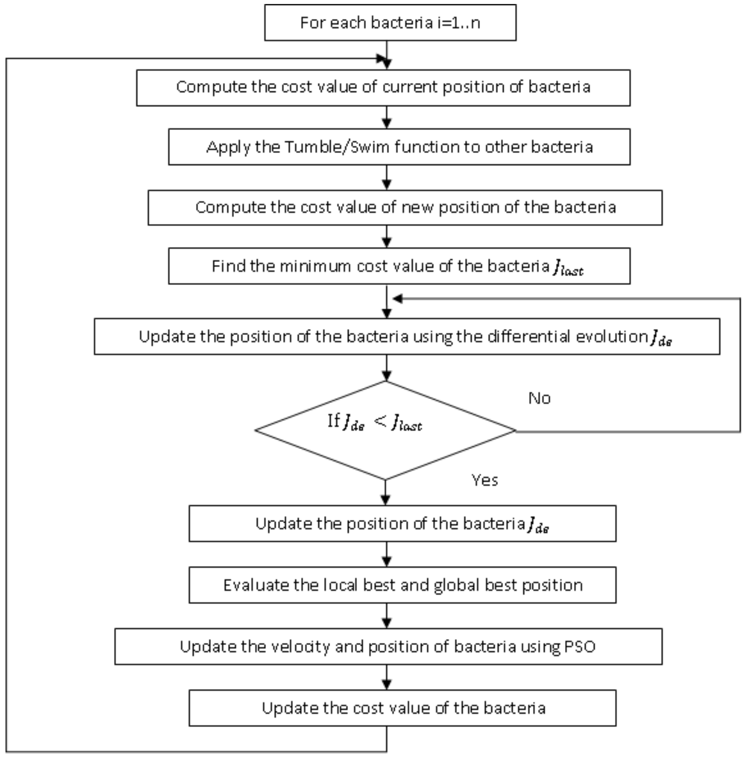


Figure 2. Flow diagram of Hybrid BFA with PSO and DE



4.3 Step by Step Procedure for the Proposed Algorithm

Step1: Sensor nodes are deployed in random position and also to generate the clusters.
Step 2: The initial cluster head is identified by using higher remaining energy.
Step 3: By using the bacteria foraging algorithm with particle swarm optimization and differential evolution for selecting the cluster head.
- **Step 3.1:** Compute the cost value of the current position of the bacteria.
- **Step 3.2:** Apply the tumble/swim function to other bacteria.
- **Step 3.3:** Compute the cost value of new position of the bacteria.
- **Step 3.4:** Compare the new and old position of the bacteria and find the minimum cost value of the bacteria.
- **Step 3.5:** Find the optimal position of the bacteria by using the differential evolution.
- **Step 3.6:** Evaluate the local best and global best position.
- **Step 3.7:** Update the velocity and position of bacteria by using particle swarm optimization.
- **Step 3.8:** Find the minimum cost value of the bacteria.
- **Step 3.9:** Repeat the step 3 for the remaining number of the bacteria.

Step 4: Fitness function is calculated by using remaining energy of the node and distance from node and cluster head.
Step 5: Lowest fitness function is identified for the cluster head selection.
Step 6: Optimal cluster head is broadcasted to the cluster members.
Step 7: Optimal cluster head is directly transmits the data to the base station.
Step 8: The values of alive nodes and remaining energy are calculated.

4.4 Evaluate the Fitness Function

The hybrid approach of the Bacteria Foraging algorithm with PSO and Differential evolution methodology is utilized to find the set of cluster heads. The base station calculates the residual energy of the node and the minimum distance between the node and cluster head. The fitness function is depicted in Eq.14 and also considered the remaining energy of the node (f_1) and minimum distance between the cluster head and sensor nodes (f_2):

$$f = \alpha\ f_1 + (1\text{-}\ \alpha)\ f_2 \tag{14}$$

The symbol 'α' represents for giving the weightage to the importance of the sub-objective, and its value between 0 and 1 where:

$$f_1 = {\sum_{i=1}^{M} E\left(n_i\right)} \Big/ {\sum_{j=1}^{N} E\left(CH_j\right)} \tag{15}$$

$$f_2 = \min \left\{ \sum_{k \varepsilon j} d\left(n_i, CH_j\right) | \, C_j \right\} \tag{16}$$

Eq.15 shows the remaining energy level of the node and finds the difference between the energy of the node and the energy of the cluster head. In Eq.(16), M represents the number of sensor nodes and N represents the number of cluster heads. Eq.16 calculates the minimum average distance between the sensor nodes and cluster heads divided by the number of nodes in the cluster. The fitness function is evaluated for each cluster head and to find the best cluster head which provides the highest residual energy and minimum distance to the base station.

5. SIMULATION STUDY

5.1 Simulation Model

Random deployment and sensor nodes (N=100) have been considered during the actual test of the proposed methodology. The experiments are carried out by using Network Simulator (NS-2.27). The performance of the BFPSODE method is compared with LEACH-C, PLEACH, BFA, FA, and BFPSO algorithms by using alive nodes, energy consumption, and network lifetime. The base station will run the proposed methodology. Experiments are executed for the random topologies and plotted as an error graph with a 95% confidence interval from the average of 20 readings with the standard deviation. Table 1 represents the values adopted for the experiment. Simulation parameters are mainly improved for the enhanced area.

5.2 Simulation Assumptions

The following assumptions of the WSN are considered in our work:

1. The homogeneous sensor network is considered and also all the sensor nodes have the same processing, battery power, transmission, and reception process.
2. Sensor nodes are randomly distributed in the size of the topology.

Table 1. Simulation parameters

Parameters	Value
Antenna type	Omni directional
Base cluster based routing protocol	LEACH
Type of the topology	Random topology
Topology Size	100X100m^2
Number of sensor nodes	100
Equal Energy	1Joule
Initial energy level of the node	1 to 5 Joules
Cluster head percentage	5% to 10%
Simulation time	3600 seconds
Position of the Base Station	(50,175)
Transmission range	175m
Packet Size	500 bytes
E_{elec} (Radio electronics energy)	50 nJ/bit
E_{fs} (Energy for free space)	10 pJ/bit/m^2
E_{DA} (Energy for Data Aggregation)	5nJ/bit
E_{mp} (Energy for multipath model)	0.0013pJ/bit/m^4

3. The base station should have sufficient knowledge about the network and also locate outside of the network.
4. In the deployment process, all the sensor nodes and base station are kept in a static environment.
5. If the sensor node energy drains then it will not select the head from each group of clusters.

5.3 Control Parameters of BFPSODE Algorithm

The selection of parameters is more important for the execution of the hybrid bacteria foraging optimization algorithm with particle swarm optimization and differential evolution algorithm. By conducting a series of experiments, the optimal value of the parameters is assayed. The BFPSODE algorithm required the value of the maximum number of iteration as 1820. The number of iterations and the number of populations are considered to fix value the convergence rate.

Table 2 shows the control parameters utilized for performing the experiments. The experiments are carried out several times for the random sensor network topology to find the optimal cluster head by varying from 3% to 10%. The benchmark for an optimal number of Cluster head is obtained from 5% of total nodes (Heinzelman et al., 2000).

The total number of iterations of BFA, FA, and BFPSO algorithm is found to be 2320, 2210, and 2130 respectively. The proposed BFPSODE methodology functions for iterations of 1820 for

Table 2. Parameter Settings for BFPSODE algorithm

Parameters	Value
Number of population size (S)	40
Number of generations	100
Swimming length of bacteria (N_s)	4
Number of Chemotactic steps (N_c)	100
Number of Reproduction steps (N_{re})	4
Number of elimination and dispersal (N_{ed})	2
Probability of elimination and dispersal (P_{ed})	0.25
Run length vector $(C(i))$	0.05
Cognitive acceleration factor $(c1)$	1.2
Social acceleration factor $(c2)$	0.5
Inertia weight (ω)	0.9
Crossover probability (cr)	1
Mutation factor (f)	0.5

obtaining the optimal clusters. With the described number of iterations, the network lifetime is maintained by BFA is 560s, for FA it is 600s, for BFPSO it is 700s, and for BFPSODE is 910s. The iteration 't' required by the BFPSODE is lower than the iterations required by the BFA, FA, and BFPSO algorithm.

5.4 Performance Metrics

1. Alive node is defined as the number of nodes active for the specified time period.
2. Energy Consumption is defined as the amount of energy consumed until the simulation time.
3. Network Lifetime (First Node Dead) is defined as the first node that expires from the sensor network.
4. Network Lifetime (Last Node Dead) is defined as the last node that expires in the evaluation process.
5. Network Lifetime (Difference between First Node Dead and Last Node Dead) is defined as the time difference between the first node dead and last node dead. This indicates the execution period of the process.

5.5 Results

Figure 3 illustrates the number of alive nodes versus simulation time. LEACH-C, PLEACH, BFA, FA, and BFPSO methods sustain the nodes alive up to 360 seconds,410 seconds, 560 seconds, 600 seconds, and 700 seconds respectively. The Proposed methodology maintains the nodes alive up to 900 seconds. It is evident that BFPSODE performs well in increasing the network lifetime when compared to the other algorithms. Table 3 represents the data values for finding the alive nodes for different algorithms.

Figure 4 illustrates the energy consumption during the simulation time. LEACH-C and PLEACH protocols have more energy consumption compared to BFA, BFPSO, FA, and BFPSODE. BFPSODE optimization method consumes a minimum amount of energy compared to BFPSO, BFA, FA, PLEACH, and LEACH-C. The proposed methodology quickly forms the clusters that consume the minimum amount of energy. Bacteria updates the best positions obtained from PSO and DE for their generations in the tumbling process and prolonged the network's lifetime. The proposed method consumes 55J energy for the communication at 450 seconds. Table 4 represents the data values for energy consumption.

Figure 5 depicts the comparison of the network lifetime (FND) with the number of sensor nodes. BFPSODE gives a better lifetime than BFPSO, BFA, FA, PLEACH, and LEACH-C algorithms. BFPSODE methodology quickly reaches the global position by using PSO and Differential Evolution algorithm to form the optimal group of clusters by selecting the appropriate cluster head. The formation of clusters requires a minimum period of time which extends the lifetime of the network. The proposed methodology achieves the first node dead at 910 seconds by increasing the alive nodes for a longer period. Table 5 represents the data values for finding lifetime with the number of sensor nodes.

Figure 6 demonstrates the evaluation of the network lifetime (FND) behavior with the six methods. When the percentage of cluster head increases, it also reduces the lifetime of the network. But the BFPSODE methodology retains the maximum lifetime (FND) compared among the LEACH-C, PLEACH, BFA, FA, and BFPSO methods. The proposed methodology maintains the lifetime up to

Figure 3. Simulation time vs number of alive nodes

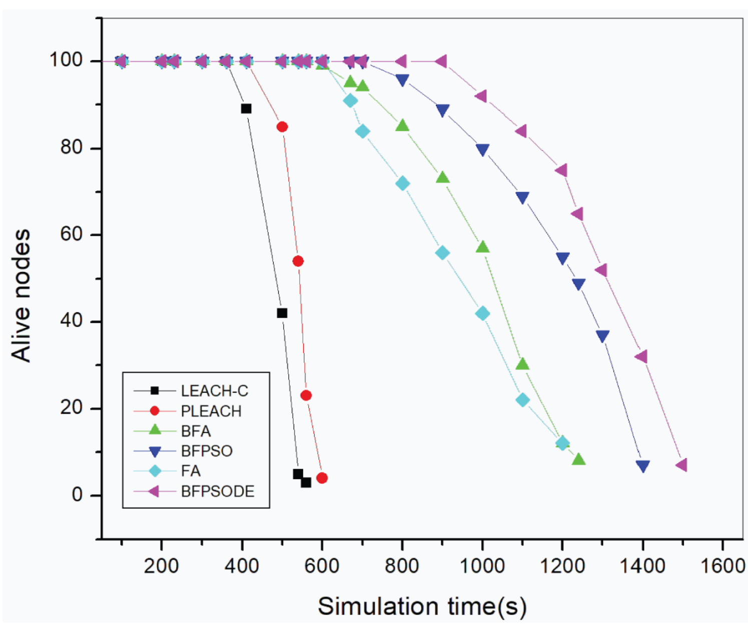


Table 3. Effect on alive nodes with simulation time

Simulation Time	LEACH-C	PLEACH	BFA	BFPSO	FA	BFPSODE
0	100	100	100	100	100	100
100	100	100	100	100	100	100
200	100	100	100	100	100	100
230	100	100	100	100	100	100
300	100	100	100	100	100	100
360	100	100	100	100	100	100
410	89	100	100	100	100	100
500	42	85	100	100	100	100
540	5	54	100	100	100	100
560	3	23	100	100	100	100
600		4	99	100	100	100
670			95	100	91	100
700			94	100	84	100
800			85	96	72	100
900			73	89	56	100
1000			57	80	42	92
1100			30	69	22	84
1200			12	55	12	75
1240			8	49		65
1300				37		52
1400				7		32
1500						7

Figure 4. Simulation time vs energy consumption

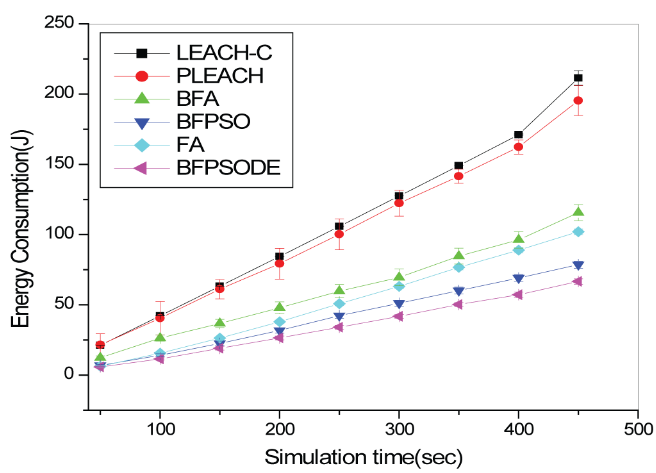
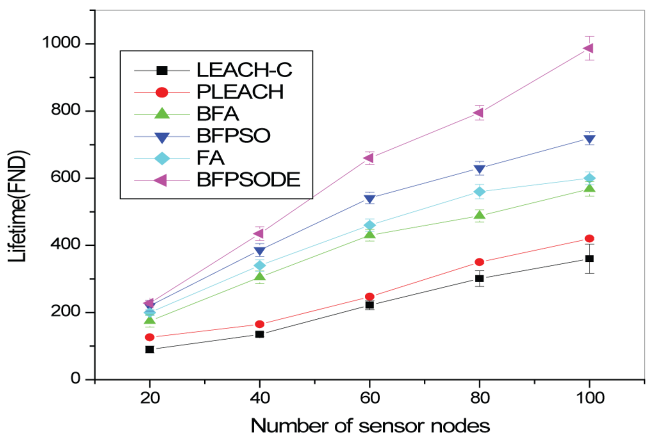


Table 4. Energy consumption

Simulation Time	LEACH-C	PLEACH	BFA	BFPSO	FA	BFPSODE
50	21.1765	21.54115	12.35034	6.9245	6.2315	5.785
100	42.215	40.472	26.285	14.0615	15.59	11.479
150	63.2735	61.114	36.755	22.565	26.355	19.089
200	84.406	79.269	47.8865	31.7465	37.94	26.456
250	105.843	100.1843	59.733	42.2965	50.795	34.051
300	127.4855	122.3685	69.5365	51.0905	63.135	41.821
350	149.034	141.547	84.704	60.152	76.665	50.205
400	171.157	162.3595	96.2405	69.1035	88.925	57.212
450	211.4985	195.381	115.6405	78.591	102.07	66.631

Figure 5. Effect of network lifetime (FND) vs the number of nodes



910s and 660s by varying the cluster head percentage from 5% to 10%. Table 6 represents the data values for finding the lifetime with cluster head percentage.

Figure 7 illustrates the network lifetime (FND) is evaluated with the different energy levels of the sensor nodes. BFPSODE optimization method gives the maximum lifetime when compared to BFPSO, BFA, FA, PLEACH, and LEACH-C algorithms. The proposed methodology maintains the lifetime up to 420s and 1780s by varying the initial energy from 1J to 5J. Table 7 represents the data values for finding the lifetime by using initial energy.

Figure 8 shows the number of alive nodes for receiving the data at the base station. In the LEACH-C, PLEACH, BFA algorithms transmit around 60800, 62200, and 70100 units of data packets to the base station respectively. In the FA and BFPSO algorithms, all the nodes are dead after passing around 72100, 77200 units of data packets. The proposed methodology transmits the maximum number of data received at the base station when compared to LEACH-C, PLEACH, BFA, FA, and BFPSO algorithms. Table 8 represents the data values for finding the number of an alive node with the number of data received at the base station.

Figure 9 illustrates the graphical representation of FND and LND for LEACH-C, PLEACH, BFA, FA, BFPSO, and BFPSODE algorithms. The proposed methodology achieves better results

Table 5. Lifetime (FND) with number of sensor nodes

Number of sensor nodes	LEACH-C	PLEACH	BFA	BFPSO	FA	BFPSODE
20	90	126	175	220	200	228
40	135	165	305	386	340	435
60	222	247	430	541	460	660
80	301	350	488	630	560	795
100	360	420	568	719	600	987

Figure 6. Effect of network lifetime (FND) vs cluster head percentage

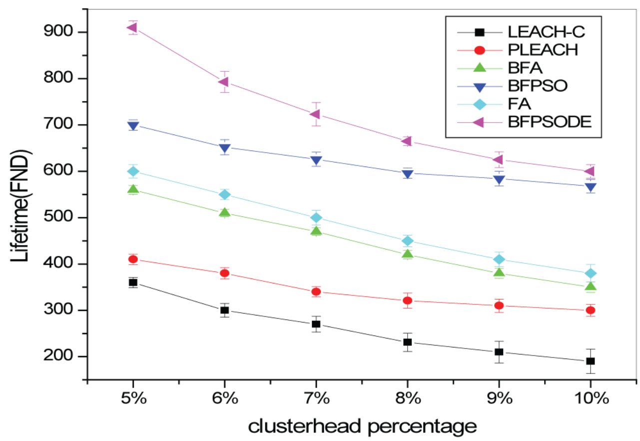


Table 6. Lifetime (FND) with cluster head percentage

Cluster head Percentage	LEACH-C	PLEACH	BFA	BFPSO	FA	BFPSODE
5%	360	410	560	700	600	910
6%	300	380	510	652	550	793
7%	270	340	470	626	500	723
8%	231	321	420	596	450	665
9%	210	310	380	584	410	625
10%	190	300	350	568	380	600

for comparing with other algorithms. The proposed methodology maintains 910s and 1820s for the first node dead and last node dead. Table 9 represents the data values for identifying the number of rounds with different algorithms.

Figure 10 depicts the mean, max, and variance of residual energy. The performance comparison is measured at 400 seconds with different methodologies such as LEACH-C, PLEACH, BFA, FA, BFPSO, and BFPSODE. The proposed methodology maintains the maximum residual energy of 165J. Table 10 represents the data values for finding the residual energy.

Figure 11 demonstrates to measure the network lifetime by increasing the distance to the base station from 25m to 100m. The network lifetime is measured based on first node dead for all the

Figure 7. Effect of network lifetime (FND) vs initial energy

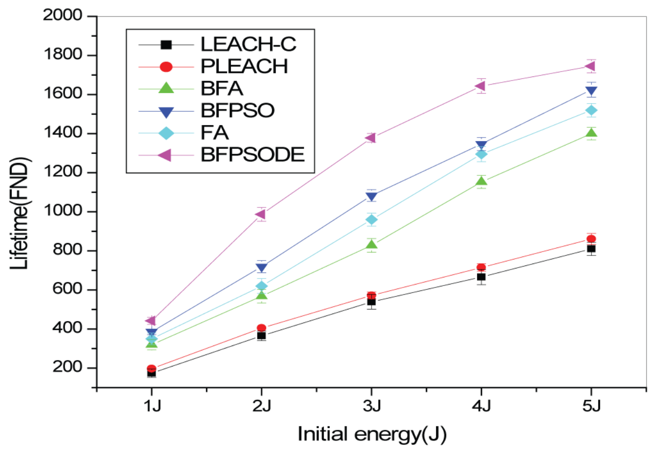


Table 7. Lifetime with initial energy

Initial Energy	LEACH-C	PLEACH	BFA	BFPSO	FA	BFPSODE
1J	174	197	320	386	350	442
2J	365	405	568	719	620	987
3J	539	572	828	1083	960	1378
4J	666	715	1153	1347	1295	1644
5J	810	861	1400	1625	1520	1745

Figure 8. Effect of number of alive vs number of data received at base station

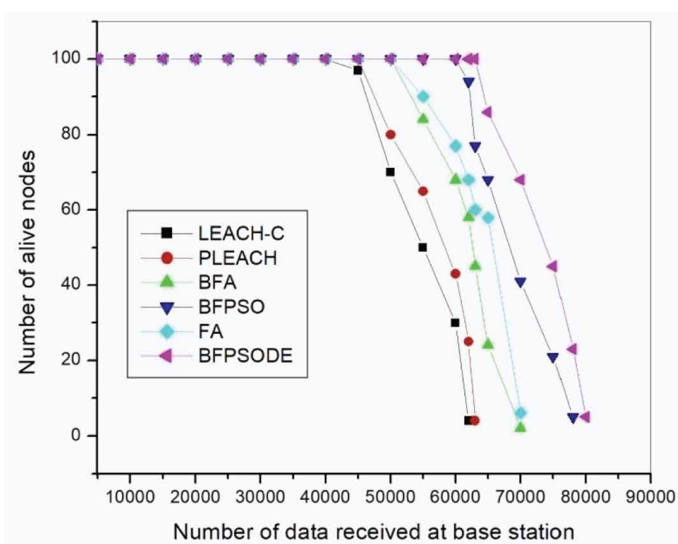


Table 8. Alive node with number of data received at Base station

Number of data received at BS	Number of alive nodes					
	LEACH-C	PLEACH	BFA	BFPSO	FA	BFPSODE
5000	100	100	100	100	100	100
10000	100	100	100	100	100	100
15000	100	100	100	100	100	100
20000	100	100	100	100	100	100
25000	100	100	100	100	100	100
30000	100	100	100	100	100	100
35000	100	100	100	100	100	100
40000	100	100	100	100	100	100
45000	97	100	100	100	100	100
50000	70	80	100	100	100	100
55000	50	65	84	100	100	100
60000	30	43	68	100	90	100
62000	4	25	58	94	77	100
63000		4	45	77	60	100
65000			24	68	58	86
70000			2	41	6	68
75000				21		45
78000				5		23
80000						5

Figure 9. Mean values of FND and LND

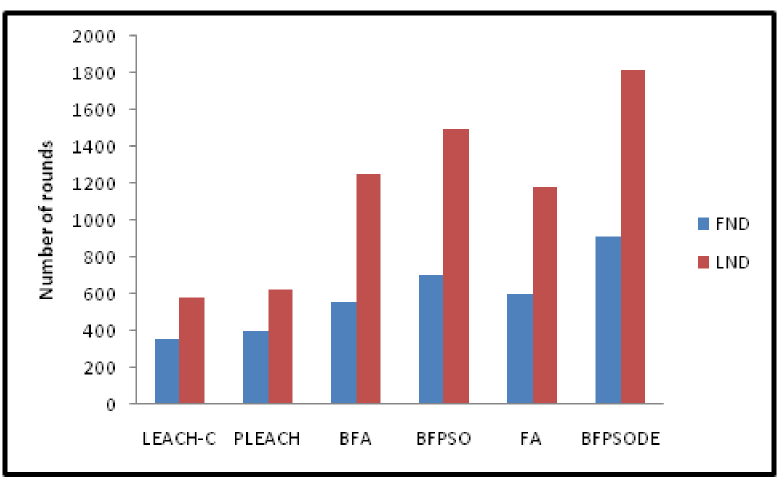


Table 9. Number of rounds for different algorithms

Algorithms	Number of rounds	
	FND	LND
LEACH-C	360	580
PLEACH	400	630
BFA	560	1250
BFPSO	700	1500
FA	600	1180
BFPSODE	910	1820

Figure 10. Mean, max and variance of residual energy

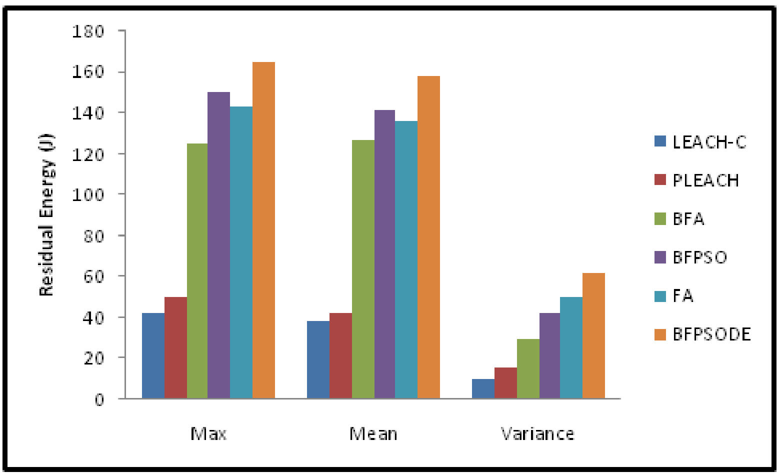


Table 10. Mean, Max and variance of residual energy

Algorithms	Residual Energy(J)		
	Max	Mean	Variance
LEACH-C	42	38	10
PLEACH	50	42	16
BFA	125	127	30
BFPSO	150	142	42
FA	143	136	50
BFPSODE	165	158	62

algorithms. When the distance increases that also reduces the network lifetime. The proposed methodology achieves a better network lifetime when compared to LEACH-C, PLEACH, BFA, FA, and BFPSO algorithms. Table 3 shows the performance analysis for all algorithms. Table 11 represents the data values for finding the network lifetime with the distance to the base station.

Figure 11. Distance to the base station vs lifetime (FND)

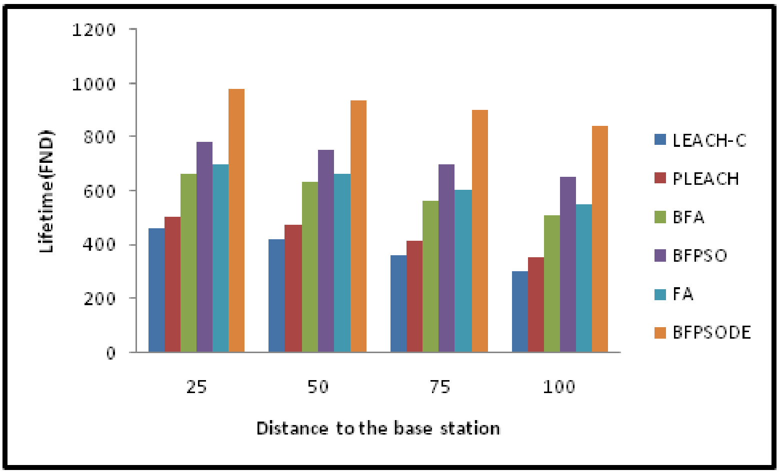


Table 11. Network lifetime with distance to the Base station

Algorithms	Distance to the Base Station			
	25	50	75	100
LEACH-C	460	420	360	300
PLEACH	500	470	410	350
BFA	660	630	560	510
BFPSO	780	750	700	650
FA	700	660	600	550
BFPSODE	980	940	900	840

5.6 Analysis

Bacteria Foraging algorithm with Particle Swarm Optimization with Differential Evolution Algorithm is presented in LEACH-C algorithm and also to perform the analysis of the proposed methodology with other conventional algorithms. The analysis is performed with the help of alive nodes and energy consumption. The proposed methodology increases the alive node percentage of 40%, 45.5%, 62%, 66%, and 77% when compared to LEACH-C, PLEACH, BFA, FA, and BFPSO algorithms. The proposed methodology increases the alive node for a longer period of time to prolong the network lifetime. LEACH-C, PLEACH, BFA, FA, and BFPSO algorithms consume the percentage of energy 85%, 81%, 48%, 44%, 34% respectively. The proposed methodology consumes 28.5% of the energy for the data communication process. The proposed methodology consumes minimum energy when compared to other conventional algorithms.

6.CONCLUSION

Energy efficiency is one of the important factors in Wireless Sensor Networks. LEACH-C algorithm was used to find the effective cluster head with the help of the simulated annealing optimization. But this method consumes more time for calculating the fitness function and also affects network lifetime. This paper presents the hybrid approach of a bacteria foraging algorithm with particle swarm optimization and differential evolution optimization technique to find the solution for an energy-efficient optimal clustering problem. The local best and global best values are generated by PSO and these values are fine tuned with differential evolution algorithms. These best solutions are utilized in the tumbling process of BFA. The proposed methodology is utilized in the LEACH-C algorithm for selecting an efficient cluster head from each group of the cluster. The performance of the proposed methodology is evaluated by conducting experiments with random topologies. Simulation results demonstrate that the proposed methodology gives better results when compared to the LEACH-C, PLEACH, BFA, FA, and BFPSO algorithms for considering the metrics of network lifetime, energy consumption, throughput. The BFPSODE methodology enhances the lifetime of the network and reduces energy consumption.

FUTURE SCOPE

This paper can be extended for the possible scope of future work:

1. The proposed methodology can be tested for real-time applications with a large number of nodes in the sensor network.
2. The proposed methodology can be extended in the heterogeneous environment for identifying the optimal cluster head selection process.
3. The proposed methodology can be tested for the mobility of the base station in wireless sensor networks.
4. This work can be extended for applying the other meta-heuristic techniques for finding the optimal cluster head selection in wireless sensor networks.

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