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Energy aware clustering and routing for wireless sensor networks using metaheuristics optimization algorithms

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ABSTRACT

Wireless sensor networks (WSNs) and their applications reduce energy consumption to enhance the lifetime of the network. WSN applications require energy-efficient communication, but the network includes resource constraint tiny sensors across monitoring area. Data processing, aggregation, and clustering are energy-intensive, and deployment and discovery of nodes are complex. In order to overcome certain issues in WSN application, optimal selection of fine cluster heads (FCHs) and cluster heads (CHs) and optimal routes to the base station (BS) are proposed, still lot of optimizations are essential to enhance lifetime of the network. This research paper employs bacterial foraging and ant colony optimization (BFACO) to identify optimal gateways (FCHs), CHs, and energy-efficient paths from sensor modes to BS while optimizing node energy consumption. The algorithm dynamically creates routing paths with lower network overhead, enabling long-term network utilization and enhanced lifetime. Performance is evaluated against parallel research algorithms using metrics such as energy-usage, network lifespan, and packet delivery ratio (PDR). An energy-usage (52.8% of energy reduction over best case), packet delivery ratio (8.7% of enhancement over best case), and network lifetime (4.3% of rounds over best case) are WSN performance outcomes for 300 sensors. The BFACO using a clustering and routing algorithm outperforms over parallel research.

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1. INTRODUCTION

Wireless sensor networks (WSNs) are infrastructure-less networks consisting of limited-resource small devices deployed over a targeted area to monitor and collect changes from the area. In many real-time applications, such as smart healthcare systems, smart cities, battlefield surveillance, and wildlife monitoring, the diverse characteristics of WSNs are utilized. Due to the limited resources of nodes, it is crucial to use them effectively [1]-[3]. WSNs face many difficulties due to their limited capabilities, such as low battery power, limited communication range, and low storage of nodes; these challenges directly limit the performance and overall lifespan of the network. One of the major limitations of sensor nodes is limited battery power in WSN applications; replacing and recharging device batteries is a complex task in hostile environments and certain areas like battlefields and deep forest zones [4], [5].

Consequently, designing a model that efficiently utilizes sensor resources in WSNs is important in many applications that enhance the lifespan of the network. Clustering is a basic approach generally applied in WSNs to efficiently utilize sensor battery power. Basically, in clustering, the entire targeted area's deployed sensors are divided into multiple groups; each group considered as a cluster. In each cluster, one optimal node is selected as the cluster head (CH), and all other nodes in the group are treated as cluster members (CM). The CMs continuously monitor and collect changes in the surroundings and forward them to their corresponding CH. In clustering-based WSNs, CHs can route collected data directly to the base station (BS) or through intermediate CHs. A base station in WSNs is a resource-rich device that collects data from CHs and relays it to a workstation for processing and public accessibility [6]-[8].

WSN with clustering-based routing designate CHs to aggregate and forward changes in the observations to the base station, but these CHs consume disproportionately more battery power than other nodes. Multi-hop minimizes communication distances but generates energy holes due to uneven energy utilization, leading to premature node death and minimized network lifetime. Ensuring energy awareness and efficient utilization among nodes is critical in addressing issues such as improper and delayed neighbour discovery, CH selection, and premature node death. This, in turn, enhances the average lifespan of sensor devices and maximizes network throughput [9]-[11]. Fuzzy logic with multidimensional routing models is significantly more efficient than classical LEACH by configuring multiple routes between CHs and the sink node, enabling CHs to dynamically select the shortest route with less hop count. While these approaches enhance node lifespan, they result in uneven power utilization patterns accross nodes during data communication from CHs to BS [12].

Recent WSN optimization algorithms incorporated metaheuristic approaches including PSO-based models, gray wolf optimizers (GWO), and unequal clustering algorithms that consider node battery power, distance, density, and neighbor parameters for intelligent CH selection and energy-aware path identification. These parameter-integrated models achieve network load balancing and significantly enhance network lifespan by decreasing overall power utilization while maintaining connectivity to the BS [13]-[17]. Summarized as in Table 1, research in nature-inspired and metaheuristic optimization has been integrated to WSN routing and clustering. Each study directly addresses one or more of the issues evaluated in the bacterial foraging and ant colony optimization (BFACO) approach such as quality cluster head selection, energy expenditure, packet delivery ratio, and network lifespan enhancement.

Table 1. Summary of parallel research in nature-inspired and metaheuristic optimization

Authors and Year	Methodology	Key metrics	Core contribution
Rambabu *et al.* and 2022 [18]	EEM-LEACH ABC with area-based energy-aware clustering, and multi-hop ABC optimization.	Lifespan, Energy, and packet delivery reliability (PDR)	Addresses a three-mechanism protocol combining network devisioning, hierarchical tree data aggregation, and ABC-driven CH election to reduce enegy expenditure in dense WSN deployments
Zhang *et al.* and 2025 [19]	CHHFO	Lifespan, Energy, and PDR	Simulates that fusing swarm intelligence with fuzzy membership procedures for CH selection significantly enhances network lifetime while preserving delivery ratio across heterogeous topologies
Hu *et al.* and 2024 [20]	MACOA	Lifespan, Energy, and PDR	Introduces a heuristic function that simultaneously targets battery power minimization, load distribution, and route efficiency, outperforming traditional ACO variants in lifetime and throughput standards
Tawfeek *et al.* and 2025 [21]	MOEACR-LM	Lifespan, Energy, and PDR	Processes the gap between single-objective and multi-objective WSN optimization based on designing a two-phase lifespan maximization framework that balances remaining battery power and intra-cluster distance
Kurangi *et al.* and 2024 [22]	RSA – enhanced IT2FLS	Lifespan, Energy, and PDR	Jointly implements battery power expenditure and routing security through interval type-2 fuzzy rules, achieving a 25% end-to-end latency reduction while maintaining resistance to compromised-node attacks
Ambareesh *et al.* and 2025 [23]	Enhanced ACO with adatitive pheromone transfer probability and IoT-specific constraints.	Lifespan, Energy, and PDR	Extends traditional ACO to IoT enabled WSN applications by adapting pheromone concentration updates to project node power levels and traffic load, improving convergence movement and route quality

A nature-inspired metaheuristic algorithm that improves WSN efficiency by optimizing CH selection to enhance node lifespan and extend data collection and aggregation performance beyond traditional algorithms [24]. This article outlines the major objectives of this work, which aim to enhance the lifespan of the network and the contributions discussed.

Bacterial Foraging Optimization is adopted for fine cluster head (FCH) and CH construction. Ant Colony Optimization is used to obtain energy-aware routes between the cluster head and fine cluster heads, and between FCHs. The proposed hybrid metaheuristic model is compared with parallel research techniques.

The subsequent sections of the article are structured as follows: Section 2, presents a BFACO approach for WSN clustering and routing, validates the proposed algorithm through simulation analysis in Section 3, and concludes with findings in Section 4.

2. RESEARCH METHOD

In the hierarchical network structure, it is divided into clusters, and based on the clusters, the network is further divided into fine clusters. Each fine cluster comprises a fine cluster head, able to collect data from cluster heads and forward it to the base station. For every cluster, there can be a cluster head responsible for collecting data from cluster members, aggregating data within the cluster, and forwarding it to the FCH. The basic organization of CHs, FCHs, and CMs in WSNs is shown in Figure 1. The WSN system has a single base station (BS) and a collection of similar resource-tiny devices (sensors) in a network area. WSN separates and creates efficient sensor clusters to save node battery power. The cluster member/devices accumulate environmental data and forward it to the cluster head. The CM node unanimously chooses a CH device. Data from the CM is consolidated and sent to the Fine Cluster Head (FCH or Gateway node), these FCH nodes are responsible for forwarding detected data to the base station (BS). The process of energy-efficient clustering and routing is represented in Figure 2. For continuous monitoring of environmental attributes, ‘n’ nodes are randomly deployed within a monitoring area. Every node in the network area is responsible for communicating monitored data to the CH, each tiny device in the network has different capabilities. As per the node directional antenna, the node's remaining energy, the distance between FCHs, and the distance between CHs. The primary objective will be to adopt probabilistic mechanisms to generate a computational representation based on the routing primitives. As a result, an effective metaheuristic optimization is recommended for the selection of the intermediate FCH at every step of route generation.

Bacterial Foraging Optimization is a vital nature-inspired metaheuristic model that replicates the foraging behavior of Escherichia coli bacteria inside the human colon. As per the researchers, BFO has been effectively used in many optimization challenges, including the selection of cluster heads in WSNs. Escherichia.coli navigates its environment to find nutrients based on tumbling (exploration), swimming (exploitation), and chemotaxis, and BFO manages many competing challenges, such as energy, connectivity, and distance. Bacteria go towards nutrient-dense areas, like an optimal solution. Tumble and swim approaches avoid getting blocked and adjust to changing network circumstances. BFO consists of three important stages: chemotaxis allows tumble and swim behavior for local search around the current location; reproduction where bacteria with less fitness die and best bacteria divide into two cells, and random bacteria will be eliminated.

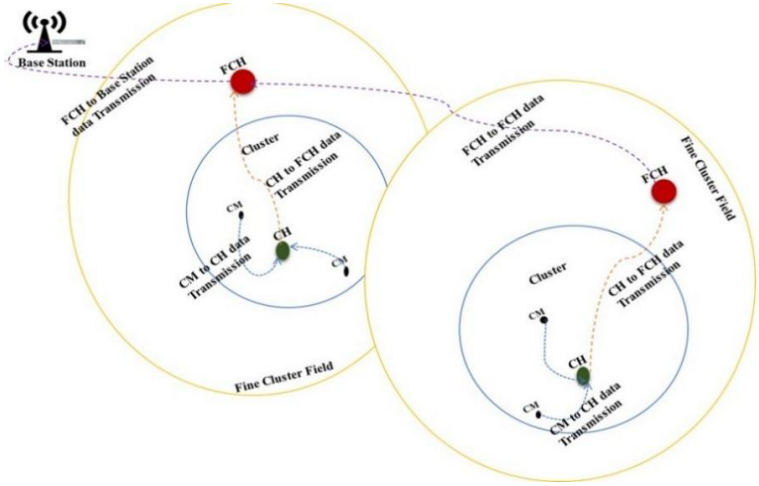


Figure 1. Organization of CMs, clusters with CHs, and fine clusters with FCHs in WSNs

The major objective in WSN is cluster formation and cluster head selection: identifying optimal sensor nodes from randomly deployed nodes to act as cluster heads. Each node can be elected at most once as

a cluster head; this must be provide network coverage, minimize energy consumption, and balance load across clusters and consequently enhancing the lifetime of the network. Each bacterium indicates a node CH election; the dimension specifies a node in the monitoring area. The nutrient concentration at a location is the fitness of that CH configuration, where high fitness indicates a valid CH election and lower fitness shows an invalid CH election. The detailed algorithm for BFO-based CH and FCH selection in Algorithm 1. The fitness function is a necessary module of CH election using BFO.

$$NF(CH) = w1 * NF_{Energy(CH)} + w2 * NF_{Connect(CH)} + w3 * NF_{Cover(CH)} + w4 * NF_{Dis(CH)} \quad (1)$$

Where, w1 to w4 are normalized weights.

$NF_{Energy(CH)}$ Maximizing the residual energy of elected CHs in WSNs can be defined as (2).

$$NF_{Energy(CH)} = \frac{1}{k} * \sum[i \in CH] \ (E_{resi}(i)/E_{init}) \quad (2)$$

$NF_{Connect(CH)}$ to enhance the network coverage and connectivity can be defined with in (3).

$$NF_{Connect(CH)}(i) = \frac{|neighbor_{node_{count}}|}{N}$$
$$NF_{Connect(CH)} = \frac{1}{k} * \sum[i \in CH] \ NF_{Connect(CH)}(i) \quad (3)$$

$NF_{Dis(CH)}$ to manimize the CH communication distance by specifying in (4).

$$NF_{Dis(CH)} = 1 - [\frac{1}{k} * \sum dist[CH, FCH]/long_dist) \ ] \quad (4)$$

$NF_{Cover(CH)}$ to make sure that all deployed nodes at least cover under one CH defined as (5).

$$NF_{Cover} = |\{n: \exists CH \in CH_{list}, dist(n, CH) \leq N_{tr}$$
$$NF_{Cover(CH)} = NF_{Cover} / N \quad (5)$$

The BFO based CH election algorithms process in various levels in two different phases (CH election and FCH election), such as initialization, chemotaxis level, and swarming level.

In phase 1 (CH selection) basically considers node remaining battery power levels, distance to the BS, and neighbour node density. During initialization, a population of bacteria randomly generated, each replicates the node CH configuration. The system parameters are defined, such as chemotactic step size, number of chemotaxis steps, reproduction levels, and elimination probability. During the chemotaxis level constructs basic finding operation, Each bacterium will take a level in a random direction and configure the location of fitness. If the fitness is high (specifies good CH election), the bacterium continues swimming in that direction only. Otherwise, it fall into a new direction. In swarming, bacteria guides each other movement.

In phase 2 (FCH selection) applies futher optimization to elect the fine cluster heads from the deployed nodes that also considers node remaining power levels, distance to the BS, and neighbour CH density. During initialization, a population of bacteria randomly generated, each replicates the node FCH configuration. The system parameters are defined, such as chemotactic step size, number of chemotaxis steps, reproduction levels, and elimination probability. During the chemotaxis level constructs basic finding operation, Each bacterium will take a level in a random direction and configure the location of fitness that calculates the normalized sum of remaining energy among elected CHs, reduces the communication afforts withthe help of intra-cluster and CH-BS distances, and minimizes load balancing by ensuring the similar size clusters. If the fitness is high (specifies good FCH election), the bacterium continues swimming in that direction only. Otherwise, it fall into a new direction. In swarming, bacteria guides each other movement.

Ant colony optimization (ACO) construct and maintains the efficient route for data communication between FCH and BS. The proposed layered architecture minimizes the routing challenages complexity significantly. ACO gains attention from how real ant colonies detect shortest route to food sources. Ants provides pheromones while moving, and subsequent ants probabilistically follow route with higher pheromone concentrations. The important findings from that approach include pheromone deposition, evaporation, and probabilistic route identification. Cluster members (nodes) transmit their findings to associated CH based one-hop and or multi-hop communication. ACO obtain optimal path to BS through FCH (identified to faciliate inter-CH routing), this is where sophisticated routing optimization occurs. CHs can forward data directly to the BS if within range, or forward through other FCHs using multi-hop route constructed by ACO. The proposed ACO-based routing for WSNs represented in Algorithm 2.

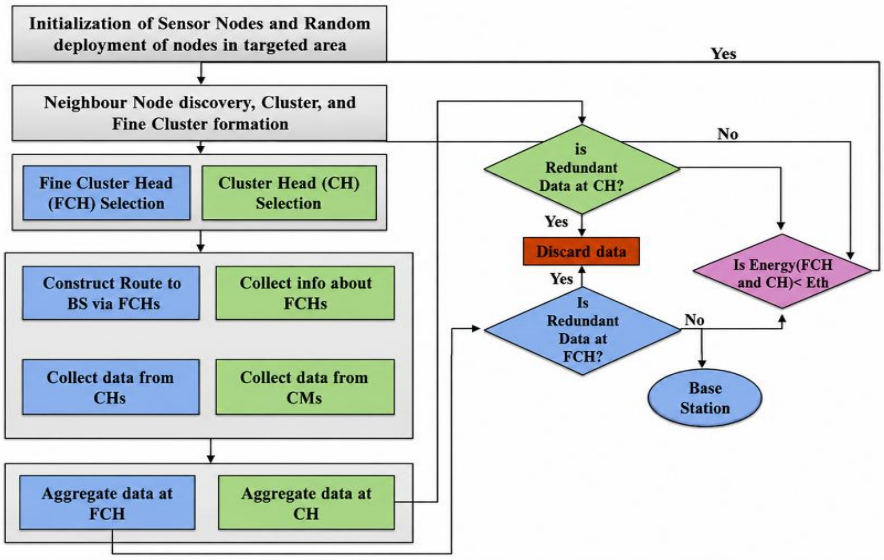


Figure 2. Process from initialization of nodes to sending data to Base Station (BS) using CHs, and FCHs

Algorithm 1. Cluster head and fine cluster head election using BFO

```
Input: N: number of deployed nodes, K: required number of cluster heads, E[]:
       remaining energy of each node, loc[]:location (x,y) of each node, and BS:
       Base Station. Parameters: B: number of bacteria (B=N/10), Cs: Chemotaxis
       steps (Cs=5), and S: step size (S=4).
Output: CH[]: elected cluster head (CH) list, and FCH[]: selected fine cluster head
(FCH) list.
1.  Intialize B bacteria at random node locations:
       for i in B then
              B[i].location=random(0, N-1)
              B[i].fitness= Eval_Fitness(B[i].location)
2.  for i in Cs then
       for each B in i then
              new_loc=B[i].location; new_fitness=B[i].location
              direction = random(0,2*Pi)
              next = S * cos(direction); new_loc1= (new_loc + int(next)) mod N
              if new_loc1 < 0 then new_loc1=new_loc1+N
                     new_fitness1 =Eval_Fitness(new_loc1) #To obtain new location
              if new_fitness1 >new_fitness then #movement decision
                     B[i].location=new_loc1; B[i].fitness =new_fitness1
                     for swim to swim_len then
                            new_loc1 =(B[i].location +int(next)) mod N
                            if new_loc1 < 0 then new_loc1 + =1
                            swim_fitness = Eval_fitness(new_loc1)
                            if swim_fitness > B[i].fitness then
                                   B[i].location=new_loc1;
       B[i].fitness=swim_fitness
3.  Construction fitness for all nodes #CH Election
    for i in n-1 then
       n_fitness[i]=Eval_fitness(i)
4.  Arrange node by fitness: n_sorted=Sort_fitness(n_fitness)
5.  Elect first K nodes as CH and append them to CH[]
    for i in n-1 then
       if n_sorted[i].fitness > Energy(Threshold) and count<K then
              CH.add(n_sorted[i])
6.  Elect first J nodes as FCH and append them to FCH[]
    for i in n-1 then
       if n_sorted[i].fitness > Energy(Threshold) and count<J then
              FCH.add(n_sorted[i])
7.  Return CH and FCH
```

Algorithm 2. Routing between inter-FCH and CH and FCH using ACO

```
Input: CH[]: Set of cluster heads, and FCH[]: list of fine cluster heads
Output: Routing table for each FCH to BS
   1.  Intialize pheromone matrix L with L_0, construct heuristic list k using energy and
       distance, m number of ants
```

```
2.  for i=0 to max_rounds then
            for each ant at=1 to m:
                    new_route=Intitial_CH; route_a=[new_route]; visit_done={new_route}
                    repeat if new_route!=BS
                            node_new=neighbors(new_route)-visit_done
                            if node_new is empty then
                                    ingnore failed ant
                                    break
                            for each x in node_new then
                                    prob[x] = (L[new_route][x]) ** α *
            (n[new_route][x])**β
                            next_route=route_selection(prob)
                            route_a.add(next_route)
                            visit_done.append(next_route)
                            new_route=next_route
                    if ant not ignored
                            cost=find_route_cost(route_a)
                            node_energy=find_energy_consumption(route_a)
                            fitness=eval_fitness(cost,node_energy)
3.  for all (i,j) then
            r[i][j] = (1-r) * r[i][j]
4.  for each ant in top k ants then
            for each edge(i,j) in ant route then
                            r[i][j] = r[i][j]+ (Q / cost_ant) * wieght
            if fintness_best_node > fitness_global_best then
                    global_best_route =best_ant_route
                    fitness_global = fitness_ant
            for each CH i then
                    route_table[CH_i] = construct_next_hop(global_best_route,CH_i)
    return route_table
```

3. RESULTS AND DISCUSSION

This study investigated the effectiveness of a hybrid BFACO procedure for WSN routing and cluster head (CH) selection. While earlier researches have implemented metaheuristic algorithms such as bio-inspired fuzzy optimization, artificial bee colony (EECABCO) optimization, cooperative cluster head selection (ECEEC), and chicken swarm optimization (BCOCOA) and they have not specifically rendered the simultaneous optimization of quality CH selection and multi-path routing reliability under dynamic network densities. The proposed algorithm is evaluated using NS2 simulator to measure power utilization, throughput, packet delivery ratio, and network longvity, with randomly deployed nodes and parametrs like battery power, transmission range, density, and packet size specified in Table 2.

Table 2. Network simulation parameters

Parameter Name	Value
Monitoring area	200 * 200
Deployment type	Random
Number of nodes	100, 200, 300
Node Energy	10j
Packet size	512bytes
Communication range	40m (100), 30m (200), 20m (300)
Simulation Rounds	10000
Round duration	5Sec

3.1. Packet delivery ratio (PDR)

The simulation analysis of the proposed BFACO algorithm correlates strongly with end-to-end data delivery across all deployment densities. The proposed alogirthm consistently demonstrated a higher proportion of successfully delivered packets with respect to the standard benchmark algorithms such as energy efficient clustering using artificial bee colony optimization (EECABCO) [25], energy-efficient cooperative clustering and routing (ECEEC) [26], and energy efficient clustering with enhanced chicken swarm optimization algorithm with adaptive position routing protocol (BCOCOA) [27]. The BFACO algorithm provides an average enhancement approximately 6.7 % in PDR over the best-competing model. This enhancement because from the FCH election process providing optimal CH organization for reliable data aggregation, and the ACO based routing approach identifying multiple routes to improve delivery reliability. As defined in Table 3 and illustrated in Figure 3, the performance of packet delivery ratio based on deployed node configurations.

Table 3. PDR with different deployed nodes in the monitoring area

Number of nodes	EECABCO	ECEEC	BCOCOA	BFACO	Enhancement % over best case
100	77.2	81.7	85.7	91.3	5.6
200	84.4	84.2	91.6	97.5	5.9
300	75.7	78.8	81.4	90.1	8.7

3.2. Energy consumption

The node level energy consumption correlates inversely with the degree of intelligent CH allocation a relationship that is generally pronounced in the proposed BFACO algorithm. The proposed BFACO approach in this research consistently showcased substantially lower average energy expenditure with respect to all three reference approaches, reading average reductions of 62.3%, 73.7%, and 52.8% for 100, 200, and 300 node strategies, respectively, as summerized in Table 4 and Figure 4. Across all dymanic node strategies an averge energy minimization of approximately 62.5% compared to the adjacent research algorithms using metahueristic nature inspired models. Our simulation suggests that higher node density is not associated with proportionally higher energy expenditure in BFACO deployements.

The multi-objective BFO layers balances remaining power across monitoring nodes, while the FCH selection approach suppresses long-range direct transmissions a known critical factor in WSN power usage. The ACO routing layer complements this by configuring shorter, less-cost forwarding routes. The proposed model may benefit from further tuning of pheromone evaporation parameters to acheive these improvements across extended simulation monitoring areas without adversely impacting convergence movement.

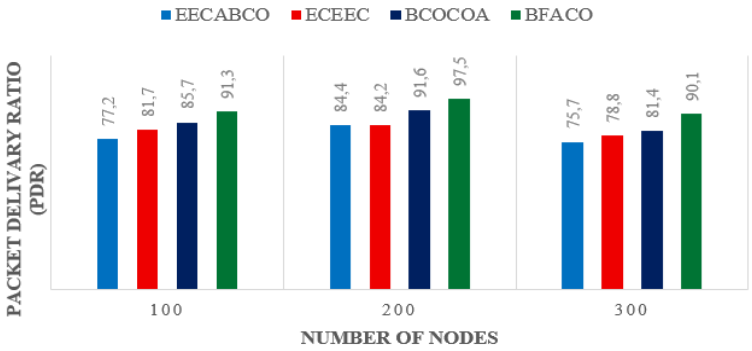


Figure 3. Comparison analysis of PDR using BFACO with other algorithms

Table 4. Energy consumption nodes in the monitoring area

Number of nodes	EECABCO	ECEEC	BCOCOA	BFACO	Energy reduction (%) over best case
100	47.12	54.17	65.70	17.76	62.3
200	36.23	43.80	56.76	9.53	73.7
300	39.86	45.87	65.67	18.80	52.8

3.3. Network lifetime

This study found that network operational lifetime evaluated in active simulation rounds correlates directly with the efficiency of energy-aware routing in BFACO. The proposed BFACO approach enhanced an average network lifespan enhancement of approximately 16.9% compared to the existing traditional metahueristic nature inspired models. The proposed model results from BFO with 200-sensor node scenario demonstrates exceptional enhancement of 33.3%, shows optimal algorithm performance at medium network densities.

Table 5 and Figure 5 demonstrates the performance of lifetime (no of rounds) based on all three deployed node configurations. These reaseach simulation suggets that the superior lifetime of BFACO is not integrated with an inherent trade-off over delivery reliability or throughput. Rather, by preventing premature device deleption through balanced workload distribution, the algorithm sustains connectivity longer, integrating continued packet delivery. The proposed BFACO approach may benefit from adaptive round duration adjustment to further extend network service slots, specifically in strategies where traffic demands fluctuate over time.

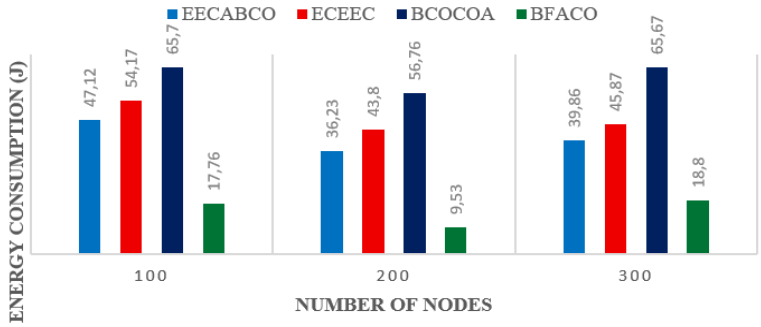


Figure 4. Comparative analysis of energy consumption nodes using BFACO with other research algorithms

Table 5. Lifetime (no. of rounds) with different deployed nodes in the monitoring area

Number of nodes	EECABCO	ECEEC	BCOCOA	BFACO	Enhancement % of rounds over best case
100	6910	6100	5710	7970	15.3
200	7440	6990	6310	9920	33.3
300	6900	6300	5980	7300	4.3

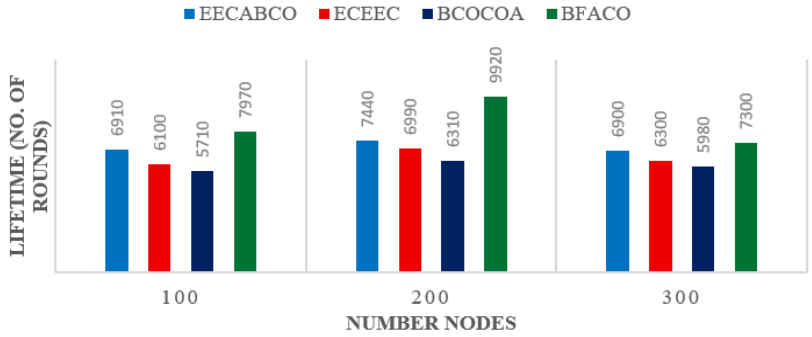


Figure 5. Comparative analysis of Lifetime of the network using BFACO with other research algorithms

4. CONCLUSION

The BFOACO approach with FCH election indicates a spohisticated optimization framework for WSNs. By combining bacterial foraging exploration features with ant colony routing efficiency, and appending the optimal election approach for precise CH, the proposed algorithm achieves significant performance improvements in PDR, power utilization, and network lifespan compared to parallel research and tradentional approaches. The hierarchical architecture scales effectively across different network capacity and monitoring areas, making it suitable for many variety of WSN applications. Therefore, the BFACO algorithm specifies superior performance over parallel research algorithms for static FCH/CH and mobile sensor configurations, with future work focusing on dynamic mobility of CH nodes in WSNs.

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The authors declare no financial competing interests.

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

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

DATA AVAILABILITY

The simulation data that support the findings of this study are available on request from the corresponding author, Sagar Mekala. Derived simulation data supporting the findings of this study are available from the corresponding author, Sagar Mekala, on request.

Other than simulation data, availability does not apply to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] M. Trigka and E. Dritsas, "Wireless sensor networks: from fundamentals and applications to innovations and future trends," *IEEE Access*, vol. 13, pp. 96365–96399, 2025, doi: 10.1109/ACCESS.2025.3572328.

[2] F. Tossa, Y. Faga, W. Abdou, E. C. Ezin, and P. Gouton, "Wireless sensor network deployment: architecture, objectives, and methodologies," *Sensors*, vol. 25, no. 11, p. 3442, May 2025, doi: 10.3390/s25113442.

[3] R. Priyadarshi, R. R. Kumar, R. Ranjan, and P. V. Kumar, "AI-based routing algorithms improve energy efficiency, latency, and data reliability in wireless sensor networks," *Scientific Reports*, vol. 15, no. 1, p. 22292, Jul. 2025, doi: 10.1038/s41598-025-08677-w.

[4] R. K. Yadav and R. P. Mahapatra, "Hybrid metaheuristic algorithm for optimal cluster head selection in wireless sensor network," *Pervasive and Mobile Computing*, vol. 79, p. 101504, Jan. 2022, doi: 10.1016/j.pmcj.2021.101504.

[5] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proceedings of the 33rd annual Hawaii international conference on system sciences*, IEEE Comput. Soc, 2000, p. 223. doi: 10.1109/hicss.2000.926982.

[6] W. S. Kiran, S. Smys, and V. Bindhu, "Enhancement of network lifetime using fuzzy clustering and multidirectional routing for wireless sensor networks," *Soft Computing*, vol. 24, no. 15, pp. 11805–11818, Aug. 2020, doi: 10.1007/s00500-020-04900-0.

[7] S. Goel *et al.*, "Energy efficient clustering protocol in wireless sensor networks using an adaptive hybrid optimization algorithm," *Scientific Reports*, vol. 16, no. 1, p. 6300, Jan. 2026, doi: 10.1038/s41598-026-36957-6.

[8] D. Agrawal and S. Pandey, "FUCA: Fuzzy-based unequal clustering algorithm to prolong the lifetime of wireless sensor networks," *International Journal of Communication Systems*, vol. 31, no. 2, Jan. 2018, doi: 10.1002/dac.3448.

[9] G. Kponhinto, S. Khemiri-Kallel, A. A. Abba Ari, A. M. Gueroui, O. Thiare, and J. Hwang, "A hybrid biologically-inspired optimization algorithm for data gathering in IoT sensor networks," *Journal of Network and Systems Management*, vol. 33, no. 2, p. 23, Apr. 2025, doi: 10.1007/s10922-025-09899-z.

[10] P. Rawat, P. Kumar, and S. Chauhan, "Fuzzy logic and particle swarm optimization-based clustering protocol in wireless sensor network," *Soft Computing*, vol. 27, no. 9, pp. 5177–5193, May 2023, doi: 10.1007/s00500-023-07833-6.

[11] S. Harihara Gopalan, M. Muzammil Parvez, A. Manikandan, and S. Ramalingam, "Cognitive radio spectrum allocation using Nash equilibrium with multiple scheduling resource selection algorithm," *Ain Shams Engineering Journal*, vol. 15, no. 5, p. 102688, May 2024, doi: 10.1016/j.asej.2024.102688.

[12] B. R. Parvathala, A. Manikandan, P. Vijayalakshmi, M. Muzammil Parvez, S. Harihara Gopalan, and S. Ramalingam, "Bio-inspired metaheuristic algorithm for network intrusion detection system of architecture," in *Bio-Inspired Intelligence for Smart Decision-Making*, R. Jaganathan, S. Mehta, and R. Krishan, Eds., in Advances in Computational Intelligence and Robotics. , IGI Global, 2024, pp. 62–84. doi: 10.4018/979-8-3693-5276-2.ch004.

[13] G. Mahalakshmi, S. Ramalingam, and A. Manikandan, "An energy efficient data fault prediction based clustering and routing protocol using hybrid ASSO with MERNN in wireless sensor network," *Telecommunication Systems*, vol. 86, no. 1, pp. 61–82, May 2024, doi: 10.1007/s11235-024-01109-6.

[14] V. Nivedhitha, P. Thirumurugan, A. Gopi Saminathan, and V. Eswaramoorthy, "Combination of improved Harris's hawk optimization with fuzzy to improve clustering in wireless sensor network," *Journal of Intelligent and Fuzzy Systems*, vol. 41, no. 6, pp. 5969–5984, Dec. 2021, doi: 10.3233/JIFS-202098.

[15] Y. Xiuwu, Z. Zixiang, P. Wei, and L. Yong, "A novel multi-hop clustering routing algorithm based on particle swarm optimization for wireless sensors networks," *Wireless Personal Communications*, vol. 130, no. 2, pp. 935–956, May 2023, doi: 10.1007/s11277-023-10314-6.

[16] J. Singh *et al.*, "Energy-efficient clustering and routing algorithm using hybrid fuzzy with grey wolf optimization in wireless sensor networks," *Security and Communication Networks*, vol. 2022, pp. 1–12, May 2022, doi: 10.1155/2022/9846601.

[17] R. Bandi, V. R. Ananthula, and S. Janakiraman, "Self adapting differential search strategies improved artificial bee colony algorithm-based cluster head selection scheme for WSNs," *Wireless Personal Communications*, vol. 121, no. 3, pp. 2251–2272, Dec. 2021, doi: 10.1007/s11277-021-08821-5.

[18] B. Rambabu, A. Venugopal Reddy, and S. Janakiraman, "Hybrid artificial bee colony and monarchy butterfly optimization algorithm (HABC-MBOA)-based cluster head selection for WSNs," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 5, pp. 1895–1905, May 2022, doi: 10.1016/j.jksuci.2019.12.006.

[19] S. Zhang, X. Liu, and M. Trik, "Energy efficient multi hop clustering using artificial Bee Colony metaheuristic in WSN," *Scientific Reports*, vol. 15, no. 1, p. 26803, Jul. 2025, doi: 10.1038/s41598-025-12321-y.
[20] H. Hu, X. Fan, and C. Wang, "Efficient cluster-based routing protocol for wireless sensor networks by using collaborative-inspired Harris Hawk optimization and fuzzy logic," *PLoS ONE*, vol. 19, no. 4, p. e0301470, Apr. 2024, doi: 10.1371/journal.pone.0301470.
[21] M. A. Tawfeek, I. Alrashdi, M. Alruwaili, L. Jamel, G. F. Elhady, and H. Elwahsh, "Improving energy efficiency and routing reliability in wireless sensor networks using modified ant colony optimization," *Eurasip Journal on Wireless Communications and Networking*, vol. 2025, no. 1, p. 22, Apr. 2025, doi: 10.1186/s13638-025-02449-w.
[22] C. Kurangi, K. K. Paidipati, A. S. K. Reddy, J. Uthayakumar, G. Kadiravan, and S. Parveen, "Metaheuristic optimization-based clustering with routing protocol in wireless sensor networks," *International Journal of Communication Systems*, vol. 37, no. 16, Nov. 2024, doi: 10.1002/dac.5914.
[23] S. Ambareesh, P. Chavan, S. Supreeth, R. Nandalike, P. Dayananda, and S. Rohith, "A secure and energy-efficient routing using coupled ensemble selection approach and optimal type-2 fuzzy logic in WSN," *Scientific Reports*, vol. 15, no. 1, p. 38, Jan. 2025, doi: 10.1038/s41598-024-82635-w.
[24] H. Han, J. Tang, and Z. Jing, "Wireless sensor network routing optimization based on improved ant colony algorithm in the Internet of Things," *Heliyon*, vol. 10, no. 1, p. e23577, Jan. 2024, doi: 10.1016/j.heliyon.2023.e23577.
[25] Z. Wang, H. DIng, B. Li, L. Bao, and Z. Yang, "An energy efficient routing protocol based on improved artificial bee colony algorithm for wireless sensor networks," *IEEE Access*, vol. 8, pp. 133577–133596, 2020, doi: 10.1109/ACCESS.2020.3010313.
[26] L.-L. Hung, F.-Y. Leu, K.-L. Tsai, and C.-Y. Ko, "Energy-efficient cooperative routing scheme for heterogeneous wireless sensor networks," *IEEE Access*, vol. 8, pp. 56321–56332, 2020, doi: 10.1109/ACCESS.2020.2980877.
[27] R. Reka, A. Manikandan, C. Venkataramanan, and R. Madanachitran, "An energy efficient clustering with enhanced chicken swarm optimization algorithm with adaptive position routing protocol in mobile adhoc network," *Telecommunication Systems*, vol. 84, no. 2, pp. 183–202, Oct. 2023, doi: 10.1007/s11235-023-01041-1.

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