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Energy Efficient Cluster-Based Routing Protocol for Wireless Sensor Network Using Hybrid Bio-Inspired Swarm Intelligence Algorithm

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Abstract: Wireless Sensor Networks (WSNs) have gained significant popularity due to advancements in wireless communication enabled by low-cost and low-power sensors. However, since WSN nodes are powered by batteries, they eventually lose their autonomy, limiting the network's lifespan. This energy constraint impacts the overall network performance. Clustering is a strategy that can enhance network lifetime while reducing energy consumption by grouping similar sensors for data collection and transmission to the Base Station (BS). However, the Cluster Head (CH), responsible for data collection and transfer, consumes more energy, so efficient identification of CHs is crucial for extending the WSN's lifespan and minimizing energy use. Developing a routing algorithm that addresses the challenges of reducing energy consumption and maximizing network lifetime remains a complex task. This paper introduces an energy-efficient clustering routing protocol based on a hybrid GSO-FF (Global Search Optimization - Firefly) algorithm to address these critical issues in WSNs. The GSO algorithm selects the optimal CH from a set of nodes, while the Firefly optimization algorithm determines the best route between the CH and BS. Simulation results demonstrate that the proposed methodology improves energy consumption by 10.22%, 11.26%, and 14.28%, and normalizes energy by 9.56%, 11.78%, and 13.76%, outperforming existing state-of-the-art approaches.

Keywords: *- WSN, LEACH, PSO, GSO, FA, Cluster, Routing, MATLAB*

Introduction

A wireless sensor network (WSN) is a self-organized, dynamic network designed to support emerging technologies, including fifth-generation (5G) communication systems [1,2]. These networks consist of low-energy sensors operating with dedicated transmission protocols, enabling a broad range of applications such as agriculture, military operations, transportation, and more. Since sensor nodes are powered by limited-capacity batteries, energy efficiency is critical to extending the network's operational lifetime [3,4,5]. Dividing clustering-based routing protocols into three primary phases—cluster setup, cluster head election, and data transmission—has proven to be an effective approach for minimizing energy consumption. During the cluster setup phase, sensor nodes are grouped into clusters of varying sizes across the detection area. Extensive research has been conducted on energy-efficient routing algorithms [6]. Among these, cluster-based hierarchical routing algorithms exhibit superior energy conservation and adaptability compared to flat routing algorithms [7]. Clustering Routing Protocols (CRPs) [8] are typically divided into two categories: uniform clustering and non-uniform clustering. These protocols partition the monitored area into multiple regions, each forming a cluster. Each cluster consists of a head node and member nodes, with the head node of a lower-level cluster often acting as a member node of a higher-level cluster. This hierarchical structure facilitates efficient communication, as the top-level cluster head is responsible for transmitting data to the base station or sink node [9].Meta-heuristic optimization techniques have proven highly effective for selecting optimal cluster heads (CHs), thereby enhancing network lifespan. These techniques also have applications in fields such as electrical system optimization [10] and remote sensing models [11]. However, they face challenges like rapid convergence, limited local search capabilities in fitness functions, and higher computational costs. Meta-heuristic algorithms are particularly beneficial when exhaustive searches for optimal solutions are computationally infeasible. Effective algorithms must explore the entire solution space to locate global optima and develop innovative, improved solutions. Examples include Particle Swarm Optimization (PSO) and Cuckoo Search for global optimization (exploration) and Simulated Annealing (SA) and Harmony Search Algorithm (HSA) for local optimization. The initial population-based approach in PSO mimics the social behaviour of birds in flight, where each "particle" represents a potential solution. The algorithm iteratively updates particle positions based on their fitness evaluations, with the swarm collectively converging toward optimal solutions. Building upon this, this paper proposes a hybrid swarm intelligence algorithm for

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cluster-based routing protocols. The proposed algorithm integrates Glowworm Swarm Optimization (GSO) and the Firefly Algorithm (FA). GSO is used for cluster head selection during data reporting and transmission, while FA optimizes energy factors within the clustering algorithm. The hybrid approach incorporates the LEACH protocol, leveraging the synergy of its two major components—similarity and unidirectional processing—to minimize energy consumption and extend the lifetime of WSNs The rest of the paper is described as follows: related recent work in energy-based routing protocols Section III describes swarm intelligence and the proposed methodology. In Section IV, which describes the experimental analysis of simulation, In section V, we conclude our research work.

II. Related Work

Meta-heuristic functions play a vital role in cluster head selection for energy-efficient routing protocols. The employed heuristic functions reduce and minimize the inter- and intra-cluster distances during the selection of the cluster head (CH). Recently, several authors have proposed meta-heuristic functions for wireless sensor networks. This section explores the recently proposed methods for wireless sensor networks. [1] Introduced temporary clustering using an adaptive coefficient. However, multi-objective sailfish optimization was found unsuitable for large WSNs, leading to increased dead nodes. [2] Focused on extending network lifetime amidst noise interference affecting data transmission and energy consumption. One-hop transfer was deemed unsuitable for large networks due to cluster head (CH) selection issues. [3] Proposed maximizing throughput using a mixed-integer linear programming formulation. Limited focus was placed on homogeneous wireless mesh networks, with no consideration of inter-cluster gateway placement. [4] Integrated SSA with machine learning for automatic image classification. Deployment constraints and communication interruptions were encountered in underground mine applications. [5] Developed an efficient fitness function for clustering and routing optimization in WSN-based IoT. However, there was a lack of real-world implementation and limited comparison with other routing protocols. [6] Reduced energy hole occurrences using non-uniform clustering and improved cluster head selection with an enhanced shuffled frog leaping algorithm, achieving a 20% energy efficiency gain. Despite this, energy-hole issues persisted due to unbalanced energy consumption. [7] Modified particle-swarm optimization for optimal cluster head selection. Demonstrated superior performance compared to other techniques but faced energy constraint issues. [8] Introduced unique features and detailed energy models, highlighting inefficiencies in existing protocols and a lack of raw simulation data. [9] Utilized Salsa20 encryption and a zone-based blockchain consensus model. However, high energy consumption and complexity affected overall efficiency. [10] Used OGSA for optimal route selection, achieving maximum network lifetime. Challenges were faced in large search spaces, with efforts to enhance the GSO method using quantum computing. [11] Provided a detailed classification and discussed future challenges and trends, identifying open research challenges affecting network efficiency. [12] Optimized network lifetime by reducing dead nodes and increasing residual energy. However, DE suffered from stable convergence issues, and SA required longer durations for non-optimal solutions. [13] Evaluated efficiency using the NS-2 simulator. Clustering methods neglected criteria beyond energy and distance, leading to network failures. [14] Evaluated routes based on energy, network life, and data delivery rate. Local optima and permutation parameters affected network paths, causing delays. [15] Compared with traditional techniques, highlighting a lack of history for the best solutions across iterations. [16] Addressed global issues due to sensor node deployment and redundancy traffic. [17] Proposed CEPOC clustering and MHR-GOA routing techniques, facing challenges such as underwater currents, low bandwidth, and high error probability. [18] Validated performance through simulations, addressing energy efficiency issues. [19] Focused on metaheuristic-based clustering and routing. High communication costs and low scalability were identified. [20] Optimized multiloop path selection. Limited battery power affected energy efficiency, especially when over 70% of nodes were dead. [21] Utilized fuzzy logic-based routing for WSN-assisted IoT networks, facing challenges with exploration and exploitation in the GWO algorithm. [22] Minimized energy consumption and total messages to the base station. However, limited energy sources posed significant constraints. [23] Focused on energy-efficient clustered routing, identifying challenges in CH selection and optimal routing. [24] Discussed energy consumption and network lifetime limitations. [25] Enhanced energy efficiency using the EETTC-MRP model. Addressed NP-hard clustering and routing problems with bio-inspired techniques. [26] Identified high power utilization and network lifespan issues due to inappropriate CH selection. [27] Proposed secure, energy-aware routing with deep learning for energy prediction. Faced concerns with arbitrary number systems and energy balance in CH selection. [28] Proposed the EORO algorithm with swarm intelligence for energy and QoS efficiency. Highlighted issues with energy consumption, packet collisions, and high latency. [29] Discussed CH selection modifications and bio-inspired algorithms, facing evolving constraints in clustered networks and drawbacks in homogeneous networks. [30] Enhanced load balancing and resolved spam attacks. Improved network throughput using SVMs with genetic algorithm tuning, though challenges with unbalanced energy consumption persisted.

III. Proposed Methodology

This paper proposed a novel hybrid GSO-FF algorithm is combination of GSO and firefly to resolve the issue of selection of optimal cluster head in each cluster. The define sensor network map each sensor node as glow-worm emitting a light substance called luciferin and intensity of the luciferin is dependent on the distance between sensor node and its neighbor of sensors. A sensor node is drawn to its neighbors who have lower levels of luciferin and chooses to travel in that direction. ACO has the benefits of being simple to search through in parallel, finding excellent solutions quickly, adapting to changes like additional distances, and ensuring convergence. The fact that GSO does not require centralized control makes it easily scalable, and it also has the potential to learn quickly and is suitable for non-linear modelling. The traditional algorithm only takes into account the global searching process, however the expert algorithms in this field take into account both the global and local searching processes in this study. Furthermore, we have hybridized in a way that allows the global and local searching capabilities to be used as necessary. This refines and coarsens the CHS selection process. The traits might also be felt in the outcomes. The processing of firefly and GSO algorithm describes here.

Glow-worm swarm optimization (GSO)[33.34]

The process of algorithm used the concept of local sharing information and update the feature set of parameters.

The process of algorithms defines following parameters

1. Luciferin update: - the value of luciferin update depends on fitness value and pervious value of luciferin [15,16]
   $$l_i(t+1) = (1-\rho)l_i(t) + \gamma fitness(xi(t+1)$$
   $here\ li(t)\ denotes\ the\ luciferin\ value\ of\ glowworm\ i\ at\ time\ t$
2. Neighbourhood selection
   The selection of neighbourhood Ni(t) as
   $$N_i(t) = \{J: d_{ij}(t) < r_d^i(t); l_i(t) < l_j(t)\}$$
   $here\ dij(t) euclidean\ distance\ between\ glowworm\ i\ and\ j\ at\ time\ t$
3. Compute probability
   Glow-worm applied function of probability to measure the movements of glow-worm
   $$P_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in Ni(t)} l_k(t) - l_i(t)}$$
4. Movement process
   $$x_i(t+1) = x_i(t) + s(\frac{x_j(t) - x_i(t)}{|\ \ x_j(t) - x_i(t)|})$$
5. Decision rule update

$$r_d^i(t+1) = \min\{r_{s,max}\{0, r_d^i(t) + \beta(n_t - |N_i(t)|\ \ )\}\}$$

Here β is constant, $r_{s,}$ shows radius of glowworm

Firefly Algorithm

Firefly algorithm is meta-heuristic optimization algorithm based on the flashing behaviors of fireflies in environment. Firefly algorithm resolve the problem of NP-hard problem and manage the dynamic behaviors of data. It's a random algorithm, to put it another way, a random search is utilized to locate a collection of solutions. The FA, at its most basic, focuses on producing solutions inside a search area and selecting the greatest surviving option. A random search avoids being stuck in local optimums. Exploration in metaheuristic algorithms refers to discovering multiple solutions inside the search space, whereas exploitation refers to the search process focusing on the best neighboring solutions. The firefly algorithm has three basic features are (1) the firefly becomes a.The firefly becomes brighter and more attractive when it moves randomly, and all fireflies are of the same sex. (2) The attractiveness of the fireflies is proportional to the brightness of the light and the distance from it. The light absorption coefficient γ calculates the reduction in light intensity. The value of the objective function also determines the luminance of the firefly. (3) the distance between fireflies is obtained form equation (1) so that Xi,k is the kth part of the spatial coordination and ith firefly[31,32]

$$r_{i,j=} \sqrt{(xi - xj)^2 + (yi - yj)^2 \dots\dots\dots\dots\dots\dots.} (1)$$

The movement of firefly and attracted fireflies measured as

$$X_i = X_i + B0^{erij2}(Xj - Xi) + a\left(rand - \frac{1}{2}\right) \dots\dots\dots\dots.(2)$$

A is a randomizer variable, rand is a random integer between [0, 1], and B is the attractiveness of the light source. The parameter is determined by variations in attraction.

The process of stock price optimization

The firefly algorithm (FA) employed in stock data as initial population and set the value of parameters as α, γ, βmin $and\ t = 0$ and Fes=0; the factors of brightness of data is Ii at Xi is measured by f(Xi). Define light absorption coefficient γ;

While (not meet the stop conditions)

For i=1: N all N fireflies

For j=1: N all N fireflies

If Ij > Ii Then

Move firefly i towards j in all dimensions according to Equation (2);

End If

Attractiveness varies with distance

Evaluate the new solution and update its brightness; Fes=Fes+1;

End For

End For

Rank the fireflies and find the current best;

t=t+1;

End While

End

Hybrid Algorithm

1. Define number of dimension as X
2. Define number of worm as Y
3. Size of sensor network as Si
4. Deploy randomly the sensor network nodes
5. Estimare $D_{(P_t,k)}$ and $k - disimarilty(p_t)$
6. for all $DP \in GSO_{(f_t,k)}$ do
7. estimate local function$-Lp(f_t, DP)$
8. end for
9. $W_{\text{update}} \leftarrow GSO\ \{the\ set\ of\ glows\}$
10. for all $DP \in W_{\text{update}}$ and $FP \in M_{(DG,K)}$ do
11. Update $k - disimarilty(DP)$ and $cluester - ds(GSO, FF)$
12. if $DP_{(FP,k)}$ then
13. $W_{\text{update}} \leftarrow W_{\text{update}} \cup \{DP\}$
14. end if
15. end for
16. for all $DP \in W_{\text{update}}$ do
17. Update $FD(DP)$ and $FD(\{GSO_{o,k}\})$
18. end for
19. return $FD(optimal\ cluester\ Head)$
20. if value of difference is near about zero.
21. The process cluester head is selected

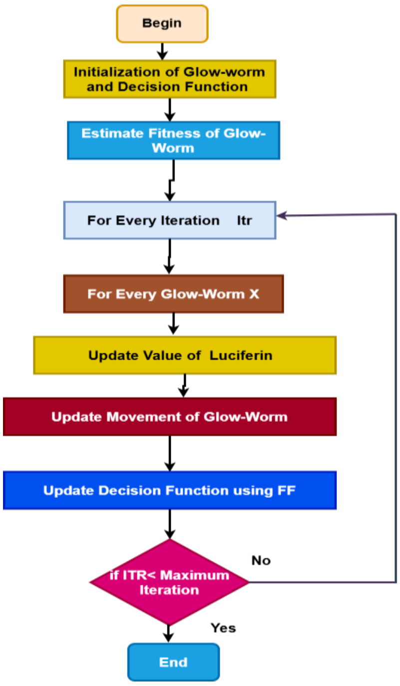

Fig 1 proposed model of hybrid swarm intelligence algorithm (GSO-FF)

IV. Experimental Analysis

The performance of the proposed algorithm for a wireless sensor network was investigated through simulations conducted using MATLAB2018R. The simulation was designed based on the parameters outlined in Table-1, with the wireless sensor network environment assumed to be homogeneous. Various performance metrics were measured during the simulation, including end-to-end delay, energy consumption, network lifetime, bit error rate, packet delivery ratio, and packet loss. These parameters were used to assess the efficiency and effectiveness of the proposed algorithm in optimizing the performance of the network under different conditions.

The applied energy model describes as the radio energy model requires an amplifier for sending message of k-bit over distance x between transmitter and receiver [15,16,17]

$$E_{TX} = \begin{cases} K\ x\ Ep + Kxdxd^2\ when\ d \le d0 \\ K\ X\ dx + KXxdd^2\ when\ d \ge d0 \end{cases} \dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

.

$$d0 = \sqrt{\frac{xd}{kx}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

Where d0 is threshold of distance and xd is amount of energy for transmitter and receiver Simulation Parameters [18,19,20]. The performance of network estimated as packet delivery ratio, energy consumption, round of rotation and packet loss

Table 1 Simulation parameter of wireless sensor network [28,29,30]

Parameters	**Value**
Area of sensor network	200 X 200
Total number of nodes	200
Initial energy of sensor node	10pJ/bit
Location of base station	100,100
Data packet	5000 bits
Aggregation energy	5pJ/bit
Cluster probability	0.08
Number of rounds	15000 and 30000
Normal distribution	101 m
Standard deviation	60m

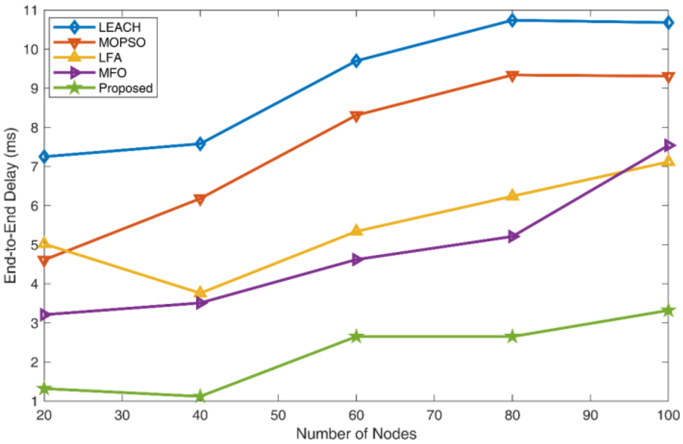

Fig 2 Performance analysis of End-to-End Delay of wireless senor network of simulation area.

Figure 2 depict energy consumption across different algorithms, including LEACH, MOPSO, LFA, MFO, and the proposed method, for varying numbers of nodes. At 20 nodes, the proposed method achieves the lowest energy consumption (1.32), outperforming all others, while LEACH consumes the most energy (7.25). As the number of nodes increases to 40, the proposed method remains the most energy-efficient (1.12), while LEACH again shows the highest consumption (7.58). For 60 nodes, the proposed method still maintains superior performance with an energy consumption of 2.65, compared to LEACH at 9.7 and MOPSO at 8.31. At 80 nodes, the proposed algorithm continues to demonstrate significant energy savings (2.65) compared to alternatives like LEACH (10.74) and MOPSO (9.34). Finally, at 100 nodes, the proposed method has an energy consumption of 3.32, which is much lower than LEACH (10.68) and MFO (7.54).

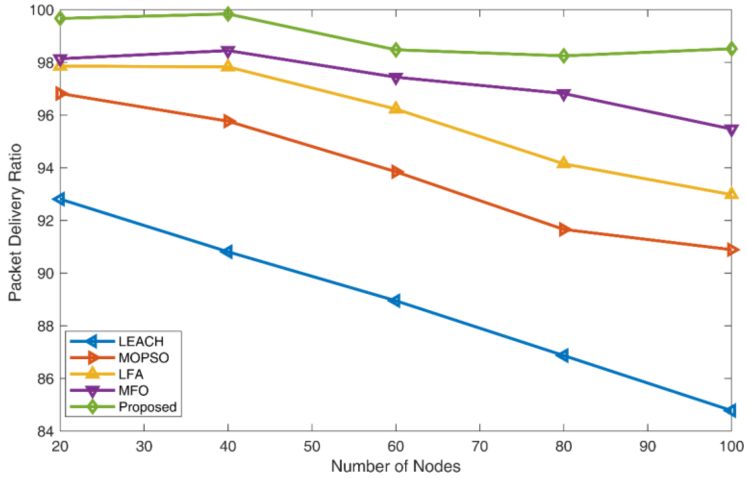

Fig 3 Performance analysis of Packet Delivery Ratio of wireless senor network of simulation area.

Figure 3 depict the performance of different algorithms—LEACH, MOPSO, LFA, MFO, and the proposed method—in terms of a specific metric (likely percentage efficiency or accuracy) across varying numbers of nodes: At **20 nodes**, the proposed method achieves the highest value (99.67), surpassing MFO (98.14), LFA (97.86), and others, with LEACH scoring the lowest (92.81). At **40 nodes**, the proposed algorithm continues to lead (99.84), followed by MFO (98.45) and LFA (97.83), while LEACH scores lowest again (90.81). For **60 nodes**, the proposed method remains superior with a score of 98.48, significantly outperforming LEACH (88.95) and MOPSO (93.85). At **80 nodes**, the proposed algorithm achieves a score of 98.25, still ahead of the rest, while LEACH has the lowest performance (86.87). Finally, for **100 nodes**, the proposed method tops the chart with a score of 98.52, whereas LEACH remains the lowest performer (84.78).

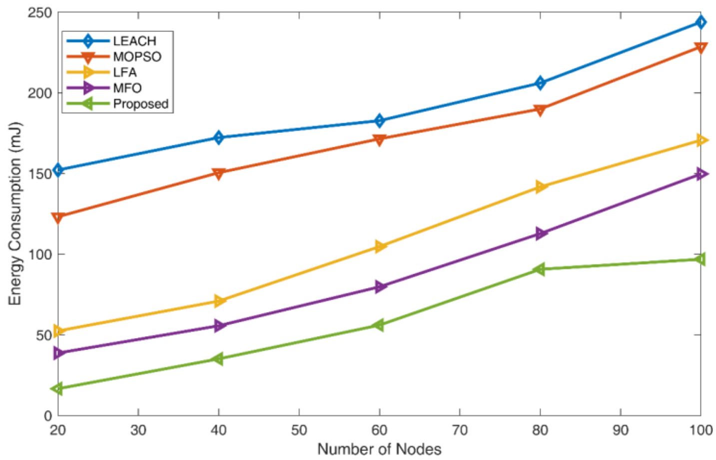

Fig 4 Performance analysis of Energy Consumption of wireless senor network of simulation area.

Figure 4 depict the performance values for various algorithms (LEACH, MOPSO, LFA, MFO, and Proposed) with respect to different numbers of nodes (20, 40, 60, 80, and 100). As the number of nodes increases, the values for each algorithm also tend to increase. Among the algorithms, the Proposed method consistently shows the lowest values compared to the others, indicating its superior performance across different node configurations. The LEACH algorithm performs the best among the traditional methods, followed by MOPSO, LFA, and MFO, which show higher values.

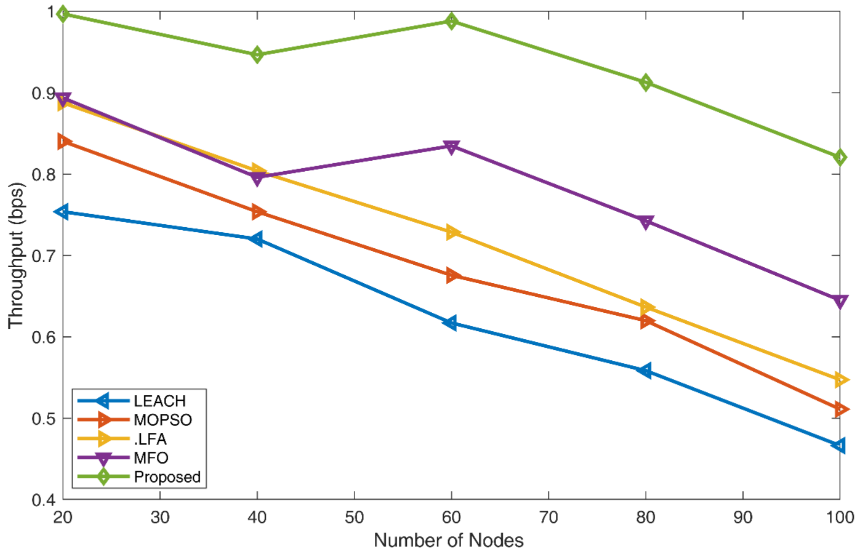

Fig 5 Performance analysis of Throughput of wireless senor network of simulation area.

Figure 5 depict the performance of different algorithms (LEACH, MOPSO, LFA, MFO, and Proposed) in terms of a specific metric (presumably efficiency or success rate) across various node configurations (20, 40, 60, 80, and 100). As the number of nodes increases, the performance values for each algorithm generally decrease. The Proposed algorithm consistently achieves the highest values, indicating it outperforms the other methods across all node configurations. LEACH performs the worst, followed by MOPSO, LFA, and MFO, which show progressively better performance as the node count rises.

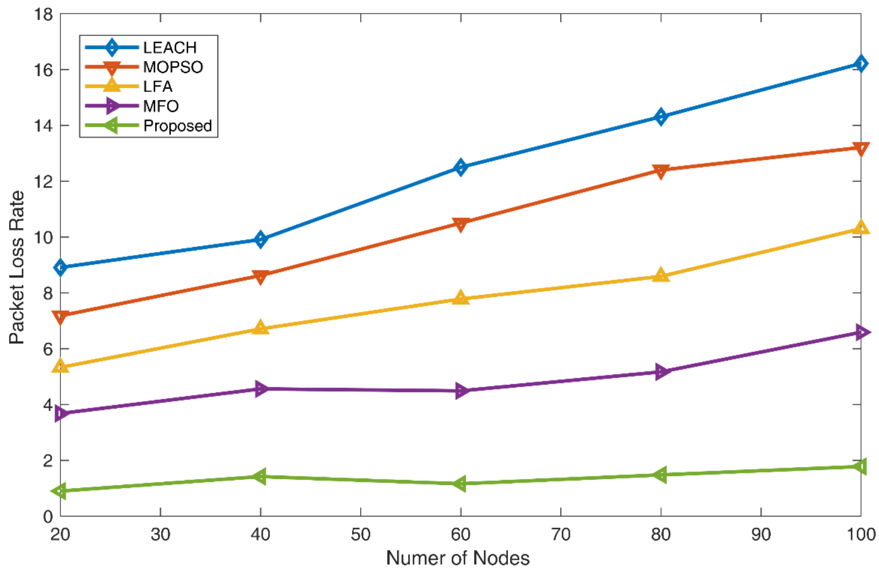

Figure 6 Performance analysis of Packet Loss Ratio of wireless senor network of simulation area.

Figure 6 illustrates the performance of five algorithms (LEACH, MOPSO, LFA, MFO, and Proposed) in terms of a specific metric (possibly time or resource usage) across different node counts (20, 40, 60, 80, and 100). As the number of nodes increases, the performance values for all algorithms tend to rise, indicating a greater resource or time requirement with more nodes. The Proposed algorithm consistently performs the best with the lowest values, followed by MFO, LFA, MOPSO, and LEACH. LEACH shows the highest values, suggesting it requires the most resources or time among the methods across all node configurations.

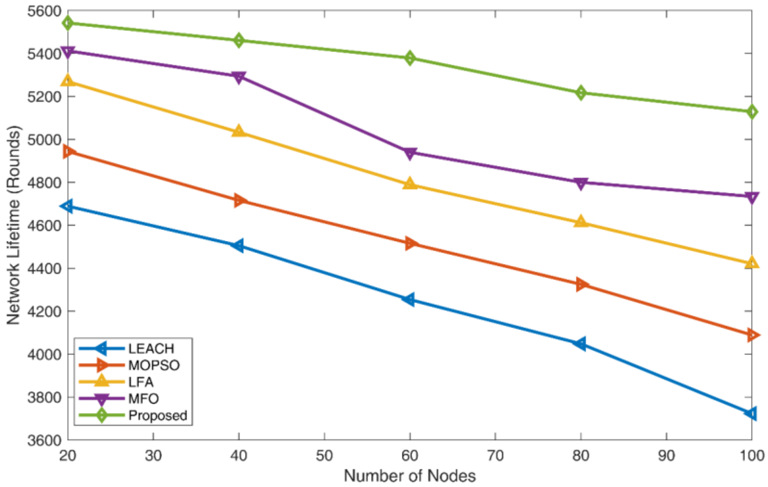

Fig 7 Performance analysis of Network Lifetime of wireless senor network of simulation area.

Figure 7 illustrates the performance of five algorithms (LEACH, MOPSO, LFA, MFO, and Proposed) in terms of a certain metric (likely cost or energy consumption) for various node configurations (20, 40, 60, 80, and 100). As the number of nodes increases, the values for all algorithms decrease, indicating that the resource or cost associated with each method improves as the node count grows. The Proposed algorithm consistently has the highest values, suggesting it performs less optimally compared to the others in terms of this metric. LEACH shows the lowest values at each node configuration, implying it is the most efficient method across all node counts

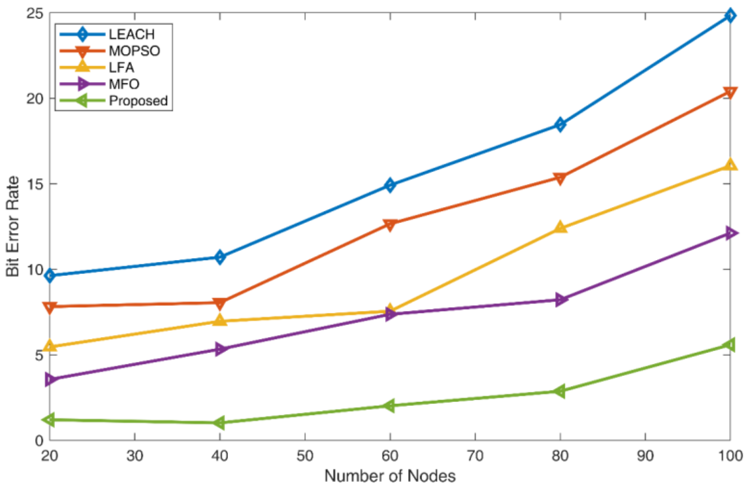

Fig 8 Performance analysis of bit error rate of wireless senor network of simulation area.

Figure 8 presents the performance of five algorithms (LEACH, MOPSO, LFA, MFO, and Proposed) in terms of a particular metric (likely response time, latency, or efficiency) across different node configurations (20, 40, 60, 80, and 100). As the number of nodes increases, the performance values for all algorithms rise, indicating higher resource usage or time with more nodes. The Proposed algorithm consistently shows the best performance with the lowest values across all node configurations, while LEACH performs the worst, followed by MOPSO, LFA, and MFO. This suggests that the Proposed algorithm is the most efficient or optimal in handling the increased number of nodes.

V. Conclusion & Future Scope

This paper presents the GSO-FF optimized method for enhancing the lifespan and energy stability of Wireless Sensor Networks (WSNs). By combining the global optimization capabilities of the GSO optimization method with the local optimization ability of FF, the proposed method achieves a balance between exploration and exploitation in selecting Cluster Heads (CHs) for long-term energy stability. The meta-heuristic characteristics of both GSO and FF are incorporated into the clustering algorithm to efficiently locate essential CHs and optimize Base Station (BS) placement, thus improving energy efficiency. Simulation results show that the proposed GSO-FF-based routing protocol outperforms existing methods such as LEACH, MOPSO, LFA, and MFO, with network lifespan improvements of 9.78%, 11.24%, and 14.25%, respectively. Moreover, the protocol reduces energy consumption by 10.22%, 11.26%, and 14.28% for varying sensor node densities, demonstrating superior performance. It also increases the median number of live nodes by 12.54%, 13.63%, and 15.28%, while maintaining a higher median normalized energy of 9.56%, 11.78%, and 13.76%. These results highlight the effectiveness of the GSO-FF method in comparison to existing schemes. Therefore, the GSO-FF method is recommended for addressing practical challenges in future work, and self-adaptive optimization techniques may be explored to further mitigate energy consumption issues in WSNs.

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