International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Efficient Energy Optimization Routing Protocol in Homogeneous Wireless Sensor Networks

[1]Amy Alice Kujur, [2]Maniram Ahirwar, [3]Virendra Singh Chaudhary

Submitted: 12/05/2024 **Revised**: 25/06/2024 **Accepted**: 05/07/2024

Abstract: The emerging communication models, such as the Internet of Things (IoT) and local communication models based on Wireless Sensor Networks (WSN), are growing rapidly. The expansion and lifespan of WSNs enhance the capacity of these emerging communication models. Despite the extensive application of WSNs, several challenges, such as energy efficiency, load balancing, security, and storage, remain. Energy efficiency is considered a critical aspect of WSN design and can be achieved through clustering and multi-hop routing techniques using metaheuristic optimization algorithms. This paper proposes a metaheuristic-based, cluster-based routing technique for energy efficiency. The hybrid algorithm focuses on improving both energy efficiency and the lifespan of Wireless Sensor Networks (WSNs) through the clustering and routing process. For effective clustering, the hybrid model utilizes Moth Flame Optimization (MFO) and Marine Predators Algorithm (MPA), which employ a fitness function that incorporates factors such as intra-cluster distance, inter-cluster distance, energy, and load balancing. To select optimal routes within the WSN, the MPA algorithm designs a fitness function that includes parameters like residual energy and distance. The proposed model is experimentally validated through a series of simulations, and a comprehensive comparative study demonstrates its superior performance compared to other recent methods.

Keywords: - *Wireless Senor Network, Energy, MFO, MPA, LEACH, QLEACH, MOPSO*

Introduction

In emerging communication technologies, wireless sensor networks (WSNs) play a tremendous role in various fields such as agriculture, medical science, and local communication modules. The successful contribution of WSNs largely depends on the energy efficiency of sensor nodes. Excessive propagation and inefficient path selection can lead to unnecessary energy consumption, ultimately causing sensor nodes to deplete their energy and fail prematurely. Energy consumption becomes a critical challenge as the demand for more sensor devices increases. This challenge motivates our research to focus on energy-efficient communication in wireless sensor networks (WSNs). To extend the network lifespan, the network is divided into clusters, each containing multiple sensor nodes. Within each cluster, one node is designated as the Cluster Head (CH), while the remaining nodes act as cluster members. The CH is responsible for gathering data from individual sensors within its area. During the CH selection process, the node with the highest residual energy compared to others in the cluster is chosen to serve as the CH. Homogeneous wireless sensor networks represent an advanced variant of traditional WSNs. They are compatible with key technologies of heterogeneous networks while leveraging the diverse characteristics of nodes to enhance overall network performance [11]. Integrating an optimal coverage algorithm within a heterogeneous network environment can better address the varying demands of real-world applications. Critical challenges in heterogeneous WSNs—such as network coverage, energy efficiency, and connection reliability—are interrelated and must be addressed urgently. Network coverage, in particular, plays a pivotal role in determining the network's ability to monitor the physical world, directly reflecting the quality of service (QoS) the network can provide. The management of energy-efficient routing protocols in wireless sensor networks often employs cluster-based routing protocols, such as the LEACH protocol. Various enhancements of the LEACH protocol have been developed, including Q-LEACH and M-LEACH. The processing of routing protocols and cluster-based routing is categorized as a non-deterministic polynomial (NP)-hard optimization problem. These NP-hard problems are addressed using several approaches, such as dynamic programming and brute-force methods. Recently, many researchers have adopted optimal solution-based computing techniques, including genetic algorithms, particle swarm optimization, moth-flame optimization, and other swarm intelligence and machine learning algorithms. Surveys indicate that numerous authors have utilized fuzzy-classical algorithms alongside recently developed machine learning approaches to tackle these challenges effectively. Wireless sensor network

1Department of Electronics & Communication Engineering Assistant Professor, Indira Gandhi Engineering College Sagar (M.P)
amykujur@gmail.com
2Department of Electronics & Communication Engineering Associate Professor, Indira Gandhi Engineering College Sagar (M.P)
maniram.ahirwar@mp.gov.in
3Department of Electronics & Communication Engineering Professor, RKDF University, Bhopal
virgwl@gmail.com

(WSN) routing optimization encounters challenges such as energy constraints, dynamic network topology, and limitations in bandwidth and capacity. Enhancing swarm intelligence algorithms can effectively address these issues. In particular, optimizing the Particle Swarm Optimization (PSO) algorithm has been shown to improve the performance and efficiency of WSN routing. However, unlike approaches that incorporate alternating search strategies for regional particles, further improvements can be explored to achieve more robust and adaptable solutions. This paper introduces a hybrid swarm intelligence algorithm for optimizing routing in wireless sensor networks. The proposed approach combines the strengths of two powerful swarm intelligence algorithms: Moth-Flame Optimization (MFO) and the Marine Predator Algorithm (MPA). By leveraging the complementary features of these algorithms, the hybrid method effectively reduces energy consumption during the search for near-optimal nodes to collect and transmit data. This energy-efficient routing strategy enhances the overall performance and longevity of WSNs, addressing critical challenges such as energy constraints and efficient data collection. The remainder of this paper is organized into six sections. Section II covers the motivation and literature review, focusing on propagation models, wireless sensor networks (WSNs), and optimization algorithms. Section III outlines the methodology for designing the WSN, detailing the interaction between propagation and optimization algorithms. Section IV describes the simulation environment used to validate the proposed method under various scenarios. Section V analyses the results, highlighting the performance and behaviour of the optimization algorithms in the given scenarios. Finally, Section VI provides conclusions regarding the different designs and optimization approaches discussed in the study.

II. Related Work

Energy optimization is a critical challenge in wireless sensor networks (WSNs) due to the limited power resources of sensor nodes, which directly impact the network's lifespan and performance. Recent advancements in optimization techniques have leveraged swarm intelligence algorithms, such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Moth-Flame Optimization (MFO), alongside machine learning approaches to address this issue. These algorithms enhance energy efficiency by optimizing routing paths, cluster formation, and node scheduling, minimizing redundant transmissions and idle states. By integrating swarm intelligence and machine learning, WSNs can dynamically adapt to network changes, balance energy consumption across nodes, and prolong the operational lifetime while maintaining effective communication and data collection. In [1], a machine learning (ML)-based green routing model for wireless sensor networks (WSNs) is proposed to enhance efficiency. The study surveys the evolution of green routing schemes, highlighting that ML algorithms, despite their potential, require significant computational resources, which conflicts with energy efficiency goals. Challenges include real-time response due to periodic network condition updates and security concerns stemming from resource constraints and low-bandwidth communication. In [2], the GAPSO-H algorithm optimizes cluster head (CH) selection and sink mobility, combining genetic algorithms (GA) for CH selection with particle swarm optimization (PSO) for sink mobility. Performance evaluation shows superiority over competitive algorithms; however, sink mobility increases energy consumption, and CH selection lacks optimization for energy conservation. In [3], the HMBCR technique addresses energy efficiency in WSNs through clustering and routing using metaheuristic algorithms. The study acknowledges limitations in energy, bandwidth, storage, and processing, with communication costs being higher than sensing or processing. In [4], a comprehensive review of clustering optimization techniques in WSNs categorizes approaches into metaheuristic, fuzzy logic, and hybrid methods. It evaluates their features, parameters, objectives, and benefits. Key issues include energy disparities between CHs and other nodes, and overhead from premature cluster formation in event-driven clustering. In [5], ML techniques demonstrate potential in improving system performance by reducing communication overhead and delays while adapting to changes. However, challenges such as anomaly detection, QoS management, fault detection, energy consumption, data dependency, and real-time validation persist in WSNs. In [6], a TSBOA algorithm selects CHs based on residual energy, distance, and reliability. The HQCA method lacks optimal cluster estimation, and energy models, while the DMEERP model omits secure routing and data availability. Though EGSMRP increases lifespan, it lacks QoS optimization, and the HABC-MBOA method overlooks CH selection energy efficiency. In [7], the BRP-ML routing protocol for UWSNs employs ML to reduce latency by 18% and increase energy efficiency by 16%. Despite improvements, challenges include routing, limited bandwidth, node localization, and void areas. In [8], the MDC-K protocol combines LEACH-K and MDC to enhance QoS. Simulations demonstrate its superiority over existing solutions, though the study is limited to minimal parameters and a small network size (two clusters with ten nodes). In [9], a bio-inspired ensemble routing protocol based on SMO optimization addresses energy consumption and data aggregation challenges in homogeneous networks. Energy constraints arise from limited battery capacities of sensor nodes. In [10], ML-based clustering improves MANET scalability and performance. A bio-inspired CH selection method minimizes congestion, while PSO optimizes CH strength and node stability. However, rapid energy drainage and network lifespan reduction remain issues. In [11], the MWCSGA algorithm introduces a novel clustering method for energy-efficient WSNs, outperforming GA-LEACH, MW-LEACH, and CSOGA. Limited comparison with advanced methods and real-world validation are noted as gaps. In [12], an optimized clustering model evaluated against PSO and BFAO reveals computational complexity and slow execution. Challenges include balancing energy efficiency with reliable data delivery. In [13], the GU-WOA algorithm introduces a security-aware CH selection model. While the performance is robust, considerations for energy harvesting and network sustainability need further enhancement. In [14], the hybrid PSO-GA for MANET CH selection achieves low BER, high PDR, minimal delay, and high energy efficiency. Despite outperforming existing methods, limitations include energy consumption issues and weak signal strength with fewer CHs. In [15], ML-based routing in SDN networks is explored, emphasizing scalability, performance optimization, security, and reliability as challenges. In [16], the EEE-RP protocol aims to enhance data forwarding and network lifetime. The RVSRP protocol addresses dynamic connection failures. However, comparison with EH-WSN and ECO-LEACH protocols is limited, and real-world implementation challenges are not discussed. In [17], the KE-CHSA algorithm employs K-Means for dynamic cluster adjustment based on node density and count. It assumes error-free environments and has limited data transmission to conserve energy. In [18], a bio-inspired artificial bee colony algorithm evaluates wireless networks. Challenges in training deep SNNs due to non-differentiability are highlighted. In [19], a hybrid PSO-VNS metaheuristic improves CluVRP routing. Specific limitations are not provided. In [20], the WOA-P method for group head estimation is proposed. However, its scalability and comparison with other metaheuristics are insufficiently discussed. In [21], GA-based routing for CH quality and energy focuses on lifespan enhancement. However, scalability and adaptability require further investigation. In [22], the LOA for CH selection in RPL increases network lifetime by 20% and PDR by 5–10%. Convergence delays in CH selection remain a concern. In [23], an energy-efficient WBAN routing protocol uses the Ant Lion Optimizer. Resource limitations include energy, memory, bandwidth, and processing. In [24], DAI and SOM-based clustering enable optimized routing for real-time WSN conditions. AI absence poses challenges for energy efficiency. In [25], the DNGSOSCC model improves CH selection. Prior methods exhibited high data loss and transmission delays. In [26], the OCRP algorithm enhances clustering and routing efficiency in hierarchical WSNs, outperforming alternatives significantly. In [27], the WOA-O-LEACH protocol improves throughput and energy efficiency but struggles with scalability in large networks. In [28], WORP employs a Levy flight strategy for CR-WSNs, addressing energy efficiency and connection reliability challenges. In [29], the Q-DAEER algorithm reviews energy-aware routing protocols, highlighting computational and routing optimization difficulties. In [30], mobile routing nodes improve cluster load distribution and lifetime but face limitations in energy and processing capabilities.

III. Proposed Methodology

The proposed energy-efficient clustering algorithm integrates the Moth-Flame Optimization (MFO) and Marine Predators Algorithm (MPA) to optimize cluster head (CH) selection in sensor networks. By leveraging the exploration capabilities of MFO and the exploitation strengths of MPA, the algorithm ensures a balanced approach to selecting CHs, considering factors such as energy consumption, node distance, and network coverage. This hybrid approach enhances communication efficiency among sensor nodes, minimizes energy consumption, and extends the network's overall lifespan. The synergy between these algorithms ensures an adaptive and robust clustering mechanism, crucial for maintaining efficient operations in resource-constrained environments like wireless sensor networks (WSNs). This section initially describes Moth flame optimization and marine predators' algorithm and finally describes the proposed algorithm of cluster node selection.

III. a Moth-Flame Optimization Algorithm (MFO)

The Moth Flame Optimization (MFO) algorithm is a bio-inspired optimization technique. The MFO algorithm is effective in optimizing various distance-based problems, such as searching for neighbouring nodes for communication purposes. The distance factor plays a vital role in wireless sensor networks, influencing the deployment of sensor nodes and the path propagation model. This optimization algorithm is inspired by the behaviour of moths. Moths naturally attempt to maintain a constant angle with nearby light sources (referred to as flames) as they approach them, following a spiral trajectory around the source. In this algorithm, moths represent the candidate solutions, while their positions in the search space represent the variables of the problem to which the algorithm is applied. Moths are represented by a matrix M , which is a $d \times n$ times n matrix, and flames are represented by a matrix F, also a $d \times n$ times n matrix. Here, n represents the number of moths (solutions to the problem), and d represents the number of variables in the problem[31,32].

The fitness values of all moths are stored in an array OM, a 1×n1 matrix. Similarly, an array OF, also a 1×n1 matrix, is used to store the fitness values corresponding to the flames. The position vector of each moth is used to calculate the fitness or objective function value.

If Mi represents the i^{th} moth and Fj indicates the j^{th} flame and S denotes the spiral function. The position of moth is estimated by following equation.

$$M_i = S(M_i, F_j) \dots \dots \dots \dots \dots (1)$$

The processing of algorithm shown in figure (1).

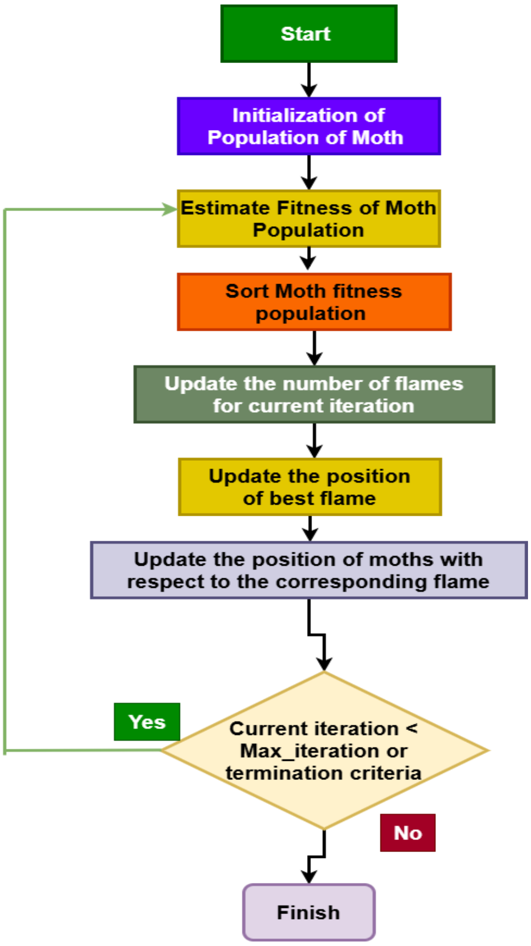

Figure 1 process block diagram of moth flame optimization

III. b Marine Predators Algorithm (MPA)

The Marine Predator Algorithm (MPA), introduced by Faramarzi et al. in 2020[20], is a novel metaheuristic optimization technique inspired by the hunting behaviour of marine predators and their interaction with prey. Marine predators utilize strategies such as Lévy motion and Brownian motion to efficiently search for food sources. MPA has gained widespread application across various fields due to its advantages, including simplicity of implementation, minimal parameter tuning requirements, and robust stability in finding optimal solutions. In MPA, both predators and prey engage in hunting activities while simultaneously searching for food. This interplay reflects a natural process governed by the principle of "survival of the fittest," which enhances the predators' chances of locating prey. In this metaheuristic algorithm, the next position of a solution is determined based on its current position and the probability of transitioning to a new position. MPA incorporates strategies to simulate marine predators' behaviour effectively. Two key mechanisms, the Lévy strategy and the Brownian process, work in tandem, complementing each other to optimize the search process and ensure a balance between exploration and exploitation. the mathematical modelling of MPA algorithm describe in equation in (2)[33,34]

$$X_0 = X_{min} + rand\, X(X_{max} - X_{min}) \dots \dots \dots \dots \dots \dots . . (2)$$

Here X_{max} and X_{min} are the upper and lower limit of boundaries of the search space, respectively and rand is a random number between [0.1]. according to the movement modes of predators and prey, the process of optimization categorizes into three phases. The process of phases describes as

Phase 1: in first phase consider, the predator moves faster than the prey, so the objective of this stage is exploring search space and finds the prey. The mathematical model shown in equation (3)

$$While\ i < \frac{1}{3}T_{max}\ i = 1,2,\dots,n \dots\dots\dots\dots..(3)$$

$$\begin{cases} stepsizei = (R_B \otimes (Elitei - R_B \bigotimes preyi)) \\ preyi = preyi + PX\ R \otimes Stepsizei \end{cases} \dots\dots\dots\dots\dots\dots (4)$$

Where i is current iteration and Tmax is maximum iteration of algorithm. Stepsize is moving step size, R_B is Brownian motion random vector obeying the normal distribution, Elitei is the matrix built by the top predator Elitei is the elite matrix constructed by the top predator, preyi is the prey matrix with the same dimension as the elite matrix, ⊗ denotes the elementwise multiplication, P is a constant value of 0.5, and R is a random number between [0, 1].

Phase2 in this phase the population is divide into predators and prey, the mathematical formulation of this stage describes as

$$While\ \frac{1}{3}Tmax < i < \frac{2}{3}\ T_{max}i = 1,2,..,\frac{n}{2} \dots\dots\dots (5)$$

$$\begin{cases} stepsizei = \left(R_L \otimes (Elitei - R_L \otimes preyi)\right) \\ preyi = preyi + PXR \otimes stepsizei \end{cases} \dots\dots\dots\dots\dots\dots (6)$$

$$While\ \frac{1}{3}T_{\max} \quad < i < \frac{2}{3}T_{Max}\ i = \frac{n}{2},\dots\dots..,n\dots\dots\dots\dots.(7)$$

$$\begin{cases} stepsizei = (R_B \otimes (R_B \otimes Elitei - preyi\ )) \\ preyi = Elitei + PXCF \otimes stepsizei \end{cases} \dots\dots\dots\dots\dots..(8)$$

Here R_L is random vector serving Levy motion, CF is the adaptive parameter that control the predators moving step, the mathematical formula of CF is

$$CF = \left(1 - \frac{i}{T_{max}}\right)\frac{2i}{Tmax}\dots\dots\dots\dots\dots\dots.(9)$$

Phase 3 the last phase of algorithm mainly explores the exploitation phase. The predator mainly approaches the prey through Levy motion. The mathematical formula shown as

$$While\ i > \frac{2}{3}T_{max,}i = 1,2,\dots,n\dots\dots\dots\dots..(10)$$

$$\begin{cases} stepsizei = (R_L \otimes (R_L \otimes Elitei - preyi)) \\ preyi = Elitei + PXCF \otimes stepsizei \end{cases} \dots\dots\dots\dots..(11)$$

In the above phase MPA algorithm also include eddy currents and the influence of Fish Aggregating Devices(FADs), the formula of influence is

$$preyi = \begin{cases} preyi + CF[X_{min} + R \otimes (\ X_{max} +\ X_{min})] \otimes U\ if\ r \le Pf \\ preyi + [Pf(1-r) + r]X(preyr1 - preyr2)\ if\ r > Pf \end{cases} \dots\dots\dots (12)$$

Here Pf is the probability of FADs influencing the optimization process, U is a binary array with value 0 and 1,r is a random number between[0,1], and the subscripts r1 and r2 are the random indices of the prey matrix.

III. c Proposed Algorithm

This section explores the proposed methodology for developing an energy-efficient routing protocol for wireless sensor networks (WSNs). The methodology integrates two advanced optimization algorithms—Moth Flame Optimization (MFO) and the Marine Predator Algorithm (MPA). The MFO algorithm is utilized to address the convergence issues in sensor networks, ensuring that the optimization process reaches a stable and effective solution. On the other hand, the MPA focuses on resolving distance-related challenges among sensor nodes. The interaction of these algorithms influences the selection of cluster heads (CHs), a critical factor in WSNs, as the distance between nodes significantly impacts energy consumption. By optimizing the cluster head selection process, the proposed approach aims to reduce unnecessary energy waste and prolong the network's operational lifespan. The baseline for comparison in this study is the LEACH (Low-Energy Adaptive Clustering Hierarchy) routing protocol, which employs time-division multiple access (TDMA) for communication and cluster head management. However, LEACH suffers from excessive energy consumption due to inefficient CH selection, leading to premature depletion of the network's lifetime. The proposed hybrid algorithm improves upon this by enhancing the CH selection process and reducing the hop count, which minimizes routing overhead. As a result, the new methodology not only optimizes energy consumption but also ensures a more balanced load across sensor nodes, significantly extending the life of the sensor network. The complete process of efficient energy optimization is described using three algorithms. Algorithm-1 addresses the convergence of sensor networks, ensuring that the network achieves stability and effective communication. Algorithm-2 focuses on managing the distance factors of sensor nodes, optimizing node placement and minimizing energy consumption due to communication overhead. Finally, Algorithm-3 outlines the process of energy utilization, aiming to maximize the efficient use of energy resources across the network while prolonging its operational lifespan.

Algorithm 1. The process of network convergence

Notation of algorithm

N→ number of sensor nodes

P→ probability function of interval [0,1]

L→ length of search space of marine predators

T→ maximum iteration of algorithm

P^{State} → phase of moth population

P^{d_max} → probability of maximum distribution

X^{min} → lower limit of search space

X^{max} → upper limit of search space

$FF \leftarrow fitness\ function(.)$

Begin

$S \leftarrow Init(.)$ // initialization of sensors network

$C \leftarrow convergence\ (S)$;

$while\ T > 1\ do$

$iter\ \leftarrow 0$;

$for\ X_{max} \leftarrow 1\ to\ X_{min}$ && $iter < X_{max}$

$Snext\ \leftarrow NeighbourNode(S)$;

$\Delta C\ \leftarrow\ conver(Snext;\ S)$;

$if\ \Delta C < 0\ then$

$S\ \leftarrow Snext$;

$S_{best} \leftarrow S$;

$Iter \leftarrow 0$;

$Else$

$Iter \leftarrow iter + 1$;

$else\ if\ AcceptProb(\ \Delta C;\ T\ )\ >\ random(0;\ 1)\ then$

$S\ \leftarrow Snext;\ C \leftarrow C + \Delta C$;

$return\ S_{best}$;

end

Algorithm 2. Distance Factor of Routing Overhead

$P \rightarrow Network.insert(Xmax)$;

$while\ Tmax$

$for\ each\ sensor\ node\ x \in N\ do$

$y\ =\ Search(P - Network)$

$[hopcount]\ =\ distance(x^l; y^l)$;

$//representativeness\ distance$

$if\ y^l ==\ x^l\ then$

$y{:}\ Rep = Rep(y) \times 2^{-\lambda T_e} + 1$;

$else$

$y{:}\ Rep = Rep(y) \times 2^{-\lambda T_e} - 1$;

$end\ if$

$end\ if$

$//maximum\ boundary\ in\ prototype\ level$

$if\ P - Network.prototypeSize\ ==\ maxP\ then$

$S_n\ =\ P - Network.getNegativePrototypes()$;

$P - Network.remove(S_n)$;

$S_u =\ P - Network.getUnchangedPrototypes()$;

$P\ =\ ConstrainedSync(S_u)$;

$P - Network.remove(S_u)$;

$end\ if$

$P - Network.insert(P)$;

$//maximum\ boundary\ in\ concept\ level$

$if\ P - Network.fitness\ function()\ ==\ maxC\ then$

$P - Network.removeOldestConcept()$;

$end\ if$

$//concept\ drift\ detection$

$if\ numObj == cluester\ head\ then$

$if\ type ==\ RB\ then$

$A =\ Selection(RB, CH)$;

$else$

$p\ = p - value(RB, CH)$;

$end\ if$

$end\ if$

$end\ if$

$end\ for$

$end\ while$

Algorithm 3. For Energy Efficiency

$Begin$

$D\_distance \leftarrow 0$;

$for\ m\ \leftarrow 1\ to\ L\ do$

$Distance\ D \leftarrow\ distance\big(S{:}\ C_{(:,:,m)}, Snext.\ C_{(:,:,m)}\big)$;

$Distance \leftarrow Distance\big(S{:}\ F_{(:,:,m)}, Snext.\ F_{(:,:,m)}\big)$;

$if\ Cluster\ Head\ CH == True\ or\ Distance\ D = = True\ then$

$E\_allocate \leftarrow AllocateEnergy\big(Snext.\ C_{(:,:,m)}, Snext.\ F_{(:,:,m)}\big)$;

$D_{distance} = D + allocate\ energy$;

$return\ Distance$;

end

IV. Experimental Analysis

To validate the proposed algorithm for wireless sensor networks, simulations were conducted using MATLAB tools on a system configured with a Windows 10 operating system, 16 GB RAM, and 1 TB HDD. The evaluation was performed on a homogeneous network model to analyse the protocol's efficiency and reliability. The energy model used in the simulation follows the radio energy model, which accounts for energy consumption in transmission and reception. Specifically, it considers the use of an amplifier to transmit a k-bit message over a distance xx between the transmitter and receiver, ensuring an accurate representation of real-world energy requirements for communication process [30].

$$E_{TX} = \begin{cases} K\ x\ Ep + Kxdxd^2\ when\ d \leq d0 \\ K\ X\ dx + KXxdd^2\ when\ d \geq d0 \cdots\cdots\cdots\cdots \end{cases}$$

.

$$d0 = \sqrt{\frac{xd}{kx}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

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, packet loss. Ratio, throughput and bit error rate.

Parameters	**Value**
Area of sensor network	200 X 200
Total number of nodes	100
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

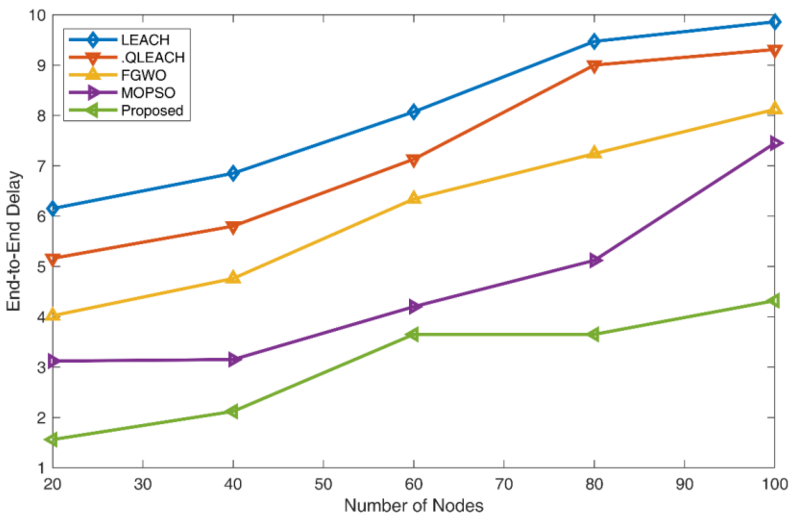

Figure 2 Performance Analysis of End-to end delay

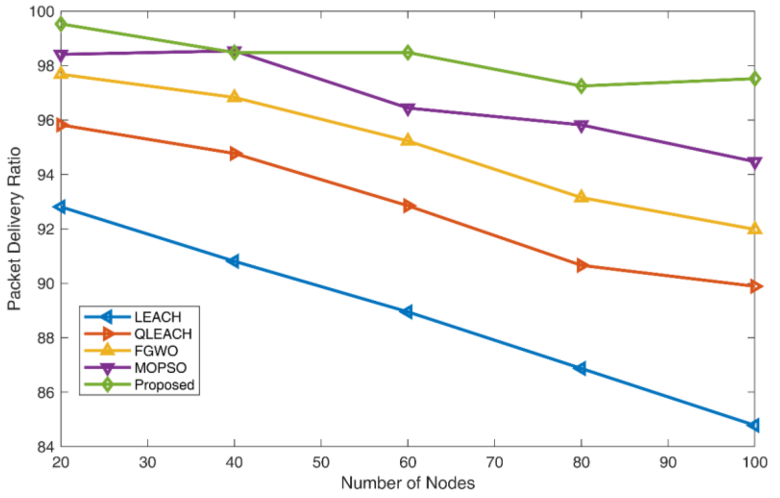

Figure 3 Performance Analysis of packet delivery ratio

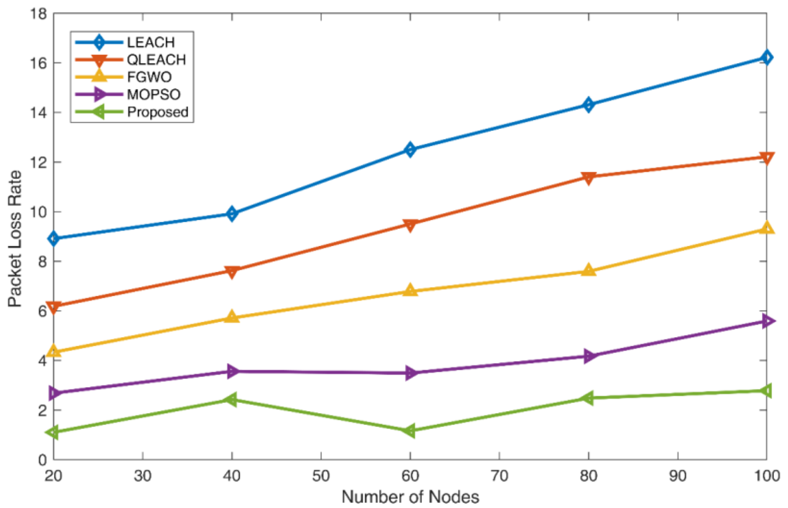

figure 4 Performance Analysis of Packet Loss Ratio

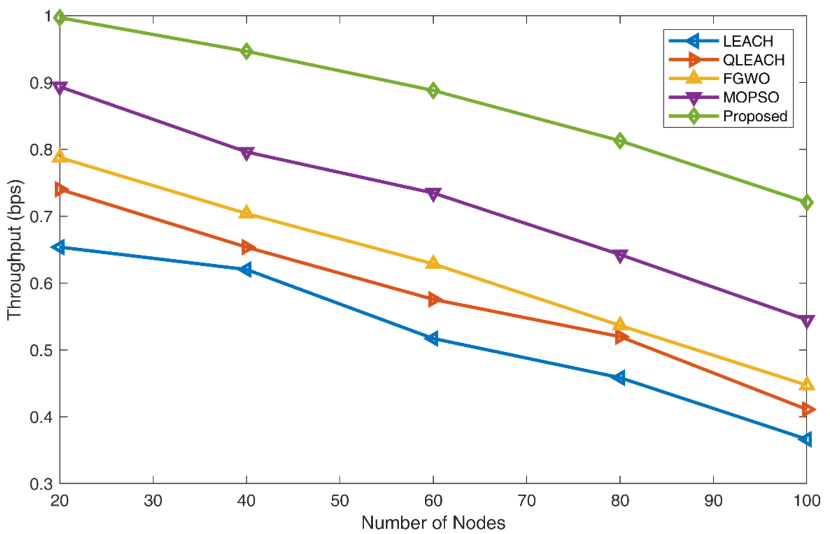

Figure 5 Performance Analysis of throughput

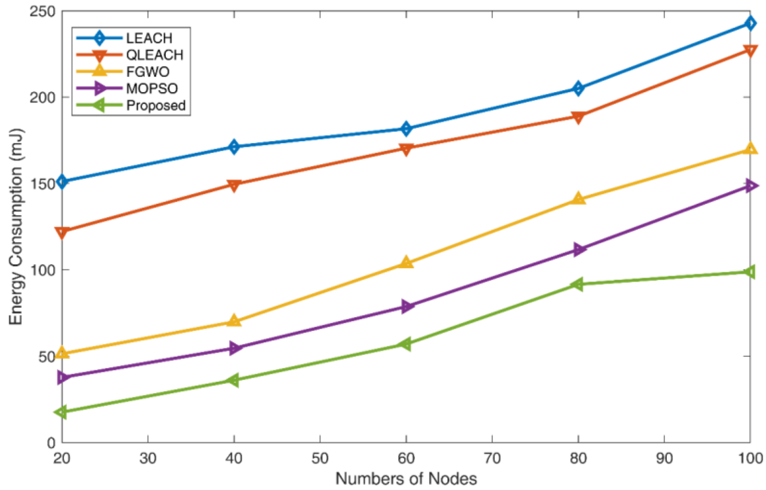

Figure 6 Performance Analysis of Energy consumption

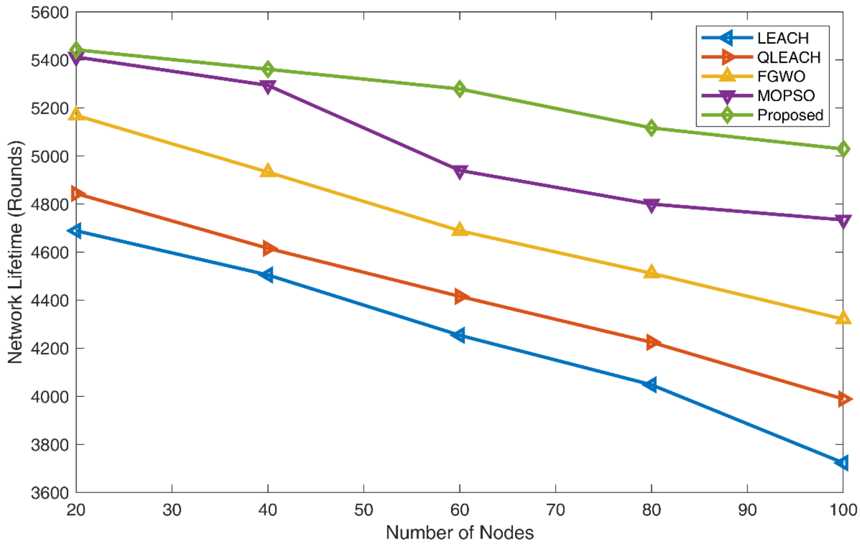

Figure 7 Performance Analysis of network lifetime

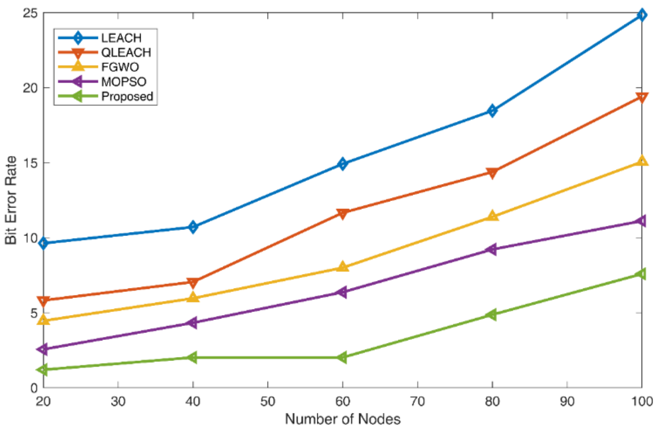

Figure 8 Performance Analysis of bit error rate

V. Results and Analysis

This section presents the result analysis of the wireless sensor network (WSN) simulation conducted within a dedicated simulation area, as outlined in Table 1. The simulation process was carried out using MATLAB2018 software, and several key performance parameters were measured, including End-to-End Delay, Packet Delivery Ratio (PDR), Throughput, Energy Consumption, Network

Lifetime, and Bit Error Rate (BER). These parameters provide a comprehensive evaluation of the network's performance and efficiency under different routing protocols and optimization approaches. To analyse the results, the proposed algorithm was implemented alongside existing algorithms, including LEACH, QLEACH, FWGO, and MOPSO, for comparative assessment. The performance metrics of these algorithms were evaluated and visualized in Figures 2 through 8. The comparative analysis highlights the proposed algorithm's superiority in terms of energy efficiency, higher throughput, improved packet delivery ratio, and extended network lifetime, demonstrating its ability to address the limitations of existing methodologies effectively. By minimizing energy consumption and reducing BER, the proposed solution significantly enhances the overall performance and reliability of the WSN. In figure 2 presents, the number of nodes increases from 20 to 100, the proposed algorithm consistently outperforms all other algorithms, achieving the lowest values across all node counts. For instance, at 20 nodes, the proposed algorithm shows a value of 1.56 compared to 6.15 for LEACH and 3.12 for MO-PSO. Similarly, at 100 nodes, the proposed algorithm's value rises to only 4.32, whereas LEACH and MO-PSO reach 9.86 and 7.45, respectively. This demonstrates the proposed algorithm's superior energy efficiency and scalability in larger network scenarios. In figure 3 presents, the number of nodes increases from 20 to 100, the proposed algorithm consistently outperforms the other methods, achieving the highest values across all node counts. For example, with 20 nodes, the proposed algorithm achieves 99.53, surpassing MO-PSO at 98.41 and LEACH at 92.81. Similarly, at 100 nodes, the proposed algorithm maintains strong performance at 97.52, significantly higher than LEACH at 84.78 and QLEACH at 89.89. This demonstrates the proposed algorithm's robustness and superior effectiveness in maintaining high network performance even as network size grows. In figure 4 presents, the number of nodes increases from 20 to 100, the proposed algorithm consistently demonstrates the lowest values, indicating superior efficiency. For instance, at 20 nodes, the proposed algorithm achieves a value of 1.1, compared to 8.91 for LEACH and 2.68 for MO-PSO. Similarly, at 100 nodes, the proposed algorithm maintains an efficient performance with a value of 2.78, significantly better than LEACH at 16.22 and QLEACH at 12.21. These results highlight the proposed algorithm's ability to minimize resource usage effectively, ensuring optimal performance even in larger network scenarios. In figure 5 presents, 20 nodes, the proposed algorithm achieves the highest value of 0.9969, outperforming MO-PSO at 0.8937 and F-GWO at 0.7877, while LEACH lags behind at 0.6538. As the number of nodes increases to 100, the performance metric decreases for all algorithms, but the proposed algorithm continues to excel with a value of 0.7207, significantly better than MO-PSO at 0.545, F-GWO at 0.4473, and LEACH at 0.3664. These results demonstrate the proposed algorithm's superior efficiency and robustness, maintaining high performance even as the network size scales. Figure 6 presents, 20 nodes, the proposed algorithm achieves the lowest value of 17.63, significantly outperforming MO-PSO at 37.74, F-GWO at 51.42, and LEACH at 151.16. As the number of nodes increases to 100, the values for all algorithms rise, but the proposed algorithm continues to demonstrate superior efficiency with a value of 98.88, compared to 148.75 for MO-PSO, 169.66 for F-GWO, and 242.86 for LEACH. This consistent performance highlights the proposed algorithm's ability to minimize resource consumption effectively, making it highly efficient for larger networks. Figure 7 presents, 20 nodes, the proposed algorithm achieves the highest value of 5442, surpassing MO-PSO at 5412, F-GWO at 5169, and LEACH at 4689. As the number of nodes increases to 100, the performance decreases for all algorithms. However, the proposed algorithm maintains its superiority with a value of 5029, significantly higher than MO-PSO at 4734, F-GWO at 4321, and LEACH at 3723. These results highlight the proposed algorithm's consistent ability to achieve higher throughput or delivery efficiency, demonstrating its robustness and scalability in larger networks. Figure 8 presents 20 nodes, the proposed algorithm demonstrates the lowest value of 1.2, significantly outperforming MO-PSO at 2.56, F-GWO at 4.46, and LEACH at 9.63. As the number of nodes increases to 100, the values for all algorithms rise, but the proposed algorithm remains the most efficient with a value of 7.59, compared to 11.12 for MO-PSO, 15.06 for F-GWO, and 24.84 for LEACH. These results emphasize the proposed algorithm's superior capability to minimize resource consumption, making it highly effective for large-scale networks.

VI. Conclusion & Future Work

The efficient utilization of energy improves lifecycle of wireless sensor network. in this study proposed hybrid swarm intelligence-based algorithm for the selection of cluster head and improves the performance of sensor network. this paper focus on two tradeoffs parameters of wireless sensor networks such as distance factor and convergence problem of network. the proposed algorithm encapsulated hybrid fitness function to manage intra-cluster distance, inter cluster distance and energy balancing factors. The hybrid swarm intelligence algorithm is combination of moth flame optimization and marine predators' algorithms. The moth flame optimization algorithm covers the problems of distance factors of cluster head and marine predator's algorithm minimize the problems of network convergence. The algorithm is simple in concept and has low computational complexity, enabling fast and efficient coverage. It achieves optimal network coverage within a minimal number of iterations. Compared to other intelligent optimization and conventional algorithms, it significantly enhances network node coverage. Furthermore, as an additional optimization objective, the algorithm notably reduces the average energy consumption of network nodes. In summary, the algorithm outperforms comparable intelligent optimization algorithms in terms of convergence speed, network coverage, and energy efficiency, making it particularly suitable for the network coverage of homogeneous wireless sensor networks. However, while the proposed hybrid algorithm improves the network's lifetime and operational efficiency, some regional nodes tend to become overly clustered during its application, which may require further refinement. In the future, the energy efficiency of the proposed model can be further enhanced by incorporating data aggregation and compression techniques at the cluster heads (CHs) within the network.

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