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A Fitness Function-Based Approach For Wireless Sensor Network Clustering with Lungs Performance Optimizer

S.Venkatasubramanian
Department of Computer Science and Business Systems, Saranathan College of Engineering, Trichy India
Email: veeyes@saranathan.ac.in

ABSTRACT

To gather and analyze physical data from the environment, Wireless Sensor Networks (WSNs) are created by a large number of spatially dispersed nodes on the wireless network. Problems with cluster head transmission line construction, redundancy of working nodes, and random selection of cluster heads all had an effect on the network and its energy usage. Because of this energy limitation, both the network longevity and energy-efficient routing are affected. Research on methods to reduce energy usage and increase the network's lifespan is, hence, focused on these two issues. Network performance is affected by energy consumption, communication overhead, and data transmission reliability, all of which are influenced by the fundamental process of cluster head (CH) selection. Using the Lungs Performance Optimizer (LPO), a bio-inspired optimization algorithm developed to improve the efficiency of CH selection and extend the lifetime of the network, to present an enhanced method for CH selection in this study. Our approach utilizes a fitness function incorporating key performance metrics: Average Intra-cluster Distance (AID), Average Sink Distance (ASD), Residual Energy (RE), and Cluster Head Balancing Factor (CHBF). The LPO algorithm ensures that CHs are optimally placed to minimize intra-cluster communication costs, maintain optimal distances from the sink node, and evenly distribute energy consumption among sensor nodes. Experimental evaluations demonstrate that the LPO-based CH selection method significantly outperforms conventional clustering techniques in terms of energy efficiency, network lifetime, and CH load balancing.

Keywords **- Cluster Head Selection, Cluster Head Balancing Factor, Lungs Performance Optimizer; Residual Energy, Wireless Sensor Networks.**

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I. INTRODUCTION

Wireless sensor networks (WSNs) use hundreds of thousands of sensor nodes to collect data through sensing, analysis, and retrieval [1]. These sensor nodes have better sensing, computation, and communication capabilities, and they're cheaper too [2]. A wide range of industrial and commercial applications, as well as medical applications, defensive performance, and weather prediction, make use of WSN [3]. The tiny WSN sensors can be powered by a little battery [4]. The sensor feeds data onto the main hub, the Base Station (BS), after processing it using an Analog-to-Digital Converter (ADC) [5]. At BS, the data is assessed for decision-making across many applications. By relaying data to other nodes in the network, WSN sensor nodes can serve as a kind of repeater [6-7]. It is important to handle the WSN's power source correctly because it can be replenished or swapped due to the sensor's placement in a hostile and no-land environment [8]. Factors influencing WSN design include energy efficiency, fault tolerance, scalability, and many more [9]. First, the WSN's sensors have sensed environmental parameters; second, data has been transmitted to the BS via the nodes, making use of the energy that the sensors consume. Environmental sensing and data processing use less energy than WSN data transfer [10].

With CHs, the WSN can reduce its power consumption. Remaining energy and the anticipated distance between the receiver and fusion center are two of the constraints that determine CH [11]. Choosing CH is important for delivering data in an energy-efficient manner. The CH in a WSN changes throughout the iterative process in order to enhance performance. In order to gather sensed data, the CH employs the Time Division Multiple Access (TDMA) technique [12]. Reducing and obtaining information in this way removes redundancies. Dynamic clustering is the most effective method for collecting data from numerous WSNs [13]. Many researchers are interested in dynamic clustering because of its potential for energy savings and efficient scaling, among other benefits.

Environmental monitoring, healthcare, industrial automation, and smart cities are just a few of the many applications where Wireless Sensor Networks (WSNs) have become essential technologies [14]. To gather and send data, these networks use a plethora of sensor nodes that can connect wirelessly. Nevertheless, WSNs face a significant problem in optimizing energy use because of their limited energy resources [15]. Selecting a subset of nodes to serve as Cluster Heads (CHs) and aggregate data from their

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clusters before sending it to the sink is one of the best ways to improve energy efficiency [16]. Choosing the right CH improves data transmission reliability, reduces communication overhead, and increases the lifetime of the network.

Inefficient clustering, excessive energy consumption, and an uneven distribution of CH are common problems with heuristic-based CH selection algorithms like LEACH (Low-Energy Adaptive Clustering Hierarchy) [17]. In response to these difficulties, to offer a bio-inspired optimization tool called the Lungs Performance Optimizer (LPO) as part of our sophisticated CH selection strategy. When it comes to CH selection, LPO is the way to go. It uses a fitness function to assess important network parameters including AID, ASD, RE, and CHBF, which are all measures of performance. The suggested method guarantees balanced energy usage, efficient CH deployment, and longer network lifetime by integrating these metrics. These research aims primarily to:

- Develop an optimized CH selection mechanism using the Lungs Performance Optimizer (LPO) to enhance energy efficiency in WSNs.
- Minimize Average Intracluster Distance (AID) to reduce intra-cluster communication overhead and improve energy savings.
- Optimize Average Sink Distance (ASD) to ensure efficient data transmission from CHs to the sink, reducing overall network energy consumption.
- Maximize Residual Energy (RE) by balancing CH selection to prevent premature energy depletion of nodes.
- Improve Cluster Head Balancing Factor (CHBF) to ensure an even distribution of CHs, avoiding energy imbalances and network instability.

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II. RELATED WORKS

Cluster Head (CH) selection, enhanced routing strategies, and optimization methods such as Cuckoo Search, Harmony Search, K-Nearest Neighbors (KNN), and Ant Colony Optimization (ACO) have been the primary areas of interest for Swapana et al., [18]. To show how these methods increase network longevity, boost packet delivery rates, and improve network efficiency. Outlining the benefits and drawbacks of both classic and modern algorithms, this paper provides a comprehensive comparison. Better integration with AI technology and the necessity for flexible and dynamic algorithms are two examples of the research gaps highlighted. Presenting a road map for future developments in WSNs, this paper concludes by investigating emergent themes, such as hybrid optimization techniques and AI-driven approaches. Researchers and practitioners can use this synthesis as a roadmap to create WSNs that are more efficient and sustainable in the future.

Using an Improved Type-2 Fuzzy Logic System (IT2FLS) optimized using the Reptile Search Algorithm (RSA), Ambareesh et al. [19] presented a new, stable, and power-efficient routing system. In comparison to existing protocols, this state-of-the-art framework uses weighted ensemble clustering and matched ensemble choice techniques to improve cluster formation, which in turn increases community lifetime by 98%, improves packet delivery ratio (PDR) by 80%, and reduces average power consumption by 45%. While the RSA algorithm fine-tunes the bushy common sense club features to guarantee the best cluster head choice and reliable multi-hop communication paths, the IT2FLS model adapts routing selections in real time based on important parameters such as dynamic accept as true with factors, node power ranges, course delays, and energy consumption fees. Furthermore, our suggested method enhances safe routing by effectively mitigating the impact of hacked nodes, hence preserving the integrity of the community. The updated IT2FLS system from RSA routinely beats the new benchmarks, according to a battery of tests. It greatly improves efficiency and cuts down on work from beginning to end by 25%. These results indicate that this strong routing approach ensures both performance and efficient data delivery. The overall network stability is also ensured by it. In order to extend the lifespan of WSNs and boost confidence in critical applications, this research presents a complete routing solution that integrates energy conservation, security, and quality of service. It paves the way for implementation scenarios that require secure, low-power, and real-time data transmission, which is a major contribution to the WSN field.

To tackle the problems of energy balancing and routing in heterogeneous WSNs, Vijayaragavan et al., [20] created the FOAEAUC-SARP framework, which incorporates the innovative Fox Optimization Algorithm (FOA) and Snake Algorithm (SA). For CH selection, FOAEAUC-SARP uses FOA-based uneven clustering, and for optimal data transmission, it uses SA-based routing. By analyzing simulations extensively, the suggested FOAEAUC-SARP outperforms state-of-the-art models in terms of energy efficiency and performance. It solves important problems with previous methods and provides a solid solution for improving WSN performance. Three distinct case scenarios were considered in the investigation, each of which involved comparing the suggested approach's performance to that of several existing approaches and reproducing the approach with real-world applications. Compared to the other approaches, this one performs far better across the board.

For this reason, Shwetha et al. [21] propose an ML-based routing protocol that integrates GMCML with the energy-efficient Sea Lion Emperor Penguin Routing Protocol (EESLEPRP) in order to solve these issues. Finding the best route for a network is done using the EESLEPRP. To choose the best route, to take into account each node's leftover energy, latency, and distance. When compared, the proposed method achieves significant improvements, such as a throughput of 90.56%, a packet delivery ratio (PDR) of 97.76%, and a minimal packet loss ratio (PLR) of 2.23%. The model ensures optimal energy use with a delay of 1.38 ms from end to end. The outcomes show that the proposed method can extend the life of networks and boost UWSN performance.

A novel approach, suggested by Sachithanandam et al., [22], is the Energy-based Multi-Objective Donkey Smuggler Optimization approach (EM-DSOA). Optimizing the efficiency, security, and stability of WSN has never been easier than with our technique, which integrates multi-aspect optimization with a lightweight blockchain protocol. In its current form, EM-DSOA integrates blockchain technology to ensure secure data transport while optimizing energy consumption through adaptive routing and dynamic clustering. The method is evaluated in comparison to state-of-the-art methods using simulation examples of various network densities, such as Multi Weight Chicken Swarm Based Genetic Algorithm (MWCSG) and Adaptive Hybrid Cuckoo Search and Grey Wolf Optimization (AHCS-GWO). With a throughput gain of 1000%, a decrease of 91% in packet loss, and an energy efficiency of 99.13%, the results are clearly improved. Also, the model's end-to-end latency is incredibly low, making it ideal for real-time applications. The research highlights the fact that EM-DSOA may be adaptable and scalable, performing admirably in a wide range of dynamic contexts. The suggested approach advances our understanding of WSN optimization by focusing on energy efficiency, low latency, and secure communications all at once. In addition to meeting the technological demands of the present, this work lays the groundwork for the Internet of Things (IoT) and smart city deployments of the future and ensures the security of networks over the long term.

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III. Proposed Methodology

An opportunistic routing algorithm that is both energy-efficient and based on optimizers is suggested in this study. A novel opportunistic routing method is suggested for use in wireless sensor networks; it lessens power consumption and distributes it evenly among nodes. In the suggested model, a new parameter is introduced to choose the CHs. The following is an explanation of the vocabulary used in the suggested approach as well as the fitness function used in the suggested protocol.

A. System Model.

Whenever the threshold distance (d_0) is larger than propagation distance (d), node's energy consumption is relativeto d^2. Each node's total energy consumption during the transmission of an L-bit data packet can be described by the following equation:

$$E_{tx}(L,d) = \begin{cases} L \times E_{ele} + L + \varepsilon_{fs} \times d^2 & if\ d < d_0, \\ L \times E_{ele} + L + \varepsilon_{mp} \times d^4 & if\ d \geq d_0 \end{cases} \quad (1)$$

where $E_{tx}$and the amount of energy required to send εfs represents the amplification energy in the free space model, εmp stands for the multipath model, and d0 is the threshold transmission range. E_ele is the energy dissipated per bit to operate the circuit, which can be either transmitters or receivers.

When it comes to receiving data bits, the following equation gives the energy consumption of the receiver circuit.

$$E_{rx}(L) = L \times E_{ele} \quad (2)$$

whereE_{rx}modulation, digital coding, signal spreading, and filtering are among the many aspects that impact the energy consumption needed to receive information, while E_ele is the energy dissipation per bit needed to operate the circuit, i.e., the transmitters or receivers.

As a rule, radio wave propagation is quite complex and subject to a great deal of variation; the following equation is used to determine the overall energy loss:

$$E_{total} = E_{tx} + E_{rx} \quad (3)$$

B. Selection of Cluster Heads Using Proposed Approach.

A significant number of the planned research assumed various parameters for the clustering process, according to the literature review. When positioning the CHs in the WSNs, the SNs' residual energies were taken into account. To select a certain node to serve as CH, the suggested method takes residual energy, node centrality (NC), and neighborhood overlap (NOVER) into account. In addition, the suggested approach takes into account the evaluation of connection quality for routing in WSN.

A significant obstacle in WSN cluster construction is selecting the best cluster head. The CH node acts as a data aggregator and sender to the base station on behalf of all the SNs. Researchers working with WSNs have shown that fuzzy logic is more useful for choosing the best CH in recent years. In order to choose CH, three criteria were considered. To prolong the life of sensor networks and save energy, combine their NC, NOVER, and residual energy. The input parameters are listed below.:

Residual energy: the CH will be picked from nodes with highest energy. Consider E_i to be initial energy of node. After time "t," the energy spent by node $E(t)$ is expressed as follows:

$$E(t) = (n_{tpkts} \times a) + (n_{rpkts} \times b) \quad (4)$$

$$E_{RES} = E_i - E_i \quad (5)$$

wheren_{tpkts} and n_{rpkts} denote the number of data packets transmitted and received, respectively. "a" and "b" are constants with values between and (0, 1).

NC: it indicates the degree to which the selected CH is central to the entire network of its neighbors:

$$NC = \frac{\sqrt{\sum d^2(c_i, c_j)/T}}{M} \quad (6)$$

Where $d(c_{i,j})$ is the length between the cluster head node and any of its child nodes.

NOVER: A measure of the mutual neighborhood across a link's termination nodes is the NOVER approach. A low-NOVER link joins two separate networks, whereas a high-NOVER link can only join nodes inside the same network. The neighbors of nodes u and v are determined independently by N(u) and N(v).

$$NOVER(u-v) = \frac{2*|N(u)\cap N(v)|}{|N(u)|+|N(v)|-2} \quad (7)$$

A value of "1" for NOVER indicates that u and v have the same group of neighbors.

Fuzzy groups are transformed by the system inputs named NC, NOVER, and residual energy. Basic characteristics with low, medium, or high residual energy are at your disposal. The three requirements for membership in NC are proximity, suitability, and distance. There are three categories for NOVER's qualities: good, medium, and bad.

1) Nascent of the Fitness Functions.

The following parameters are responsible for deriving the fitness function.

The CHs are chosen using a fitness function. This fitness function makes sure that the most energetic node and the one closest to the base station are more likely to be chosen as CH.

(1)Average Intracluster Distance (f_1). The total of the distances between each sensor node and its corresponding CH is known as the intracluster space. Reducing this intracluster distance is necessary to lower network energy consumption. It is provided as follows since sensor nodes spend some energy when corresponding with their own CHs:

$$f_1 = \sum_{j=1}^{m}\left(\frac{1}{l_j}\sum_{k=1}^{l_j} dis\left(s_{k,CH_j}\right)\right) \quad (8)$$

(2) Average Sink Distance (f_2). An average sink distance is calculated by dividing the distance between the base station and the cluster head by the total number of sensor nodes in that CH. Because of the outsized effect that space has on power usage, this factor is taken into account. Consequently, cutting down on this distance is essential for energy conservation.

$$f_2 = \sum_{j=1}^{m}\left(\frac{1}{l_j} dis(CH_j, BS)\right) \quad (9)$$

(3) Energy Residual (f3). Energy consumption needs to be decreased because a network's life cycle depends on energy utilization. Because of this, this parameter is

$$f_3 = \frac{1}{\sum_{j=1}^{m}(E_{CH_j})} \quad (10)$$

CH Balancing Factor (f4), figure four. The cluster needs to be evenly distributed, while the random placement of sensor nodes increases the likelihood of both big and small groups forming. Therefore, when balancing energy usage, this feature is considered.

$$f_4 = \sum_{j=1}^{m}\frac{n}{m} - l_j \quad (11)$$

The aforementioned fitness functions are perfectly aligned with each other. The following is the fitness function:

$$Fitness\ function = (p \times f1) + (q \times f2) + (f3 \times r) + (f4 \times (1 - p + q + r)) \quad (12)$$

where p, q, and r represent constant value and p + q + r=1
.

C. Lungs Performance-based Optimization (LPO)

Lungs Performance-based Optimization (LPO) [23] is an optimization algorithm inspired by the functioning of the human lungs. It incorporates principles such as gas exchange, exploration, exploitation, and convergence mechanisms to efficiently find optimal solutions to complex problems.

1. Initialization

- **Population Initialization:** Generate an initial set of candidate solutions randomly or using heuristics. Each solution represents a potential answer to the optimization problem.
- **Fitness Evaluation:** Assess each solution's quality using a fitness function.
- **Parameters Setup:** Define parameters such as respiratory_rate (controlling exploration vs. exploitation) and max_iterations (limiting the number of iterations).

2. Inhalation Phase (Exploration)

- **Generate Candidates:** For each solution, generate new candidates by perturbing the current solution, exploring new areas of the solution space.
- **Evaluate Candidates:** Assess these candidate solutions with the fitness function.
- **Update Solutions:** Replace current solutions with better candidates.

3. Exhalation Phase (Exploitation)

- **Selection:** Choose top-performing solutions based on their fitness.
- **Replacement:** Replace less fit solutions with top solutions to focus on promising areas.

4. Diffusion of Gases (Convergence Mechanism)

- **Convergence Check:** Determine if the algorithm has converged based on criteria like minimal improvement in fitness.
- **Break if Converged:** Exit early if convergence criteria are met.

5. Adjust Respiratory Rate

- **Tune Exploration/Exploitation Balance:** Adjust the respiratory_rate to balance between exploring new solutions and exploiting current solutions.

6. Logging and Monitoring

- **Track Progress:** Optionally log the best solution and its fitness value for analysis.

7. Return the Best Solution

- **Final Solution:** After iterations or meeting convergence criteria, return the best solution found.

LPO_Algorithm (parameters): Initialize population of solutions, Evaluate initial population, Set respiratory_rate to initial value, Set max_iterations

For iteration = 1 to max_iterations:

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```
    # Inhalation Phase (Exploration)
    For each solution in population:
        Generate new candidate solutions (neighbors)
        Evaluate new candidate solutions
        # Update solutions based on fitness
        If candidate solution is better:
            Replace the current solution with the candidate solution
    # Exhalation Phase (Exploitation)
    Select top solutions based on fitness
    Replace less fit solutions in the population with top solutions
    # Diffusion of Gases (Convergence)
    Perform a convergence check
    If convergence criteria are met:
        Break
    # Adjust Respiratory Rate
    Adjust respiratory_rate based on current iteration
    # Optional: Logging and Monitoring
    Log the best solution and its fitness value
Return the best solution found
```

D. Energy-Efficient Opportunistic Routing (EEOR) Protocol.

To evaluate the effectiveness and dependability of the method, routing protocols need to be examined. The following are the steps involved in routing:
Step 1: Every node routinely sends data regarding the links' quality.
Step 2: A node determines the default path, and using this information, a list of transferring nodes is sent.
Step 3: The node then sends out a data packet with this information.
Step 4: A transfer timer is displayed and the packet is saved by the nodes of the transfer list.
Step 5: The node closest to the destination sends the packet first, using a tiny timeout.
Step 6: The other nodes will remove the pertinent packet from their queues to prevent repeated broadcasts.
An important consideration in WSN is the energy efficiency of the network, which encompasses both the number of sink nodes (base stations) and SN. In sink nodes, you can find both fixed and detachable sinks. Every node in the cluster communicates with CH. Now CH is the transmitter and the nodes that receive are the sinks. Consequently, there should be minimal power consumption, delay, and traffic throughout the route from the transmitter to the receiver [24].

It is of the utmost importance to select the shortest route for message transmission. The routing schedule dictates the use of the fastest route, even though it has other potential connections. Link quality and shortest path discovery are two crucial problems in routing programs. To provide an approach for data transfer called energy-efficient opportunistic routing (EEOR) to deal with these two problems. In routing areas, EEOR is employed to address link issues, resulting in a significant reduction in time complexity.

The quantity of data acquired by larger networks is a major energy hog, leading nodes to power down too soon. In order to prolong the life of the network, various protocols have been developed to reduce the power consumption during data sampling and gathering. Despite its best efforts, the EEOR protocol fails to account for residual energy balance or packet delay in its pursuit of network energy efficiency [25]. In order to minimize power usage, this protocol optimizes algorithms for candidate selection and prioritization. Also, the transmission power can be changed with the help of EEOR. As the transmit power rises to the maximum threshold, the number of neighboring candidates will be increased.
So, for varying degrees of transmit strength, the transmitter will insert more nodes into the sequence. Among all reachable nodes, the sender sorts them by energy cost and selects the one with the lowest consumption. With EEOR, data transmission and reception are faster and the routing list is less than with the current protocol. In comparison to the current method, EEOR reduces energy consumption overall. Outperforming other current protocols, EEOR achieves the best packet loss rates and end-to-end latency

IV. RESULTS AND DISCUSSION

The experiments are carried out on MATLAB environment and the proposed model istested by using different metrics.

A. Validation analysis of proposed model

Table 1 and Figure 1 mentions the validation analysis of proposed model with existing optimizer for energy consumption.

Table 1: Analysis of Energy Consumption (in mJ)

No. of nodes	**100**	**200**	**300**	**400**	**500**
Butterfly optimizer	0.08	0.120	0.160	0.180	0.190
Wolf optimizer	0.06	0.10	0.135	0.140	0.145
Sea Horse optimizer	0.04	0.080	0.090	0.095	1.10
Proposed	0.01	0.04	0.05	0.06	0.08

The comparative analysis of energy consumption across different optimization techniques (Butterfly Optimizer, Wolf Optimizer, Sea Horse Optimizer, and the Proposed Model) based on the number of nodes (100 to 500). The Butterfly Optimizer exhibits the highest energy consumption, starting at 0.08 for 100 nodes and increasing to 0.19 for 500 nodes, indicating inefficient energy utilization. The Wolf Optimizer performs better, consuming 0.06 at 100 nodes and reaching 0.145 at 500 nodes, but still shows a steady rise in energy usage as the network scales. The Sea Horse Optimizer is more efficient initially, consuming just 0.04 at 100 nodes, but its energy consumption unexpectedly spikes to 1.10 at 500 nodes, suggesting instability and inefficiency in larger networks. The Proposed Model significantly outperforms all existing techniques, consuming the least energy across all configurations—starting at 0.01 for 100 nodes and gradually increasing to just 0.08 for 500 nodes. This demonstrates its superior energy efficiency, optimized resource allocation, and effective network management, ensuring prolonged network lifetime. The drawbacks of existing models include Butterfly and Wolf Optimizers' inefficient energy usage over time, and the Sea Horse Optimizer's unstable energy consumption at higher node counts. The Proposed Model effectively overcomes these limitations by incorporating energy-aware optimization strategies, reducing power consumption, and ensuring a more sustainable and scalable network performance.

Table 2 and Figure 2 mentions the validation analysis of proposed model for network lifetime. The comparative analysis of network lifetime across different optimization techniques (Proposed Model, Sea Horse Optimizer, Wolf Optimizer, and Butterfly Optimizer) based on the number of nodes (100 to 500). The Proposed Model achieves the highest network lifetime across all node

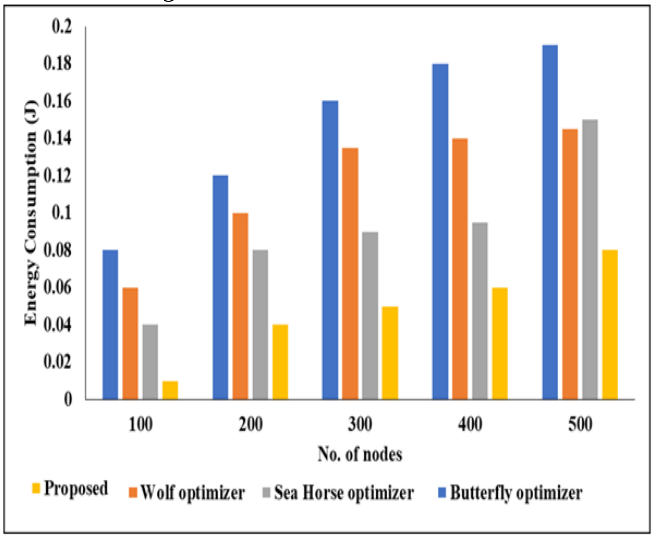

Figure 1: Energy Consumption of the proposed model

Table 2: Network lifetime(in ms)

No. of nodes	100	200	300	400	500
Proposed	9804	9713	9624	9542	9467
Sea Horse	6821	6603	6490	6290	6098
Wolf optimizer	5678	5598	5432	5309	5256
Butterfly optimizer.	3934	3876	3760	3640	3560

configurations, starting at 9804 for 100 nodes and gradually decreasing to 9467 for 500 nodes, indicating superior energy efficiency and resource management. The Sea Horse Optimizer follows, with a significantly lower network lifetime (6821 at 100 nodes, reducing to 6098 at 500 nodes), demonstrating moderate efficiency but higher energy depletion over time. The Wolf Optimizer performs worse, with network lifetimes ranging from 5678 (100 nodes) to 5256 (500 nodes), showing faster energy consumption and reduced longevity. The Butterfly Optimizer has the lowest network lifetime, starting at 3934 for 100 nodes and dropping to 3560 for 500 nodes, indicating poor energy conservation and rapid depletion of network resources. The drawbacks of existing models include the Butterfly Optimizer's weak energy management, the Wolf Optimizer's lower stability in large-scale networks, and the Sea Horse Optimizer's moderate efficiency but suboptimal longevity. The Proposed Model outperforms all by significantly extending network lifetime through optimized energy utilization, load balancing, and improved routing strategies, making it the most efficient approach for prolonged network sustainability.

V. CONCLUSION

In this study, to introduced an optimized Cluster Head (CH) selection strategy for Wireless Sensor Networks (WSNs) using the Lungs Performance Optimizer (LPO). The primary objective was to enhance network lifetime, improve energy efficiency, and ensure balanced CH selection through an

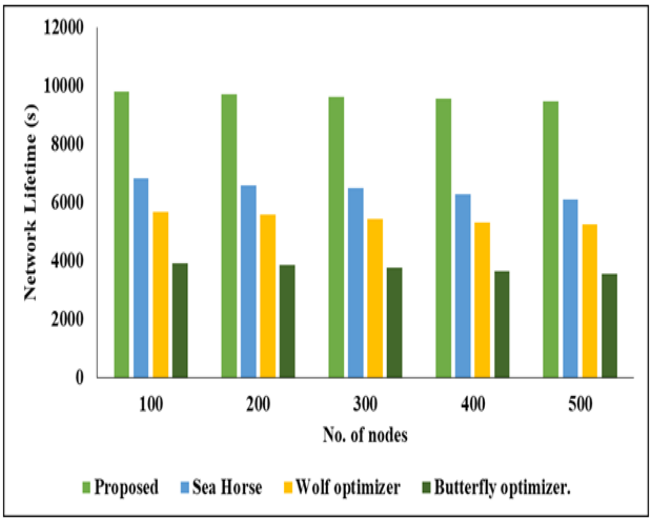

Figure 2: Network Lifetime of the proposed model

adaptive optimization technique. The effectiveness of the proposed approach was evaluated using a well-defined fitness function incorporating key performance metrics: Average Intra-cluster Distance (AID), Average Sink Distance (ASD), Residual Energy (RE), and Cluster Head Balancing Factor (CHBF).Our experimental results demonstrate that the LPO-based CH selection significantly enhances WSN performance compared to traditional clustering algorithms. The key findings include:

Reduced Average Intra-cluster Distance (AID): The optimization process ensures that sensor nodes are grouped into clusters with minimal intra-cluster distances, leading to lower intra-cluster communication costs and reduced energy dissipation.

Optimized Average Sink Distance (ASD): The selected CHs maintain an optimal distance from the sink node, ensuring efficient multi-hop communication and reducing overall transmission energy.

Higher Residual Energy (RE): The proposed LPO-based approach balances energy consumption across CHs,

preventing premature energy depletion and extending the overall network lifetime.
Improved Cluster Head Balancing Factor (CHBF): The algorithm ensures a well-distributed CH selection process, preventing CH congestion and enhancing fairness in energy utilization among sensor nodes.

The results confirm that the LPO-driven CH selection method provides a well-balanced trade-off between energy efficiency, communication cost reduction, and cluster stability. By optimizing CH selection through an effective fitness function, our approach significantly prolongs network lifespan and enhances data transmission reliability in WSNs.

A. Future Scope

Future work can focus on dynamic CH re-selection mechanisms to adapt to changing network conditions and further improve stability. Additionally, integrating LPO with hybrid metaheuristic algorithms could provide enhanced optimization capabilities for large-scale WSN deployments. The approach can also be extended to heterogeneous WSNs, IoT applications, and real-time monitoring systems, where energy efficiency and adaptive clustering play a critical role in network sustainability.

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Author Biography

Dr.S.Venkatasubramanian received a B.E. degree in Electronics and Communication from Bharathidasan University, M.E. degree in Computer science from Regional Engineering College,Trichy and Ph.D from Annamalai University. He has 26 years of teaching experience. His areas of interest include mobile networks, Network Security and Software Engineering. He has published 60 papers in international journals and 25 papers in international conferences. He has also registered four patents. At present, he is working as an Associate Professor in the Department of Computer science and Business systems at Saranathan College of Engineering, Trichy, India. He is also AWS Certified Cloud Practitioner and Microsoft certified Azure fundamentals. He has also passed NPTEL certification exams. He has given many technical talks outside his institution and participated in many workshops and FDPs. He has also authored books on “Software Engineering” and “Fundamentals of Mobile and Pervasive Computing”, “Big data Analytics”, “Basic Electrical and Electronics Engineering”,“python programming” and “Industrial Data Communication”. He is the recipient of the Global teacher award from AKS academy , Dr.Sarvepalli Radhakrishnan lifetime achiever national award and Best Teacher award from Institution of Engineers in 2024.