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Adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm (aHSSOGA) in clustering of Wireless Sensor Networks

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Abstract

Wireless Sensor Networks face significant energy constraints that directly impact network lifetime and data collection efficiency. While Low-Energy Adaptive Clustering Hierarchy (LEACH) has been foundational since the early 2000s, persistent challenges including isolated nodes and energy hotspots limit its effectiveness. This work proposes adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm (aHSSOGA), a metaheuristic approach that combines adaptive parameter tuning with refined objective functions to optimize cluster head selection. Unlike conventional methods, aHSSOGA dynamically adjusts crossover and mutation probabilities based on operator performance and incorporates velocity dampening to balance exploration and exploitation. The five refined objective functions specifically target isolated node and hotspot mitigation. Implemented with an enhanced LEACH re-clustering mechanism that reduces overhead, aHSSOGA demonstrates substantial improvements over LEACH, HSAPSO, HFAPSO, HGWOSFO, and standard HSSOGA across six key performance metrics: average residual energy (5.55% to 9.12% improvement), network lifetime (7.18% to 19.26% improvement), re-clustering frequency (93.5% reduction), total data delivery (11.98% to 32.36% improvement), network throughput, and end-to-end delay. These results confirm that adaptive hybrid metaheuristics with refined objectives provide a practical and effective solution for extending WSN operational lifespan.

Keywords: Wireless Sensor Networks, Cluster Head Selection, Energy-Efficient Clustering, Network Lifetime

1. Introduction

Wireless Sensor Networks (WSNs) consist of hundreds or thousands of tiny sensor nodes capable of collecting, processing, and transmitting data for analysis in communications between military and disaster management applications. [1], [2] These nodes are small and have limited battery power and memory. In the early 2000s, a low-energy Adaptive Clustering Hierarchy (LEACH) was introduced to conserve their limited Energy. [3]. LEACH randomly selects a few nodes as cluster heads (CHs), with other nodes joining them rotationally. However, it falls short due to isolated nodes and hotspot problems.

Inefficient clustering or CH selection can isolate distant nodes, forcing them to act as their leader and transmit directly to the sink, causing rapid battery drain and network instability. It also strains nodes closer to the sink, creating energy “holes” [4], [5]. Researchers have introduced cost-effective and easy-to-implement metaheuristic algorithms based on biological and natural optimization theories to address the challenges of Wireless Sensor Networks. These algorithms are crucial in handling Cluster Head (CH) selection with specific objectives for efficient clustering. Their exploration and exploitation capabilities help locate optimal solutions to maintain a stable and energy-efficient network [6]. In WSNs, these algorithms handle CH selection with specific objectives for efficient clustering. Their exploration and exploitation capabilities help locate optimal solutions to maintain a stable and energy-efficient network [7]

These advantages led us to develop a hybrid metaheuristic algorithm that combines two nature-inspired methods for adaptive exploration and exploitation in CH selection. The approach effectively addresses isolated node and hotspot issues by adjusting these capabilities based on factors like energy level and node status. The method's adaptability ensures it can respond to changing network conditions, thereby improving overall network lifetime, residual energy, and throughput.

The paper is organized as follows: Section 2 reviews related WSN clustering, Section 3 details the WSN model and assumptions, Section 4 presents the proposed adaptive hybrid metaheuristic, Section 5 discusses results and analysis, and Section 6 concludes the work. This comprehensive structure ensures that all aspects of the research, from the theoretical background to the practical implications, are thoroughly explored and analyzed, providing a robust foundation for the proposed aHSSOGA method.

2. Related Works

LEACH operates in two main phases: set-up and steady state, and employs adaptive clustering and cluster-head rotation to balance energy distribution [3]. While LEACH selects cluster heads before forming clusters, some variants reverse this sequence to improve efficiency [8]. Subsequent enhancements like LEACHDistance and LEACHDistance-M refine cluster head selection using threshold distances and residual node energy, improving network lifetime and data reception rate [9].

Nature-inspired algorithms have gained significant attention for their cost-effective ability to find near-optimal solutions in large-scale WSN applications. GA employs mutation and crossover operations to balance exploration and exploitation [10]. When applied to WSN cluster head selection in 2019, GA outperformed K-Means and LEACH by extending network lifetime and balancing node loads [11]. PSO updates particle positions and velocities to locate optimal solutions [12]. In 2016, EPSO-CEO applied PSO to cluster head selection using distance and energy-based fitness functions, reducing energy consumption [13]. While PSO-EECS improved network stability through hybrid approaches, PSO remains susceptible to local optima [14].

Sperm Swarm Optimization (SSO), introduced in 2018 [15], offers an alternative to PSO inspired by the sperm fertilization process. Empirical comparisons using benchmark functions demonstrated SSO's superiority over PSO and GA in unimodal optimization [16]. Hybrid approaches combining multiple metaheuristics demonstrate enhanced exploration-exploitation balance. HSAPSO integrates Harmony Search and PSO for cluster head selection using Euclidean distance and node energy criteria [17]. In high-dimensional problems, HSAPSO outperformed single-algorithm approaches, extending network lifetime and improving throughput.

In 2020, the HFAPSO combined Firefly Algorithm and PSO for cluster head selection using node energy and distance criteria, extending network lifetime and reducing energy consumption when integrated with LEACH-C [18], [19]. Subsequently, Iwasaki et al. introduced HGWOSFO [20] a hybrid of Grey Wolf Optimizer and Sunflower Optimization, focusing on energy and distance-based cluster head selection. While HGWOSFO outperformed non-hybrid algorithms in network lifetime, direct comparisons with other hybrid methods remained limited. Alnajjar et al. employed GA to optimize cluster head placement and sensor distribution (2022), enhancing coverage and network stability [21]. In 2023, GWO was adapted to LEACH; however, the emphasis on balancing exploration and exploitation remained insufficient to fully address isolated node and hotspot issues [22].

Most recent developments employ opposition-based learning and quantum principles. In 2024, Houssein et al. introduced Sea-Horse Optimizer with Opposition-Based Learning (SHO-OBL), integrating opposition-based learning to boost search diversity and employing greedy selection to retain high-quality solutions [23]. SHO-OBL outperformed GWO and Differential Evolution in network lifetime and energy stability.

However, its reduced robustness in high-dimensional symmetrical search spaces limits practical applicability, as opposition-based learning generates only a single opposite point. In a separate research, Rathee et al. [24] proposed Quantum-Inspired Genetic Algorithm approach Q-GEMS, leveraging quantum principles (q-bit representation) to improve convergence speed and solution diversity. Q-GEMS extended network lifetime by 5.1%, 21%, and 24% over comparable algorithms. Despite these gains, quantum operations remain computationally intensive, restricting scalability in dense networks.

Sharada et al. presented adaptive ant colony-based clustering (AACDIC), dynamically selecting cluster heads and adjusting clusters in real-time, reducing node power usage by 9.6% for primary users and 24.2% for secondary users compared to existing algorithms [25]. However, high communication overhead and real-time data demands pose scalability challenges for very large WSNs. Recent studies consistently demonstrate that adaptive parameter tuning enhances metaheuristic performance. Adaptive PSO parameter adjustment from exploration to exploitation outperforms static inertia weight strategies. Similarly, tuning GA's mutation and crossover values improves results in complex optimization and deceptive problems.

A comprehensive systematic review by Masum et al. [28] examined WSN anomaly detection methods, identifying that lightweight deep learning models enhanced with bio-inspired optimization, particularly SSO, achieve practical balance between detection accuracy and resource constraints. This finding aligns with the effectiveness of adaptive parameter tuning strategies in WSN optimization across multiple problem domains. While significant progress has been achieved through hybrid metaheuristics and adaptive tuning, two critical challenges persist: (1) isolated nodes that cannot efficiently reach any cluster head, forcing direct transmission to the base station and rapid energy depletion, and (2) energy hotspots where cluster heads near the base station deplete rapidly, creating communication voids. Existing methods address these issues individually but lack integrated solutions combining adaptive exploration-exploitation with refined multi-objective functions specifically designed to mitigate both challenges simultaneously. This work proposes aHSSOGA with five refined objective functions to comprehensively address these remaining challenges in wireless sensor network cluster head selection.

3. WSN Modelling and Assumptions

A. First Order Radio Model

The first-order radio energy model quantifies energy consumption based on transmission distance [3]. For transmissions beyond a threshold distance, the propagation model transitions from free space to multi-path attenuation[29], [30]. This crossover distance d_0 , is calculated as

$$d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \quad (1)$$

Where d_0 is the crossover distance, E_{fs} is the free-space amplifier energy, and E_{amp} is the multi-path amplifier energy.

Transmissions beyond d_0 incur significantly higher energy depletion than shorter transmissions. The transmission energy dissipation for normal nodes and CHs is expressed below: [29], [30]:

$$E_{TX}(k, d) \begin{cases} k * E_{elec} + k * E_{fs} * d^2, & d < d_0 \\ k * E_{elec} + k * E_{amp} * d^4, & d \geq d_0 \end{cases} \quad (2)$$

Where E_{TX} is the node transmission energy, E_{elec} is the per-bit electronics energy for transmit operations, and k is the packet size.

The energy dissipation of cluster nodes during reception is given by:

$$E_{RX} = (E_{elec} + E_{DA}) * k \quad (3)$$

Where E_{RX} is the reception energy and E_{DA} is the cluster-head data aggregation energy.

B. WSN Assumptions

WSNs comprise numerous homogeneous sensor nodes randomly and statically deployed within an $M \times N$ meter rectangular sensing field. All nodes possess identical initial energy levels and unique identifiers. Nodes communicate using multi-hop routing, consuming energy proportional to transmission distance.

The proposed model incorporates the following assumptions: (1) the sensing field contains no obstacles or interference; (2) all nodes can serve as cluster heads; (3) the base station is positioned outside the sensing field; and (4) node failure results exclusively from energy depletion. The primary objective is to minimize total network energy consumption by routing sensed data through optimally selected cluster heads among the n deployed nodes.

4. The Proposed Method

A. Adaptive HSSOGA (aHSSOGA)

WSN is a large-scale optimization problem requiring adaptive parameter tuning to enhance exploration and exploitation, addressing changing energy levels and node counts during sensing. HSSOGA combines SSO [15], inspired by the sperm fertilization process, and GA [10]. GA's crossover operator enhances exploitation, while its mutation operator improves exploration [31]. SSO also adjusts exploration and exploitation through sperm velocity, where faster sperms explore new regions, avoiding local optima, and slower sperms exploit toward global solutions [32], [33]. Enhanced with adaptive capabilities, HSSOGA [34] optimally selects cluster heads in WSN systems.

The crossover and mutation probabilities adaptively change based on the operator's performance on the initial population, ensuring the best global optimum is achieved. The adaptive probability calculation is shown below:

$$pc = \begin{cases} pc + 0.001, & fitCrossInit_{ave} < fitCross_{ave} \\ pc - 0.001, & fitCrossInit_{ave} > fitCross_{ave} \\ pc, & fitCrossInit_{ave} = fitCross_{ave} \end{cases} \quad (4)$$

$$pm = \begin{cases} pm + 0.001, & fitMutInit_{ave} < fitMut_{ave} \\ pm - 0.001, & fitMutInit_{ave} > fitMut_{ave} \\ pm, & fitMutInit_{ave} = fitMut_{ave} \end{cases} \quad (5)$$

Where pc is the crossover probability, pm is the mutation probability, $fitCrossInit_{ave}$ denotes the average fitness of the parent population prior to crossover, while $fitCross_{ave}$ is the average population fitness after crossover. Similarly, $fitMutInit_{ave}$ represents the average fitness of the parent population before mutation, and $fitMut_{ave}$ is the average fitness after mutation.

To strengthen exploitation, the sperm velocity should be lower than in the exploration stage. In metaheuristic search, adequate exploration of the solution space is necessary before intensifying the

search around the global optimum. Accordingly, the velocity dampening factor is reduced progressively over the maximum number of iterations to promote convergence toward the global optimum while mitigating entrapment in local optima. Dampening factors lie in the interval (0,1). The velocity dampening factor is linearly decreased as follows:

$$Decrement = \frac{1}{MaxIt} \quad (6)$$

$$Damp = Damp - Decrement \quad (7)$$

Where $MaxIt$ is the maximum number of iterations and $Damp$ is the dampening factor. $Damp$ starts at 1 to favor exploration, and its subsequent decrease reduces the sperm velocity, as shown in the SSO velocity equation below:

$$V_i = Damp \cdot V_i \cdot \log_{10}(pH_1) + \log_{10}(pH_2) \cdot \log_{10}(Temp_1) \cdot (x_{sBest_i} - x_i(t)) \\ + \log_{10}(pH_3) \cdot \log_{10}(Temp_2) \cdot (x_{sgBest} - x_i(t)) \quad (8)$$

Where V_i represents the velocity of the i th sperm, pH_1 , pH_2 and pH_3 are randomly generated pH values ranging from 7 to 14, $Temp_1$ and $Temp_2$ represent random temperature values within the range of 35.1°C to 38.5°C, x_{sBest_i} signifies the best personal location of the i th sperm, x_{sgBest} represents the optimal global position of the sperm and x_i corresponds to the current position of the i th sperm at iteration t .

The complete pseudocode for the aHSSOGA is provided below:

Algorithm 1: Adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm (aHSSOGA)

Begin Step 1: Step 2:

Set the number of population (nPop), maximum iteration (MaxIter) and iter = 0

Set the probability of Mutation, pm = 0.3, probability of Crossover, pc = 0.7 and Damp = 1.

Step 2: *Initialize the population(sperm, i) and calculate the fitness.*

Step 3: **while** (iter < MaxIter)

Step 4: *Calculate selection probabilities.*

Step 5: *Use Roulette Wheel to **SELECT** parents.*

Step 6: *Calculate the average fitness of selected parents before crossover, fitCrossInit_{ave}.*

Step 7: *Use **Uniform Crossover** on the selected parents.*

Step 8: *Calculate the average fitness of selected parents after crossover, fitCross_{ave}.*

Step 9: *Calculate the average fitness of selected parent before mutation, fitMutInit_{ave}.*

Step 10: *Use **Mutation**.*

Step 11: *Calculate the average fitness of selected parents after mutation, fitMut_{ave}.*

Step 12: *Merge, sort and truncate the population*

Step 13: *Calculate the velocity dampening factor, Damp using **Eq.(6)** and **Eq.(7)**.*

Step 14: *Apply SSO*

for i=1:population size **do**

*Calculate the sperm's velocity by using **Eq.(8)***

Apply velocity limit

Update the position of the sperm

Apply position limit

end for

Step 15: *Obtain the **xsgBest** value.*

Step 16: *Update pc and pm according to **Eq.(4)** and **Eq.(5)***

end while

End.

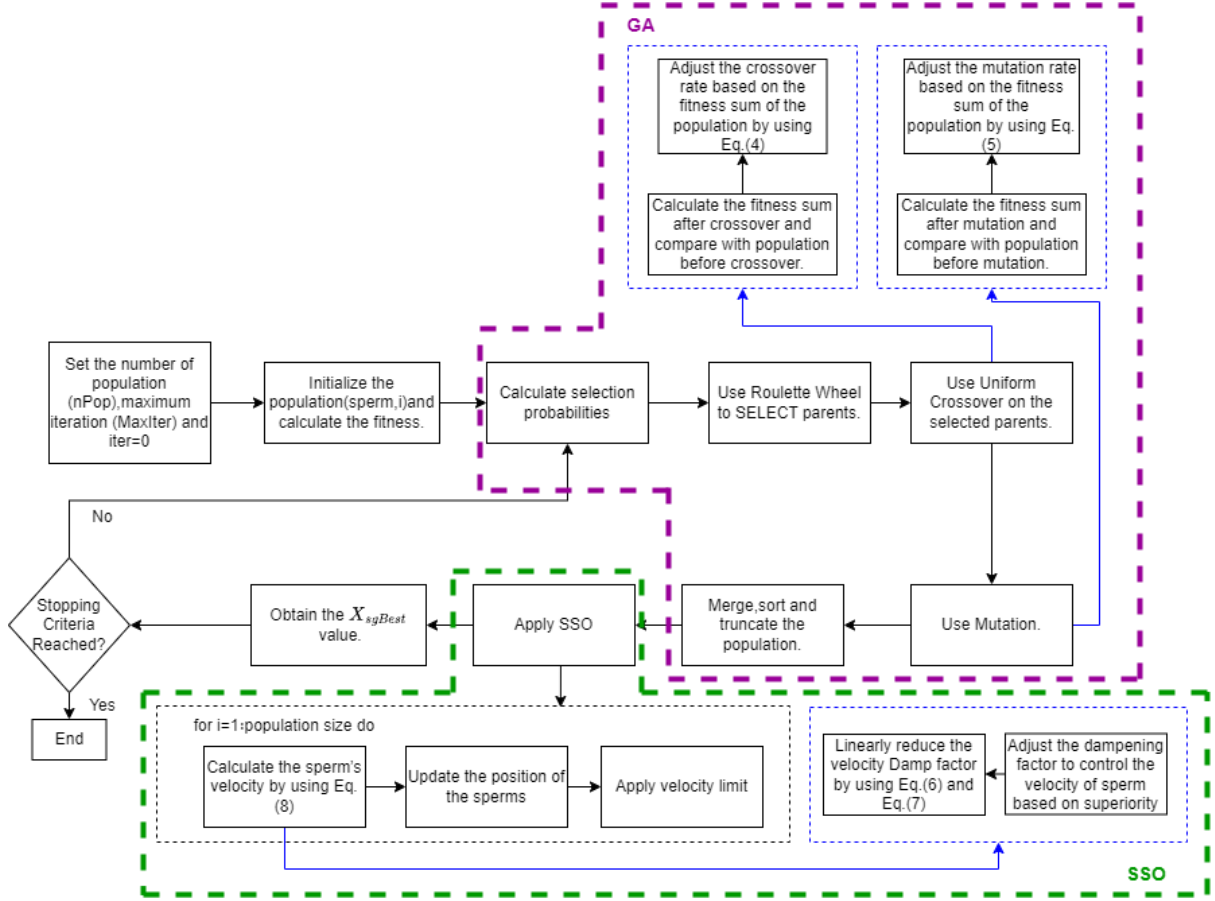


Figure 1 The process flow of the proposed adaptive HSSOGA.

B. Refined Objective Functions

This study introduces refined objective functions for adaptive HSSOGA to optimize particle fitness. These functions focus on addressing hotspot and isolated node issues, improving WSN stability and communication quality.

Objective 1: Optimize CHs, $dist(CH_i, CH_j)_{ave}$ the average distance among candidate CHs. Ensuring sufficient separation between selected CHs prevents adjacent clusters from being formed too closely, reduces isolated-node occurrences, and mitigates early energy depletion near the BS that can lead to energy holes.

$$dist(CH_i, CH_j)_{min} = \min \left(\sqrt{(CH_i - CH_j)^2} \right) \quad (9)$$

$$dist(CH_i, MN_j)_{ave} = \frac{\sum_{i=1}^{n_{ch}} (dist(CH_i, CH_j)_{min})}{n_{ch}} \quad (10)$$

Where CH are candidate cluster heads at positions i th and j th in the sensing field, and n_{ch} is the number of candidate CH nodes.

Objective 2: Optimize $dist(CH_i, MN)_{ave}$ the average distance from candidate CHs to member nodes. Ensuring short intra-cluster distances improves network coverage, reduces isolated-node occurrences, and minimizes transmission energy by shortening the required communication range.

$$dist(CH_i, MN_j)_{max} = \max\left(\sqrt{(CH_i - MN_j)^2}\right) \quad (11)$$

$$dist(CH_i, MN_j)_{ave} = \frac{\sum_{i=1}^{n_{mn}} (dist(CH_i, MN_j)_{max})}{n_{mn}} \quad (12)$$

Where CH is the candidate cluster head at position i , MN_j is the member node at position j in the sensing field, and n_{mn} denotes the number of member nodes.

Objective 3: Optimize CHs, CH_E_{ave} the average residual energy of candidate CHs, to avoid early CH death and prolong network stability.

$$E_i = E_i - (E_{TX} + E_{RX}) \quad (13)$$

$$CH_E_{ave} = \frac{\sum_{i=1}^{n_{ch}} E_i}{n_{ch}} \quad (14)$$

Where E_i is the residual energy of a candidate CH, E_{TX} and E_{RX} are the transmission and reception energy costs, and n_{ch} is the number of potential CH nodes.

Objective 4: Optimize CH_ND_{max} the maximum neighbor degree of candidate CHs, to balance cluster load and prevent early CH death from serving too many member nodes.

$$CH_ND_{max} = \max(CH_i ND) \quad (15)$$

Where $CH_i ND$ is node degree of i th candidate CH in the sensing field.

Objective 5: Optimize $CH_i INprob_{ave}$ the average isolated-node probability, to reduce isolated nodes after CH selection. A node is deemed isolated from the CH at position i if its distance exceeds the threshold, d_0 as calculated in Eq. (1), which also helps avoid energy-costly direct transmission to the BS.

$$CH_i INprob = CH_i INprob + 1, \quad dist(CH_i, MN_j) > d_0 \quad (16)$$

$$CH_i INprob_{ave} = \frac{\sum_{i=1}^{n_{ch}} CH_i INprob}{n_{ch}} \quad (17)$$

Where $CH_i INprob$ is the total isolated node for the i th CH, $dist(CH_i, MN_j)$ is the distance between the i th CH and the member nodes at j th position and n_{ch} is the number of potential cluster head nodes.

C. Proposed Clustering Techniques

In LEACH, clustering is re-executed every round and CHs are selected using the threshold, $T(n)$. Nodes elected as CHs have $T(n) = 0$ afterward, so they cannot serve as CHs in the next round, supporting CH rotation and longer network operation. $T(n)$ is calculated as in Eq. 18 [35]:

$$T(n) = \begin{cases} \frac{P}{1 - P * [r \bmod (1/P)]}, & n \in G \\ 0, & otherwise \end{cases} \quad (18)$$

Where P is the CH ratio, r election round, and, G is the set of nodes not elected as CHs in the previous $1/P$ round [35], [36].

In LEACH, re-clustering occurs every round until all nodes in the network are dead. This phase selects new CHs and forms clusters to conserve energy and balance workload. However, frequent re-clustering increases control messages, energy consumption, and routing table updates, leading to faster exhaustion of energy and memory in sensor nodes, ultimately destabilizing the network [37], [38].

To address this, enhanced LEACH clustering is proposed, reducing re-clustering by triggering it only when a CH's energy drops by 10% compared to its previous level. This approach minimizes energy depletion, prolongs node lifespan, and reduces re-clustering frequency. Enhanced LEACH is used as it mitigates the higher time complexity introduced by adaptive HSSOGA. The re-clustering trigger (RC) is shown in Eq. (19).

$$RC = \begin{cases} 1, & \text{if } CH_E_{i,j} \leq (CH_E_{i,j-1} - 0.1) \\ 0, & \text{if } CH_E_{i,j} > (CH_E_{i,j-1} - 0.1) \end{cases} \quad (19)$$

Where $CH_E_{i,j}$, and $CH_E_{i,j-1}$, represent the energy levels of the i th CH at rounds j and $j - 1$, respectively. RC is a binary flag: $RC = 1$ triggers clustering in the next round, whereas $RC = 0$ prevents clustering in the next round.

5. Experimental and Results

This section analyses the results obtained by each algorithm to optimize the CH selection process. Six methods are analyzed and compared, which consist of LEACH, HSAPSO, HFAPSO, HGWOSFO, HSSOGA, and proposed aHSSOGA. The simulations are carried out in MATLAB 2021a software in a computer running Windows 10 Pro with 16GB DDR4 RAM and AMD Ryzen 5 5600X 6-Core Processor 3.7 GHz processor with random deployment of 100 nodes on a 100x100m field. The list of parameters and environmental settings are depicted in Table 1 below.

Table 1: Simulation parameters

Parameters	Value
Packets size (k)	4000 bits
Base Station Location	(50, 150)
Area	100m x 100m
Number of Nodes deployed	100
Velocity damping factor (D)	Changed linearly (Initially = 0.1)
E_{elec}	50nJ/bit
E_{amp}	100pJ/bit/m ²
E_{fs}	0.0013pJ/bit/m ⁴
E_{DA}	5nJ/bit
Sensor Initial Energy	1J
Velocity damping factor (D)	Changed linearly (Initially = 0.1)
Mutation Percentage (pm)	Changed adaptively (Initially = 0.3)
Mutation Rate (mu)	0.02
Crossover Percentage (pc)	Changed adaptively (Initially = 0.7)
pH	Rand (7, 14)
Selection Pressure ($beta$)	8
Temperature	Rand (35.5, 38.5)

To assess the performance and efficiency of the proposed aHSSOGA in WSNs, we consider the following evaluation metrics: average residual energy, network lifetime, re-clustering frequency, total data delivered, throughput, and end-to-end delay. Each metric is defined below.

Average residual energy is a key indicator of energy efficiency and reflects how effectively the proposed approach selects optimal CHs and balances energy consumption across the network. The network's average residual energy is computed using Eq. (20):

$$E_r = \frac{\sum_{i=1}^n E_i}{n_{alive}} \quad (20)$$

Where E_r is the average residual energy in a round r , E_i is the residual energy of node i , and n_{alive} is the total number of alive nodes.

Network lifetime is measured by the number of nodes alive relative to the number of functional rounds. Key metrics include First Node Dead (FND), Half Node Dead (HND), and Last Node Dead (LND). FND marks the first node's energy depletion, HND occurs when 50% of nodes are dead, and LND represents complete energy exhaustion of all nodes. A longer FND indicates greater network stability, as node deaths disrupt information flow and coverage [36]. Re-clustering causes significant overhead and high energy consumption [38]. To address this, the proposed enhanced LEACH method reduces the re-clustering frequency. The number of re-clustering events until LND is compared with existing state-of-the-art methods to evaluate energy efficiency.

Total data delivery represents the total bits successfully transmitted during the network's operational rounds with at least one active node. Higher data delivery indicates better communication efficiency and ensures more data is collected by the base station for processing. The total data delivery for every round, TDD_r is calculated as in Eq. (21).

$$TDD_r = TDD_{r-1} + \sum_{i=1}^n P_{Delivered} \quad (21)$$

Where $P_{Delivered}$ is the total number of data delivered in bits to base station in r th round.

Network throughput, $Throughput_r$ shows the number of data being transferred over the total time it takes for the round to be completed. The higher the network throughput, the better the communication of the network will be as more data will be sent over a short period of time. These metrics can be calculated as in Eq. (22) below:

$$Throughput_r = \frac{TotalP_{sent}}{TT_r} \quad (22)$$

Where $TotalP_{sent}$ is the total data in bits sent in r th round and TT_r is the time taken for r th round to be completed.

End-to-end delay represents the time taken for packets to reach the BS. Therefore, EED_r should be minimized each round to ensure efficient data delivery. Since CH routing paths affect latency, longer multi-hop/multi-path routes tend to increase EED_r whereas optimal CH selection can reduce routing delay. The metric is defined in Eq. (23):

$$EED_r = \frac{\sum_{i=1}^{P_{received(i)}} (T_{received(i)} - T_{sent(i)})}{P_{received}} \quad (23)$$

Where $P_{received(i)}$ is the total packets received by the base station from node i in round r and $T_{received(i)}$ and $T_{sent(i)}$ are receive time and packet send, respectively..

A. Results comparison

The average residual energy measures the efficiency of CH selection, with optimal CHs reducing node energy consumption. As shown in Fig. 2, at round 1000, LEACH recorded 0.549J, while HSAPSO, HFAPSO, and HGWOSFO showed 0.534J, 0.533J, and 0.531J, respectively. In contrast, HSSOGA and its adaptive version (aHSSOGA) achieved 0.570J and 0.573J. The network retained 50% energy at round 1106 for LEACH, 1072 for HSAPSO, 1070 for HFAPSO, 1064 for HGWOSFO, and 1162 for HSSOGA. Adaptive HSSOGA achieved this at round 1171, outperforming LEACH by 5.55%, HSAPSO by 8.45%, HFAPSO by 8.63%, HGWOSFO by 9.12%, and HSSOGA by 0.77%. This demonstrates that aHSSOGA selects better CHs, minimizing unnecessary energy consumption.

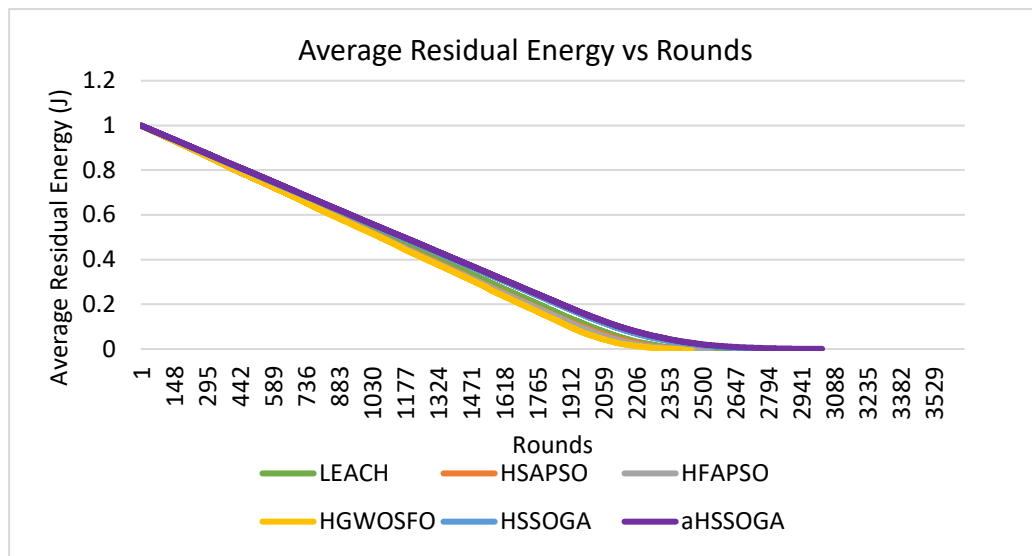


Figure 2 Average Residual Energy over Number of Rounds

To validate the performance in terms of the average residual energy recorded, a statical analysis was carried out using the “One-way ANOVA (Tukey’s test)” as depicted in table 2 below.

Table 2: Statistical analysis of average residual energy metric using “One-way ANOVA (Tukey’s test)” between aHSSOGA and the other existing methods.

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	-0.0344*	0.001*
	HFAPSO	-0.0340*	0.001*
	HGWOSFO	-0.0437*	< 0.001*
	HSAPSO	-0.0447*	< 0.001*
	HSSOGA	-0.0250*	0.032*
*. The mean difference is statistically significant at the 0.05 significance level.			

Table 2 shows that aHSSOGA outperformed LEACH, HSAPSO, HFAPSO, HGWOSFO, and HSSOGA in average residual energy, demonstrating its suitability for WSN environments in unimodal and multimodal scenarios. This analysis concludes that the adaptive method reduces energy consumption and preserves residual energy, extending the network lifetime.

Table 3 and Fig. 3 present the network lifetime metrics for each WSN clustering method, including FND, HND, and LND. While HFAPSO delayed FND to around 1904, aHSSOGA achieved it in around 1879.

However, aHSSOGA achieved the best performance in both HND and LND, indicating a prolonged network lifetime. Specifically, it increased network lifetime by **13.79%**, **18.04%**, **17.58%**, **19.26%**, and **7.18%** relative to LEACH, HSAPSO, HFAPSO, HGWOSFO, and HSSOGA, respectively. These gains are attributable to the refined objective design, which explicitly targets isolated-node occurrence and hotspot-induced energy depletion.

Table 3: Comparison of FND, HND, and LND values

Algorithm	FND	HND	LND
HGWOSFO	1788	2105	2453
LEACH	1779	2209	2619
HFAPSO	1904	2154	2541
HSAPSO	1821	2194	2490
HSSOGA	1844	2290	2820
aHSSOGA	1879	2348	3038

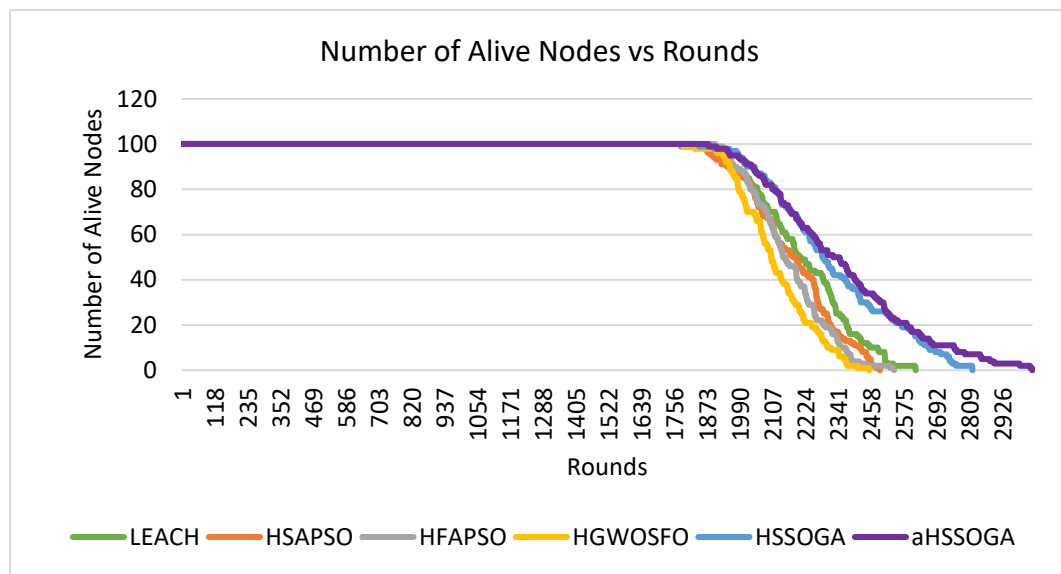


Figure 3: Total Operating Nodes over Number of Rounds

In efforts to reduce the re-clustering process to reduce the energy overhead cost [37], [38] and to maintain network stability, the total re-clustering process that takes place until all nodes die is analyzed in Table 4 below

Table 4: Comparison of total re-clustering values.

Algorithm	Re-Clustering times
LEACH	2618
HSSOGA	175
HGWOSFO	288
HFAPSO	244
HSAPSO	257
aHSSOGA	169

The results show that aHSSOGA had the fewest re-clustering calls, ensuring network stability. It performed re-clustering in only 5.56% of the total operational rounds, significantly reducing overhead

energy costs, as evidenced by the Tables and Figures. In contrast, LEACH clusters during every functional round, increasing process time and degrading performance due to excessive broadcast packet transmission [39].

The total packets delivered metric evaluates data transfer efficiency to the BS. As shown in Fig. 4, data delivery remained consistent across methods until around 1788, when the earliest node death occurred using HGWOSFO, affecting communication efficiency. HSSOGA and aHSSOGA demonstrate superior data delivery rates due to longer network lifetimes and efficient node communication. The total data transferred by LEACH, HFAPSO, HSAPSO, HGWOSFO, HSSOGA, and aHSSOGA until the last node dead are 1.65×10^{11} bytes, 1.57×10^{11} bytes, 1.52×10^{11} bytes, 1.47×10^{11} bytes, 1.91×10^{11} bytes, and 2.17×10^{11} bytes respectively. aHSSOGA outperforms LEACH by 23.96%, HSAPSO by 29.95%, HFAPSO by 27.65%, HGWOSFO by 32.36%, and HSSOGA by 11.98%, making it the most efficient for data delivery.

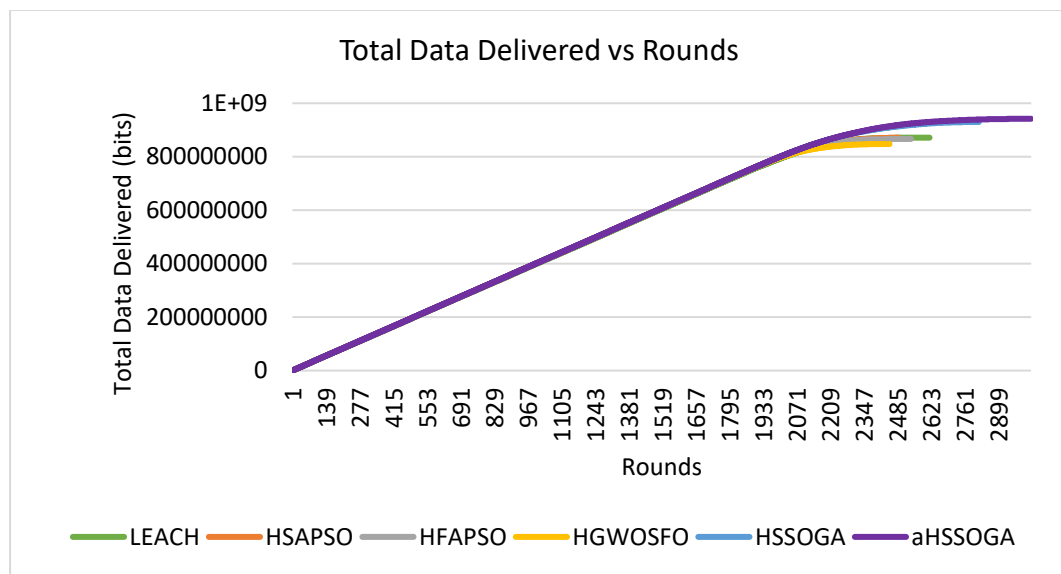


Figure 4: Total Packet Delivery over Number of Rounds.

To verify the significance of the results a One-way ANOVA (Tukey's test) statistical analysis is carried out as depicted in table 5 below.

Table 5: Statistical analysis of total data delivered metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods.

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	66783003.72*	< 0.001*
	HGWOSFO	91698142.51*	< 0.001*
	HSAPSO	83637632.86*	< 0.001*
	HFAPSO	76076316.17*	< 0.001*
	HSSOGA	28947931.26*	0.001*
*. The difference in means is significant at the 0.05 level.			

The table shows that aHSSOGA with enhanced LEACH clustering significantly outperforms LEACH, HSAPSO, HFAPSO, HGWOSFO, and HSSOGA, enabling a longer network lifetime and higher data transfer to the BS.

Higher network throughput indicates better communication efficiency. As shown in Fig. 5, LEACH achieved a higher average throughput (24,371.63 kbps) compared to HSAPSO, HFAPSO, HGWOSFO, and HSSOGA. However, aHSSOGA outperformed LEACH with 24,647.32 kbps. LEACH's direct CH-to-BS

transmission ensures uninterrupted data flow but increases energy consumption. In contrast, aHSSOGA uses multi-hop routing, slightly reducing throughput but significantly conserving node energy. A comparison of total packets delivered in the last 100 rounds (Fig. 6) reveals that LEACH frequently drops to zero throughput due to isolated node or hotspot issues, whereas aHSSOGA maintains stable throughput, even with many dead nodes.

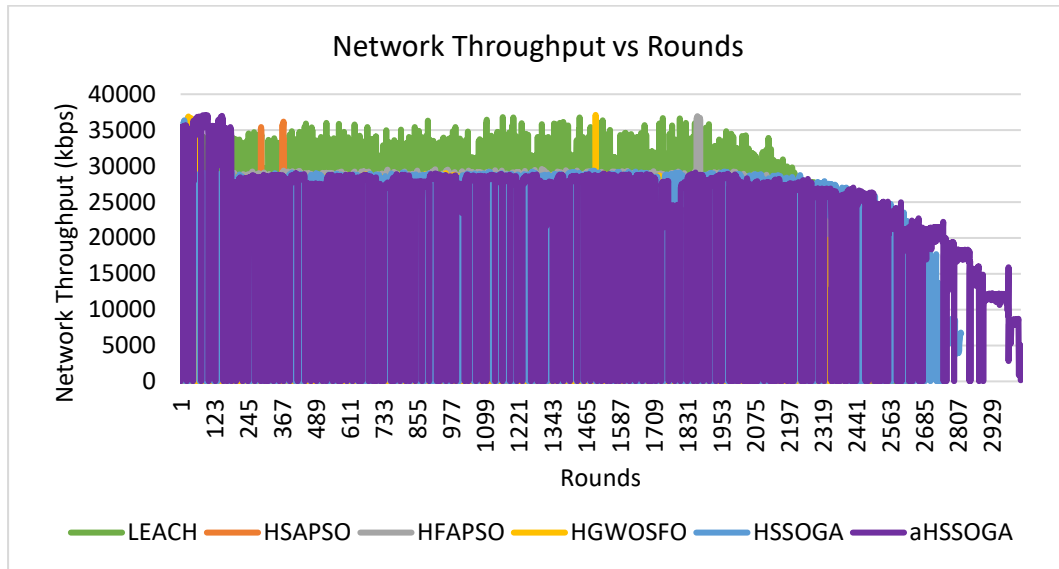


Figure 5: Network Throughput over Number of Rounds

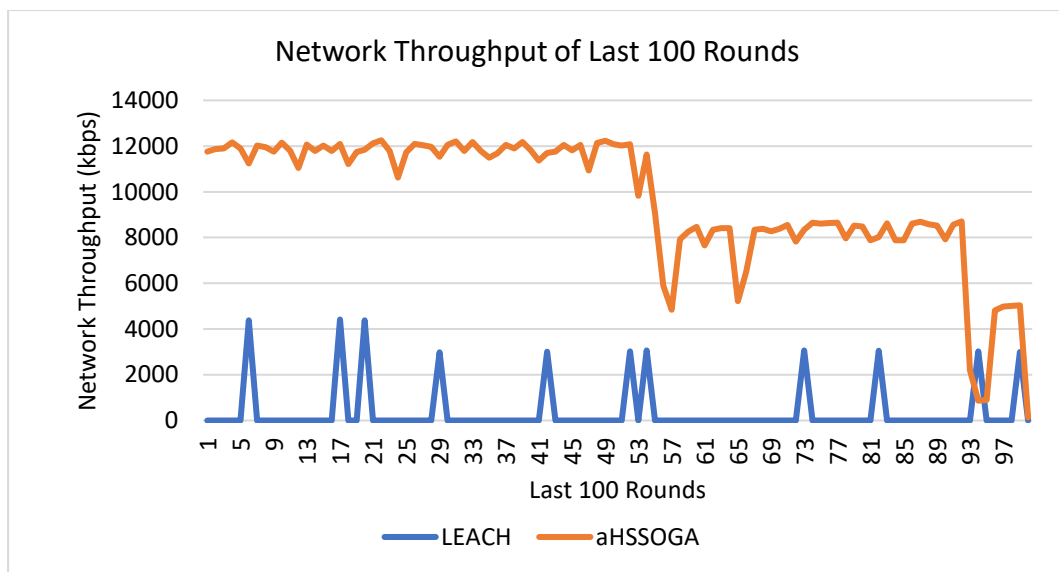


Figure 6: Network Throughput of LEACH and aHSSOGA in the last 100 rounds

The significance of network throughput achieved by the proposed aHSSOGA against the other existing methods are evaluated using the One-way ANOVA (Tukey's test) statistical analysis as depicted in table 6 below.

Table 6: Statistical analysis of network throughput metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods.

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	275.686	0.831
	HFAPSO	1757.448*	< 0.001*

	HSAPSO	1643.668*	< 0.001*
	HSSOGA	1320.476*	< 0.001*
	HGWOSFO	3535.629*	< 0.001*
*. The difference in means is significant at the 0.05 level.			

The proposed aHSSOGA significantly outperformed HSAPSO, HFAPSO, HGWOSFO, and HSSOGA at a significance level of 0.05. Its performance was comparable to LEACH due to LEACH's higher initial throughput from single-hop transmission. Overall, aHSSOGA is the most effective metaheuristic method for clustering using the enhanced LEACH technique.

A shorter end-to-end delay indicates faster data transmission to the BS within a round. The efficiency of end-to-end delay for LEACH, HSAPSO, HFAPSO, HGWOSFO, HSSOGA, and aHSSOGA is shown in Fig. 7.

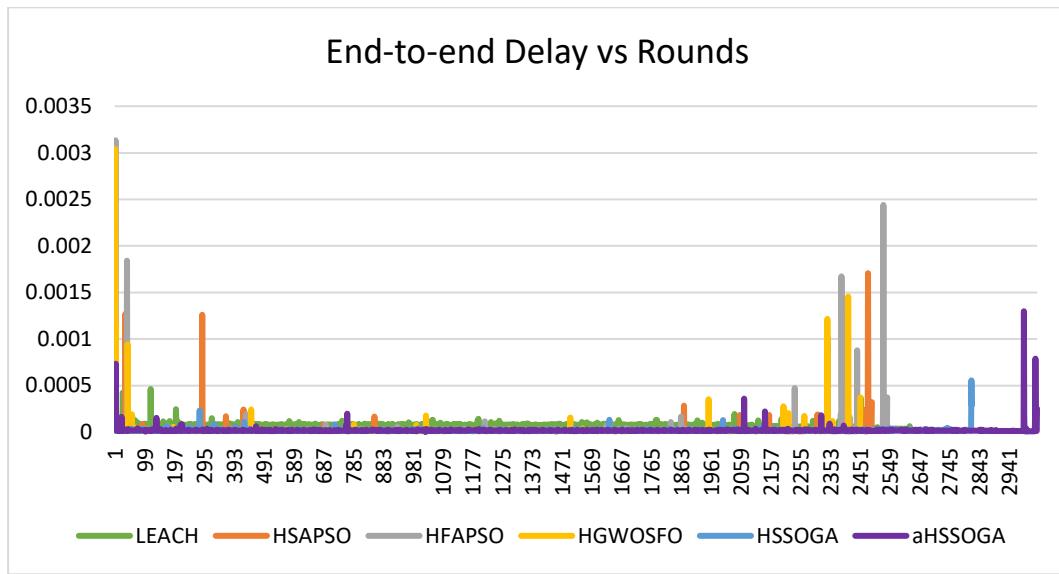


Figure 7: End-to-end Delay over the Number of Rounds.

End-to-end delay is high at both the beginning and end of the network's lifetime. Initially, delays occur due to routing table creation and route learning, while later, delays increase as fewer nodes remain, requiring longer distances to CHs or the BS. The average delays were 0.072ms for LEACH, 0.019ms for HSAPSO, 0.020ms for HFAPSO, 0.020ms for HGWOSFO, 0.020ms for HSSOGA, and 0.018ms for aHSSOGA. HSSOGA and aHSSOGA recorded the lowest delays, indicating optimal CH selection for efficient communication. The statistical significance of aHSSOGA relative to the existing clustering methods was assessed using one-way ANOVA with Tukey's post-hoc test, as reported in Table 7.

Table 7: Statistical analysis of end-to-end delay metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods.

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	-5.383E-05*	< 0.001*
	HFAPSO	-2.240E-06	0.838
	HSAPSO	-1.583E-06	0.960
	HSSOGA	-2.778E-07	1.000
	HGWOSFO	-2.095E-06	0.878
*. The difference in means is significant at the 0.05 level.			

aHSSOGA shows the most noticeable improvement over LEACH in end-to-end delay. Since LEACH uses

single-hop transmission, its delay is typically higher than that of multi-hop metaheuristic methods. Thus, even when overall gains are modest, aHSSOGA achieves the lowest delay among the compared metaheuristics.

B. Discussions

Clustering in WSN is a large-scale application requiring efficient optimization methods. The key process is CH selection, where identifying optimal CHs is crucial for scalability. This motivated the development of a hybrid metaheuristic method combining two algorithms with strong exploration and exploitation capabilities, enabling efficient CH selection by finding global optimal solutions. Given the dynamic nature of WSNs changing node counts, residual energy, and communication distances, the adaptiveness of the proposed method enhances CH selection. Additionally, objective functions aimed at addressing isolated node and hotspot problems ensure optimal CH selection at any time.

Comparison with recent hybrid methods (HSAPSO, HFAPSO, HGWOSFO) and LEACH shows that the proposed aHSSOGA selects optimal CHs, outperforming others in average residual energy and prolonging network lifetime. Its lower re-clustering frequency demonstrates consistent CH selection, reducing energy and memory overhead. In terms of communication efficiency, the extended network lifetime achieved by aHSSOGA results in a greater number of packets delivered with stable performance. While LEACH shows higher throughput due to single-hop transmission, aHSSOGA's multi-hop approach reduces energy consumption during data transfer. Furthermore, aHSSOGA achieves superior average end-to-end delay compared to LEACH, HSAPSO, HFAPSO, and HGWOSFO, maintaining shorter delays even at the network's end-of-life due to its efficient CH selection.

Accordingly, aHSSOGA can efficiently identify high-quality (near-global) solutions in practical deployment settings such as WSN clustering. The key advantages observed in this study are summarized as follows:

- Adaptive search balance: Dynamically tuning the crossover probability p_c and mutation probability p_m strengthens the exploration, exploitation trade-off during the search. In addition, adaptively regulating sperm motility enables the algorithm to alternate between broader exploration of the solution space and intensified exploitation of promising regions, leading to more appropriate CH selections.
- Mitigation of isolation and energy holes: aHSSOGA selects CH configurations that alleviate isolated-node occurrences and the energy-hole effect. Empirically, this corresponds to lower end-to-end delay and slower energy depletion toward the later stages of network operation.
- Extended network lifetime: The network lifetime is substantially improved under aHSSOGA for both the proposed LEACH-based clustering mechanism and the R-CND scheme.
- Stable communication performance: The method maintains stable connectivity among nodes, CHs, and the BS, resulting in more consistent throughput.

C. Space and time complexity of proposed aHSSOGA

Space and time complexity are crucial for evaluating algorithm efficiency. Adaptive HSSOGA shares similar complexity with HSSOGA, adding only a few steps for adjusting crossover and mutation probabilities. Space complexity refers to the memory required during execution. Initially, a population array of size n is created where each element in the array is designed to contain another array, with the maximum number of CH permitted at a given time, k as the length, which makes the space required as $O(n) * O(n) = O(n^2)$. Throughout the iterations, two additional populations, each equal in size to the initial population but differing in length, are generated and referred to as the crossover population and the mutated population. Crossover populations have a length of $pc * n$ where pc represents the crossover probability that adjusts dynamically. The crossover population still holds an array of k length

in it. Furthermore, the mutated population is represented as an array with a length of $pm * n$ where pm is the adaptively adjusted mutation probability. Both these arrays have the same space complexity of $O(n^2)$. These populations are subsequently merged and trimmed to match the initial population size, forming a single population with the best solutions, where sperm velocity is utilized to update the population's position, which has a space complexity of $O(n)$. So, the overall space complexity of the proposed aHSSOGA is as such, $O(n^2) + O(pc * n * k) + O(pm * n * k) + O(n) = O(n^2)$.

The space complexity of the HSAPSO, HGWOSFO, and HFAPSO algorithms is identical. Their initial population arrays have a length nnn , with each element containing another array of length k , resulting in a space complexity of $O(n * k) = O(n^2)$. Time complexity defines the computational time needed to run an algorithm based on the input size. aHSSOGA has a time complexity as that of HSSOGA; despite adaptively adjusting crossover and mutation probabilities initially, it defines the total number of iterations with a complexity of $O(n)$. The time complexity for computing the specified objective functions is $O(n)$, leading to an iterative complexity of $O(n * n) = O(n^2)$. When the crossover and mutated population combined and sorted in terms of velocity and position updates, this process has a time complexity of $O(n \log n)$. Therefore, the overall time complexity for both aHSSOGA and HSSOGA is $O(n) + (O(n^2) * O(n \log n)) = O(n^2 \log n)$.

The temporal complexity of algorithms such HSAPSO and HFAPSO is $O(n^2)$ as the algorithm is simplistic. The initial iteration loop has a time complexity of $O(n)$ and inside the loop, the objective function is evaluated, and the velocity and position update loop have a time complexity of $O(n)$ resulting in an overall complexity of $O(n * n) = O(n^2)$. Furthermore, HGWOSFO is a distinctive algorithm that determines whether GWO or SFO is executed based on the index number. However, its complexity remains unchanged irrespective of the specific conventional algorithm employed. Initially, the algorithm executes a setup iteration with a time complexity of $O(n)$. Subsequently, within the main iteration loop, it computes the objective function, which also has a time complexity of $O(n)$. Hence, the overall time complexity for HGWOSFO of HGWOSFO is equivalent to that of the other two algorithms, which is $O(n * n) = O(n^2)$.

In summary, while aHSSOGA and HSSOGA algorithms Exhibits greater time complexity compared to other algorithms, they excel in enhancing network stability and inter-cluster communication.

6. Conclusion and Future works

This paper presents an adaptive hybrid Sperm Swarm Optimization and Genetic Algorithm (aHSSOGA) for CH selection and clustering in WSNs. Adaptive parameter tuning is applied to mutation and crossover probabilities, guided by previous fitness, to enhance exploration and exploitation. Sperm velocity is linearly adjusted to promote exploration early and exploitation later, improving optimal solution search. Refined objective functions such as distances between CHs and nodes, average residual energy, and node isolation probability address isolated node and hotspot problems. Additionally, an enhanced re-clustering method reduces energy and memory overhead, extending network lifetime.

The performance of aHSSOGA was validated against LEACH, HSAPSO, HFAPSO, HGWOSFO, and HSSOGA. aHSSOGA demonstrated superior results in average residual energy, network lifetime, and throughput. aHSSOGA effectively mitigates isolated node and hotspot issues, ensuring better network stability and efficiency.

In conclusion, aHSSOGA adapts to environmental changes, making it highly effective for real-world applications like WSNs. Future work could extend this approach to optimize other systems, such as mobile ad-hoc networks and vehicle-to-vehicle (V2V) communication networks.

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