MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

# Energy Efficient Cluster Head Selection using Hybrid Sandpiper Harmony Search Algorithm Optimization in IoT based Sensor Networks

**S. Mageshwaran**
Research Scholar, Department of Computer Science and Engineering
Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli, Tamil Nadu, India-627012
mca.magesh@gmail.com
**P. Sundareswaran**
Assistant Professor, Department of Computer Science and Engineering
Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli, Tamil Nadu, India-627012
psundareswaran@msuniv.ac.in

## ABSTRACT

In Wireless Sensor Networks, the selections of Cluster Heads are an important task in preserving energy consumption and sustaining long-term communication performance. Earlier meta- heuristic approaches, including the combination of Sandpiper Optimization and Competitive Swarm Optimization (SOA–CSO), have shown improvements in the initial stability period, but it has uneven load distribution. To overcome this limitation, this research work hybrid Sandpiper Optimization Algorithm - Harmony Search Algorithm (SOA–HSA) introduced an effective Cluster Head selection. This proposed method uses SOA to explore the search space widely and identify best CH candidates, while Harmony Search refines these candidates by adjusting cluster formation, communication paths, and energy allocation. This two-level optimization helps in reducing unnecessary transmissions, balancing the number of nodes under each CH, and minimizing the communication distance, which collectively enhances the overall network performance. The experimental results confirm that the SOA–HSA model achieves longer stability, increased last-node survival, and improved throughput when compared with the other algorithm.

***Keywords:* *Wireless Sensor Networks (WSNs), Energy Efficiency, Cluster Head Selection, Sandpiper Optimization Algorithm (SOA), Harmony Search Algorithm (HSA) Competitive Swarm Optimization (CSO), Network Lifetime, Swarm Intelligence, IoT***

## INTRODUCTION

Wireless Sensor Networks (WSNs) have become a building blocks for various Internet of Things (IoT) applications, including smart cities, industrial automation, precision agriculture, environmental monitoring and healthcare analytics [1]. Each sensor node is equipped with sensing, computation and short-range wireless communication capabilities, but the performance is inherently restricted by limited battery energy [2]. Since most WSN deployments operate in an inaccessible environment, efficient utilization of available energy is very important to prolong network lifetime and ensure reliable data delivery. Among the various energy-saving mechanisms, clustering remains one of the most effective techniques to minimize communication overhead and enhance network lifetime [3].

In the clustering-based architectures, nodes are partitioned into groups and a Cluster Head (CH) is elected to manage intra-cluster coordination, data aggregation and forwarding of compressed information to the base station. The effectiveness of CH selection directly affects energy balancing, routing efficiency and overall network lifetime. However, classical CH selection protocols often suffer from uneven cluster formation, high packet overhead and early CH collapse, which lead to reduce throughput and stability period [4]. To overcome these issues, researchers have increasingly adopted nature-inspired meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO) and Genetic Algorithms (GA). Due to their superior capability, they are used to handle non-linear and multi-dimensional optimization problems in WSN clustering [5], [6].

Nonetheless, many of these methods encounter premature convergence, local trapping, and an imbalance between exploration and exploitation, which affects the quality of CH selection [7]. This has motivated the development of hybrid meta-heuristic strategies that combine the strengths of multiple optimization approaches to achieve more reliable and energy-efficient clustering outcomes [8].

The Sandpiper Optimization Algorithm (SOA), inspired by sandpipers' migratory foraging patterns, provides strong global exploration and rapid identification of promising CH candidates. However, its limited local refinement ability restricts fine-tuning of cluster structures. Harmony Search Algorithm (HSA) based on musical improvisation and memory-based optimization, offers better local search capability and exploitation efficiency [9], [10]. Motivated by their complementary characteristics, this research work proposes a hybrid SOA–HSA framework for energy-efficient CH selection in WSNs. By integrating SOA's global search diversity with HSA's local adjustment precision, the proposed the hybrid SOA–HSA aims to achieve balanced cluster formation, reduced communication overhead and enhanced network lifetime, thereby overcoming the performance limitations observed in earlier SOA-CSO-based models.

### 1.1. MOTIVATION

The motivation for this research work arises from the limitations seen in recent hybrid method namely SOA–CSO for Cluster Head selection in Wireless Sensor Networks. Although SOA–CSO provides better search capability than traditional clustering schemes, it still struggles when the node energy becomes uneven, leading to unstable clusters and early node failures. The competitive update process also slows convergence in dense networks, affecting the selection of suitable Cluster Heads. These issues reduce the overall lifetime and reliability of the network. Therefore, there is a need for a more adaptive and balanced optimization approach that can manage energy efficiently, maintain stronger search diversity, and provide stable communication even under changing network conditions. This leads to develop an improved hybrid method that can extend network life and enhance throughput in WSN based IoT networks.

### 1.2. CONTRIBUTION

This research work focuses the following key contributions :

1. A novel hybrid SOA –HSA optimization model is proposed for intelligent Cluster Head selection.
2. A multi-objective fitness function is developed by integrating residual energy, intra-cluster communication distance, node density, and sink distance. This ensures optimal cluster structures tailored for energy-efficient communication in WSNs.
3. The harmonized search behavior enables the network to avoid premature convergence and supports more reliable CH election under changing energy conditions.

## 2. RELATED WORKS

Raghavan et al. [11] applied the Sandpiper Optimization Algorithm (SOA) for cluster head selection in WSNs. SOA imitates sandpipers' feeding behaviour, where solution agents search widely for food-prolific zones and gradually refine their movement based on food availability. In their work, nodes with high residual energy and minimum average distance to neighbours were treated as high-fitness candidates. CH selection was made by evaluating each node's fitness using SOA's position update equations, and the node with the highest energy distance ratio was chosen as CH. Although the method enhanced global search, the local exploitation phase was weak during late rounds, causing unstable cluster boundaries. The performance was examined through alive nodes, energy usage per round, and packet delivery rate, showing the necessity for a hybrid refinement method. Shastri et al. [12] proposed a hybrid SOA–CSO mechanism. CSO operates through pair wise competition, where two solution agents compete, and the fitter one proceeds to the next stage while the weaker one learns from it. This competition strengthened exploitation by refining CH positions. The hybrid system first used SOA for broad exploration to locate energy-rich nodes and then employed CSO for fine-tuning. CHs were selected based on a weighted fitness combining residual energy, intra-cluster distance, and communication cost. However, the competition-based elimination reduced population diversity, and the increased computational load delayed in decision-making.

Vinothkumar et al. [13] incorporated the Harmony Search Algorithm (HSA) into SOA to enhance CH precision. HSA mimics musical improvisation, where harmonies (solutions) are adjusted by pitch modification and memory consideration. SOA provided global movement, while HSA handled fine-grained tuning of CH positions. The selection of CH was based on harmony memory values such as energy level, closeness to centroid, and link quality. When HSA performed pitch adjustment, the best harmonies representing strong CH candidates were retained. Although the method improved convergence reliability, it suffered from high sensitivity to harmony memory size and bandwidth parameters. Metrics included energy variance, packet delivery ratio, and convergence time, highlighting the difficulty of parameter tuning.

Prabhu et al. [14] presented a multi-objective hybrid SOA–CSO algorithm aimed at jointly minimizing intra-cluster distance and maximizing node lifetime. SOA was responsible for searching global regions, while CSO's competition updated solutions towards better exploitation. CH selection was based on a multi-objective fitness that balanced energy, distance to members, and distance to the sink. The CSO refinement improved the accuracy of final CH positions. However, the aggressive competition sometimes resulted in losing promising solutions, causing early stagnation during the exploitation phase. Metrics such as lifetime improvement, communication cost, and latency were used, and the authors found that diversity preservation was required for better performance.Karthikeyan et al. [15] proposed a triple-hybrid SOA–HSA–PSO clustering system. SOA initiated global search, PSO added velocity-driven updates to improve convergence direction, and HSA refined local optimal zones using harmony memory. CHs were chosen by computing a combined fitness score that included residual energy, centrality within the cluster, and cluster compactness. Each CH candidate's position was adjusted through PSO and HSA operators after the initial SOA-based search. The main drawback was the heavy computational burden due to three meta-heuristic layers acting sequentially. Their results were analyzed through network lifetime, cluster density, and energy decay rate, showing the need for a lightweight hybrid variant.Devi et al. [16] introduced a Fast Converging SOA (FC-SOA) combined with CSO for secure, energy-efficient IoT data aggregation. FC-SOA used adaptive step reduction to accelerate the search process, while CSO refined local solutions through competition-based learning. CHs were selected by calculating a fitness based on energy balance, link strength, and cluster stability probability. The competitive learning ensured accurate CH selection during initial rounds. The limitation emerged at high node densities (>300), where excessive competition slowed convergence and increased processing time. Performance metrics included routing overhead, packet drop ratio, and stability period, indicating that scalability requires further improvement.Murugan et al. [17] proposed a QoS-centric SOA–HSA hybrid to improve reliability in industrial IoT systems. SOA conducted a wide search to identify feasible CH candidates, after which HSA performed pitch adjustment based on QoS constraints such as delay, reliability, and available energy. CHs were selected from harmony memory elements that offered the best compromise between energy and QoS scores. While the approach improved delay metrics, repetitive harmonies in memory reduced diversity, resulting in occasional stagnation. Evaluations included delay, packet reliability, and residual energy, reinforcing the need for harmony memory diversification.

Sridharan et al. [18] developed a lightweight SOA–CSO framework tailored for long-duration WSN deployments. SOA handled the exploration phase, allowing diverse movements across the search space, while a simplified CSO module refined CH positions with minimal computational effort. CHs were chosen by ranking nodes on energy availability, minimum average hop distance, and mobility stability. The streamlined competitive refinement improved responsiveness but slightly over-emphasized nodes near the sink, creating hotspot energy depletion. Their evaluation used First Node Dead, Last Node Dead, throughput, and transmission cost, and results suggested the need for load balancing during the mid-phase exploitation.

## 3. HYBRID SOA–HSA OPTIMIZATION ALGORITHM

The proposed work introduces a Hybrid Sandpiper Optimization Algorithm–Harmony Search Algorithm (SOA-HSA) framework to achieve dependable and energy-saving Cluster Head (CH) selection in Wireless Sensor Networks. The main objective of this hybridization is to make use of the rapid searching nature of Sandpiper Optimization Algorithm (SOA) and the improvisation capability of Harmony Search Algorithm (HSA) to arrive at stable, energy-balanced CH nodes across the sensing field. The traditional Sandpiper Optimization Algorithm (SOA) focuses on exploitation, enabling fast convergence during the search for potential CH candidates. However, the algorithm often converges prematurely when the network topology is dynamic or when residual energy is varied among nodes. To overcome the above told issues, the Harmony Search Algorithm (HSA) is embedded to introduce harmony improvisation.In this hybrid mechanism, SOA initially evaluates each sensor node by considering residual energy, distance to sink, and intra-cluster communication cost, These measures help identify a preliminary set of CH candidates. The selected candidates are then passed to the HSA stage, where the harmony memory stores feasible solutions and continuously updates them based on pitch adjustment and random selection. This process enables the hybrid technique to avoid stagnation, widen the search radius, and derive an improved CH distribution that maintains energy equally among nodes.Hybrid Sandpiper Optimization Algorithm - Harmony Search Algorithm (SOA-HSA) framework operates in multiple phases. In the exploration phase, the Sandpiper Optimization Algorithm (SOA) scans the search space by imitate the foraging behavior of sandpipers and identifies regions that are promising for CH position. In the exploitation phase, the Harmony Search Algorithm (HSA) refines those regions by adjusting harmony vectors and optimizing the fitness value of each candidate CH. By combining both behaviors, the hybrid scheme reduces the long-distance transmissions, balances energy consumption among clusters, and significantly improves network lifetime and throughput.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

Hybrid Sandpiper Optimization Algorithm–Harmony Search Algorithm (SOA-HSA) technique is not only enhances the stability period but also reduces packet loss due to early CH failures. As a result, the network experiences a prolonged functional lifespan along with improved data delivery efficiency, positioning the hybrid technique as a practical choice for real-time IoT and smart-city monitoring applications. The flowchart is as follows.

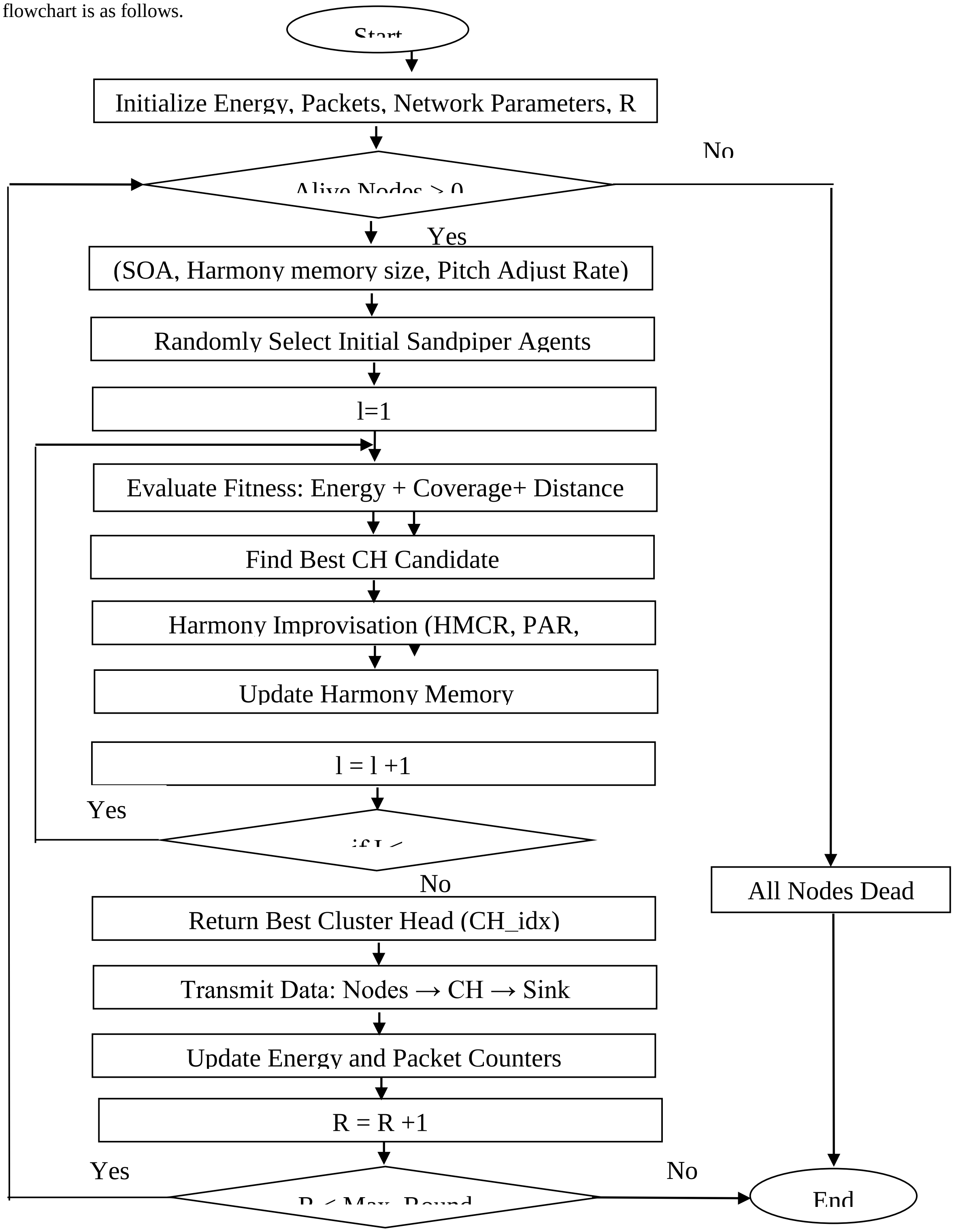


**Figure 1: Flowchart of the proposed Hybrid SOA-HSA Cluster Head Selection**

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

### 3.1. NETWORK MODEL AND ENERGY FORMULATION

Assume that a WSN consists of N homogeneous sensor nodes randomly deployed in a two-dimensional monitoring area of size L × L. Each node i is characterized by its position $(x_i, y_i)$, initial energy $E_0$, and residual energy $E_i(r)$ at round r. The sink is located at $(x_s, y_s)$.

The radio energy dissipation model follows the first order model, where the transmission and reception energy are given below.

$$E_{tx}(k,d) = \begin{cases} k\,E_{elec} + k\,\varepsilon_{fs} d^2, d < d_0 \\ k\,E_{elec} + k\,\varepsilon_{mp} d^4, d \geq d_0 \end{cases} \quad (1)$$

$$E_{rx}(k) = k\,E_{elec} \quad (2)$$

where k is the message size (bits), $k\,E_{elec}$ represents the energy per bit for transmission or reception, $\varepsilon_{fs}$ and $\varepsilon_{mp}$ are the amplifier constants for free-space and multipath models respectively, and $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$ is the threshold distance

### 3.2. FITNESS FUNCTION CALCULATION

The fitness function evaluates the selection a sensor node to become a cluster head. Since CHs do data aggregation and long-range transmission, they must have higher residual energy, nearer to member nodes, and a minimum distance from the sink. The objective of the proposed fitness function is allowing both Sandpiper Optimization Algorithm (SOA) and Harmony Search Algorithm (HSA) to intelligently find the better cluster heads. If the fitness function is minimum value, it have a higher probability of becoming CHs. So, it is ensuring uniform energy consumption and improved network lifetime.

$$F_i = w_1 \left[\frac{1}{E_i^{res}}\right] + w_2 \left[\frac{d_{i,s}}{d_{max}}\right] + w_3 \left[\frac{d_{i,avg}}{d_{max}}\right] \quad (3)$$

where $d_{i,s}$ distance of node i to sink , $d_{i,avg}$ average distance of node i to all neighbors, and $w_1 + w_2 + w_3$ =1

### 3. 3. SANDPIPER OPTIMIZATION STAGE (EXPLORATION PHASE)

During this stage, each sandpiper represents a potential CH position or a node that may act as a cluster head. It is responsible for generating diverse CH candidates across the deployment area. The Sandpiper Optimization Algorithm (SOA) simulates the foraging and migratory movement of sandpipers in search of optimal feeding regions. Each sandpiper agent represents a candidate CH vector $X_j = [\,x_{j1}, x_{j2}, \ldots, x_{jD}]$ in a D- dimensional search space

**(a) Position Update**

During the exploration stage of the Sandpiper Optimization Algorithm (SOA), the position updates mechanism controls how each sandpiper (candidate CH) searches across the WSN for better cluster-head locations. In this context, a position represents a candidate node that may potentially act as a cluster head. The goal of this step is to diversify the search space by allowing sandpipers to explore various regions of the network instead of remaining close to their initial positions.

At iteration $t_1$ , each agent update its positions as:

$$X_j^{t+1} = X_j^t + \alpha r_1 \left( X_{best}^t - \left[X_j^{t+1}\right] \right) + \beta r_2 \left( X_j^t - X_{rand}^t \right), \quad (4)$$

Where $r_1$, $r_2$, ∈ [0,1] are random coefficients, α controls the search intensity, β defines the local migration tendency, $X_{best}^t$ is the best agent in iteration t; and $X_{rand}^t$ is a randomly selected agent from the population.

This mechanism allows the agents to dynamically migrate between regions of high and low fitness, promoting global exploration and preventing premature convergence.

### 3.4. HARMONY SEARCH ALGORIHM STAGE (EXPLOITATION PHASE)

The Harmony Search Algorithm (HSA) is inspired by musical improvisation where musicians adjust pitch, rhythm, and harmony to create pleasing tones. The Harmony Search Algorithm (HSA) stage refines the CH selection by the Sandpiper Optimization Algorithm (SOA) by mimicking the process of musical improvisation. Each solution represents a harmony vector of CH candidates. The Harmony Search Algorithm (HSA) introduces memory consideration, pitch adjustment, and random selection to achieve fine-grained solution refinement. In Cluster Head optimization, The Harmony Search Algorithm (HSA) helps identify CHs that further reduce energy consumption by adjusting their pitch, that is, optimizing node choices. This hybrid stage enhances stability and avoids premature convergence observed in the Sandpiper Optimization Algorithm (SOA).

#### 3.4.1. Harmony Memory

It has the set of possible Cluster Head solution

$$HM = \left(\mathrm{X}_1^{\mathrm{best}}, \mathrm{X}_2^{\mathrm{best}}, \mathrm{X}_3^{\mathrm{best}}\right) \quad (5)$$

#### 3.4.2. Harmony Improvisation

The harmony improvisation has three stages. They are Harmony Memory Consideration, Pitch Adjustment, and Harmony Memory Update.

##### 3.4.2.1. Harmony Memory Consideration (HMCR)

The Harmony Memory consideration helps retain Cluster Head candidates that already show high residual energy and coverage.

Harmony Memory Consideration (HMC) is calculated as follows

$$X_{new}(k) = \begin{cases} X_{HM}(k), & if\ rand < HMCR \\ X_{rand(k)}, & otherwise \end{cases} \quad (6)$$

Where, $X_{new}(k)$ is Harmony Memory Consideration (HMC), HMCR is Harmony Memory Consideration Rate

##### 3.4.2.2. Pitch Adjustment (PAR, BW)

The Pitch adjustment provides micro-changes in Cluster Head position, improving cluster shape and avoiding overlap. Pitch Adjustment is calculated as follows

$$X_{new}(k) = X_{new}(k) + PAR * BW * (2r - 1) \quad (7)$$

where PAR is Pitch Adjustment Rate, and BW is Bandwidth

**3.4.2.3. Harmony Memory Update**

The Harmony Memory process is guarantees continuous refinement of CH candidates It is calculated as follows

$$\text{if } F_{new} > F_{worst} \;, HM_{worst} = X_{new} \tag{8}$$

Thus, Harmony Search Algorithm (HSA) enhances local exploitation, refining the Sandpiper Optimization Algorithm (SOA) generated solutions to ensure the final CHs are both energy-balanced and communication-efficient.

### 3.5. CLUSTER HEAD FORMATION

After completing max_iterations of the hybrid SOA–HSA optimization process, the algorithm identifies the optimal cluster-head configuration based on the best solution vector obtained in the final iteration. The optimal CH identification is computed with the help of equation (9)

$$\mathrm{CH} = \arg_{X_i \in HM}^{\max} F_i \tag{9}$$

In node CH Association process, Each node joins the nearest CH

$$\mathrm{CH(i)} = \arg_{\mathrm{CH_i}}^{\min} d(n_i CH_j) \tag{10}$$

### 3.6 ENERGY UPDATE AND TRANSMISSION MODEL

After cluster formation, data transmission occurs in two phases: They are as follows Intra-cluster communication (node → CH), and Inter-cluster communication (CH → Sink).

In the intra-cluster communication stage, each non-cluster-head node senses the environment and transmits its data to its cluster head. Since the distance between a node and its CH is small, this transmission happens under the low-energy system of the first-order radio model, resulting in minimal energy dissipation per round. The CH receives all member-node packets and reception energy accordingly, followed by data aggregation to reduce redundancy before forwarding the information toward the sink.

In the inter-cluster communication stage, each cluster head transmits its aggregated data packet directly to the sink node or base station. Unlike intra-cluster transmission, this communication involves multipath radio model. Consequently, CHs consume significantly more energy compared to normal nodes. The hybrid SOA–HSA optimization framework ensures that nodes with sufficient residual energy and distance from sink and coverage, thereby maintaining energy balance and prolonging overall network lifetime. CH transmits aggregated data to the sink:

For a member node *i* transmit to its CH:

$$\mathrm{E_i^{r+1}} = \mathrm{E_i^r} - \mathrm{E_{tx}}\,(\mathrm{k}, \mathrm{d_{i,CH}}) \tag{11}$$

$$\mathrm{E_{CH}^{r+1}} = \mathrm{E_{CH}^r} - [\mathrm{k\,E_{elec}}\,(\mathrm{n_{mem}} + 1)\,\mathrm{k\,E_{DA}}{}^{\mathrm{n}}{}_{\mathrm{mem}} + \mathrm{E_{tx}}\left(\mathrm{k}, \mathrm{d_{CH,s}}\right)] \tag{12}$$

where $\mathrm{n_{mem}}$ is the number of member nodes and $E_{DA}$ is the energy consumed for data aggregation.

### 3.7. CONVERGENCE CALCULATION PHASE

The convergence calculation phase verifies whether the hybrid SOA–HSA optimization process has reached a stable solution and can terminate early. At each iteration r+1, the best fitness value $F_{best}^{r+1}$ is compared with the best fitness from the previous iteration $F_{best}^{t}$. The convergence is finalized when the improvement between successive fitness values becomes sufficiently small, indicating that further iterations will no longer produce significant optimization gains. The algorithm terminates when either the maximum iteration $T_{max}$ is reached or the fitness improvement between consecutive iterations falls below a predefined threshold ε. The convergence calculation phase verifies whether the hybrid SOA–HSA optimization process has reached a stable solution and can terminate early. It has three scenarios. When a maximum iteration is reached is the first scenario. The fitness function became stable is the second scenario, and the third scenario is CH stability is verified for several iterations.

When the maximum iteration is reached, the algorithm converges. It is calculated as follows

$$r = r_{max} \tag{13}$$

At each iteration r+1, the best fitness value $F_{best}^{r+1}$ is compared with the best fitness from the previous iteration $F_{best}^{t}$. When the fitness function became stable, the convergence is finalized. The algorithm terminates when either the maximum iteration $T_{max}$ is reached or the fitness improvement between consecutive iterations falls below a predefined threshold ε

$$\left| \frac{F_{best}^{r+1} - F_{best}^{t}}{F_{best}^{t}} < \varepsilon \right| \tag{14}$$

When the same CH value is verified for the several iterations, the algorithm converges. It is calculated as follows

$$A = \pi r^2 \mathrm{CH(r)} \qquad = \mathrm{CH(r\text{-}1)} = \ldots = \mathrm{CH(r\text{-}k)} \tag{15}$$

## 4. SIMULATION AND DISCUSSION

The performance of the proposed SOA-HSA technique is implemented using MATLAB 2013a simulation tool. Simulation parameters include increasing number of sensor nodes ranging from 100, 200 and 300. The area of the nodes is 100×100 m². The initial energy per node is 0.5 J. The transmission energy is $E_{TX}$ = 50 n J / bit. The reception energy is $E_{RX}$ = 50 n J / bit. The amplification energy $E_{amp}$ = 10 p J / bit / m² (short range) and $E_{amp}$ = 0.0013 p J / bit / m² (long range). The packet size is 4000 bits. The base station of the network is located at (50, 50). The simulation runs for 2500 rounds.

Here, the following metric are considered for evaluating the performance of the method. They are as follows: a) Number of alive nodes, b) Cumulative energy consumption, c) overall cumulative packets, d) cumulative inter cluster packets, e) network traffic rate and f) network lifetime comparison (First Node Dead to Last Node Dead).

**SIMULATION RESULT OF 100 SENSOR NODES**

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

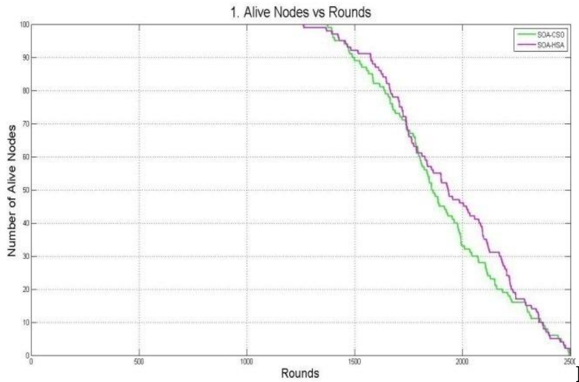


Figure 2: Alive Nodes vs Rounds

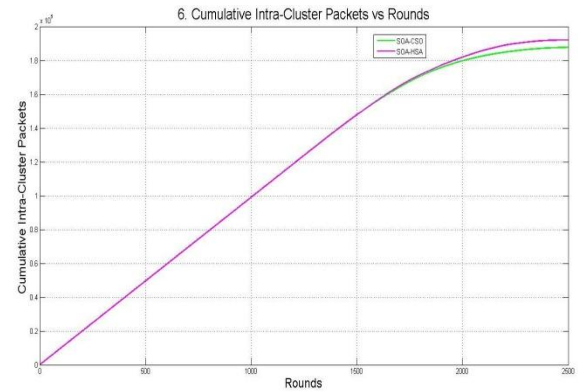


Figure 4: Overall Cumulative Packets vs Rounds

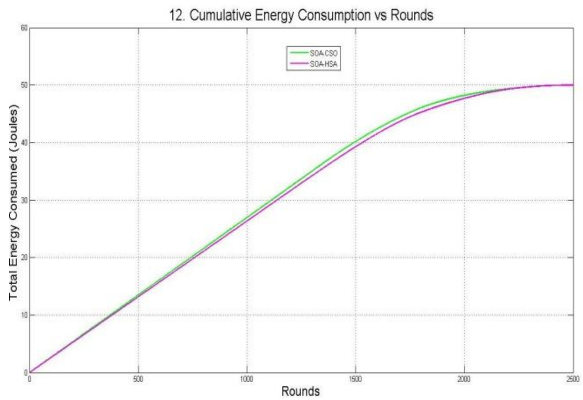


Figure 3: Cumulative Energy Consumption vs Rounds

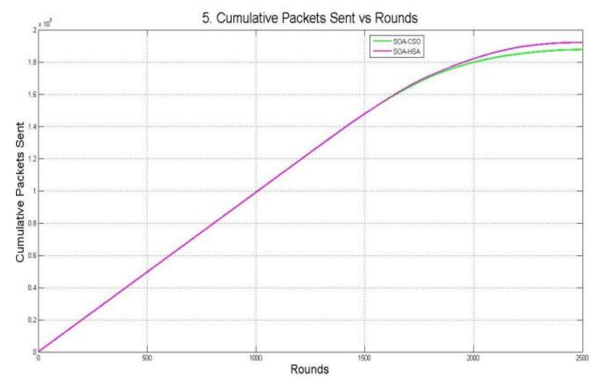


Figure 5: Overall Cumulative inter-cluster Packets vs Rounds

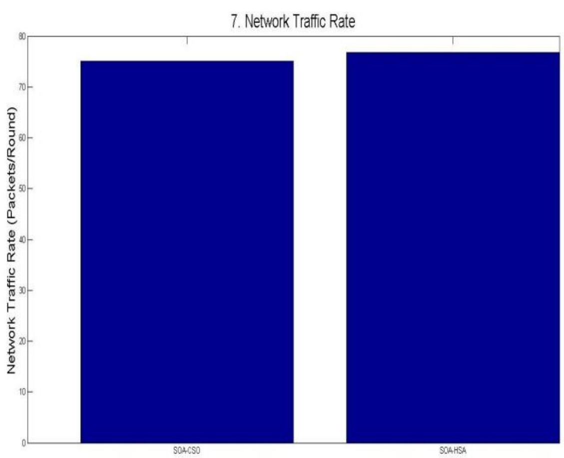


Figure 6: Network Traffic Rate vs Rounds

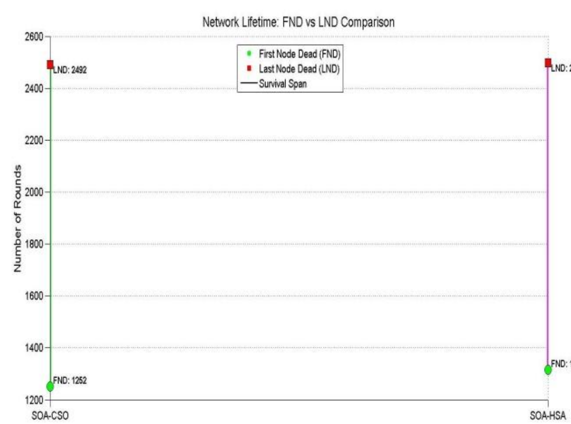


Figure 7: Network Lifetime Comparison (FND to LND) vs Rounds

Table 1: Summary of data for 100 sensor nodes

| METRIC | HYBRID SOA-CSO | HYBRID SOA-HSA |
|---|---|---|
| Total Rounds (All Dead) | 2500 | 2500 |
| First Node Dead | 1252 | 1317 |
| Last Node Dead | 2492 | 2499 |
| Network Traffic Rate (pkt/round) | 76.78 | 77.83 |
| Cumulative Intra-Cluster Packets | 191260 | 197076 |
| Cumulative Inter-Cluster Packets | 2490 | 2698 |

The performance of the Hybrid SOA-CSO and Hybrid SOA-HSA algorithms was evaluated until full sensor node depletion, with both techniques spanning a total duration of 2,500 rounds for 100 sensor nodes. The comparative analysis reveals that Hybrid SOA-HSA provides superior network stability and data handling capabilities compared to Hybrid SOA-CSO. In terms of the stability period, the First Node

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

Death (FND) in Hybrid SOA-HSA occurred at round 1317, representing a 5.19% improvement over Hybrid SOA-CSO, where the first node failure occurred earlier at round 1252.

Furthermore, the Last Node Death (LND) was slightly delayed from 2492 rounds in Hybrid SOA-CSO to 2499 rounds in Hybrid SOA-HSA, yielding a minor enhancement in the overall functional network lifetime.

Beyond longevity, the Hybrid SOA-HSA algorithm demonstrated higher data transmission efficiency across all recorded metrics. The network traffic rate increased from 76.78 to 77.83 packets per round, reflecting a 1.37% gain. Similarly, cumulative intra-cluster packet transmissions saw a 3.04% increase, rising from 191,260 to 197,076 packets, while inter-cluster transmissions improved significantly from 2,490 to 2,698 packets, an 8.35% gain.

Collectively, these results confirm that Hybrid SOA-HSA achieves higher traffic handling and a more robust stability period, making it a more reliable and efficient solution for energy-constrained wireless sensor network environments.

**SIMULATION RESULT OF 200 SENSOR NODES**

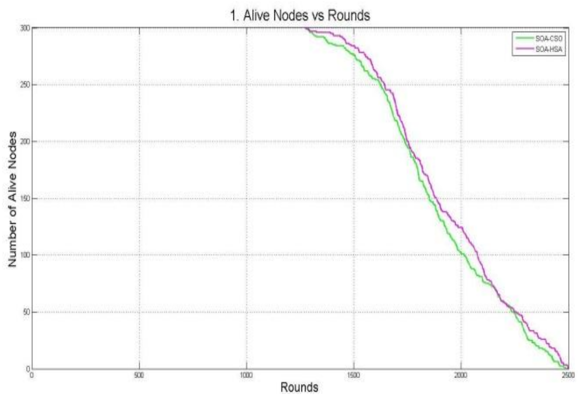


**Figure 8: Alive Nodes vs Rounds**

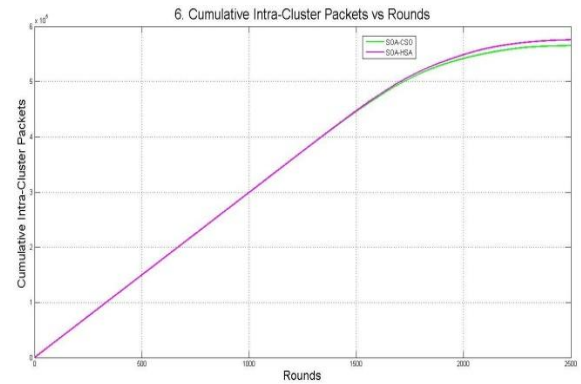


**Figure 10: Overall Cumulative Packets vs Rounds**

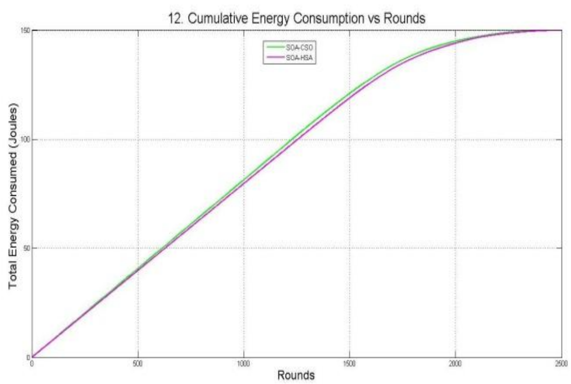


**Figure 9: Cumulative Energy Consumption vs Rounds**

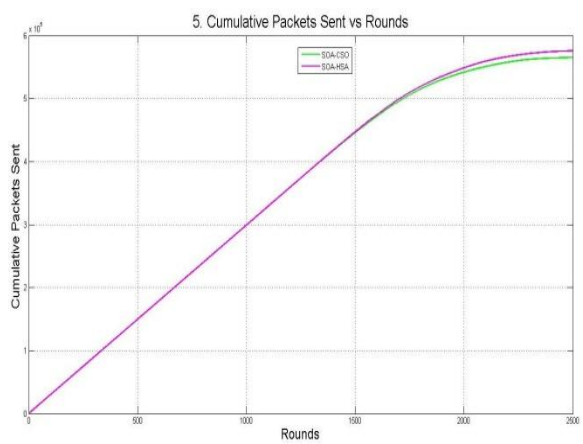


**Figure 11: Overall Cumulative inter-cluster Packets vs Rounds**

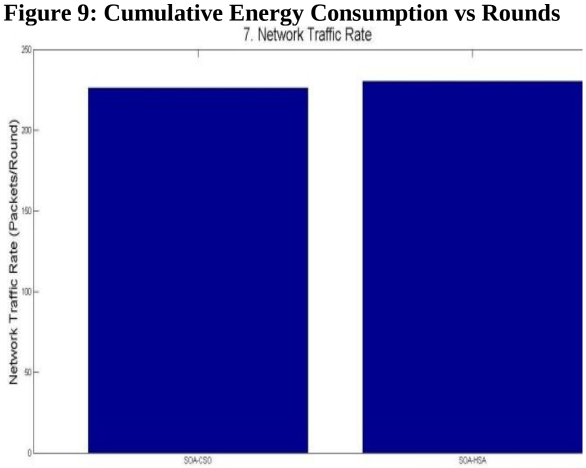


**Figure 12: Network Traffic Rate vs Rounds**

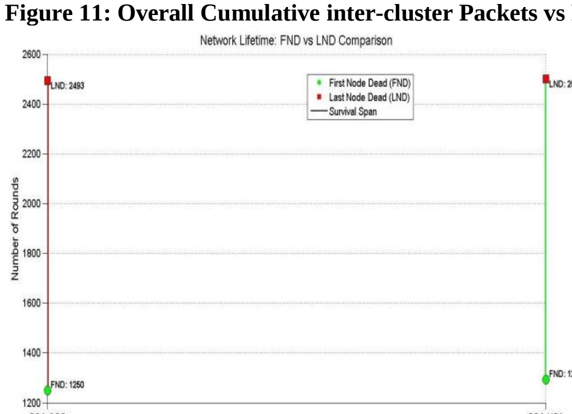


**Figure 13: Network Lifetime Comparison (FND to LND) vs Rounds**

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

**Table 2: Summary of data for 200 sensor nodes**

| METRIC | HYBRID SOA-CSO | HYBRID SOA-HSA |
|---|---|---|
| Total Rounds (All Dead) | 2493 | 2500 |
| First Node Dead | 1250 | 1294 |
| Last Node Dead | 2493 | 2500 |
| Network Traffic Rate (pkt/round) | 153.11 | 153.34 |
| Cumulative Intra-Cluster Packets | 381706 | 387368 |
| Cumulative Inter-Cluster Packets | 2492 | 2699 |

The performance of the Hybrid SOA-CSO and Hybrid SOA-HSA algorithms was evaluated until full sensor node depletion, with the simulation spanning a maximum duration of 2,500 rounds of 200 sensor nodes. The comparative analysis reveals that Hybrid SOA-HSA consistently outperforms Hybrid SOA-CSO across all primary stability and throughput metrics. In terms of network stability, the First Node Death (FND) in Hybrid SOA-HSA occurred at round 1294, representing a 3.52% improvement in the stability period compared to Hybrid SOA-CSO, where the first node failure was recorded at round 1250.

Similarly, the Last Node Death (LND) was extended from 2493 rounds in Hybrid SOA-CSO to 2500 rounds in Hybrid SOA-HSA, yielding a 0.28% enhancement in the overall network lifetime.

Hybrid SOA-HSA also demonstrated a superior data transmission capability, optimizing the network's throughput efficiency. The network traffic rate increased from 153.11 to 153.34 packets per round, reflecting a 0.15% improvement. More significantly, cumulative intra-cluster packet transmissions rose from 381,706 to 387,368 packets (a 1.48% gain), while inter-cluster transmissions increased from 2,492 to 2,699 packets, marking a notable 8.31% improvement. Overall, these results confirm that Hybrid SOA-HSA achieves higher traffic handling and an improved total lifetime by maintaining a more effective energy balance throughout the operational cycle, making it a robust solution for energy-constrained wireless sensor network environments.

**SIMULATION RESULT OF 300 SENSOR NODES**

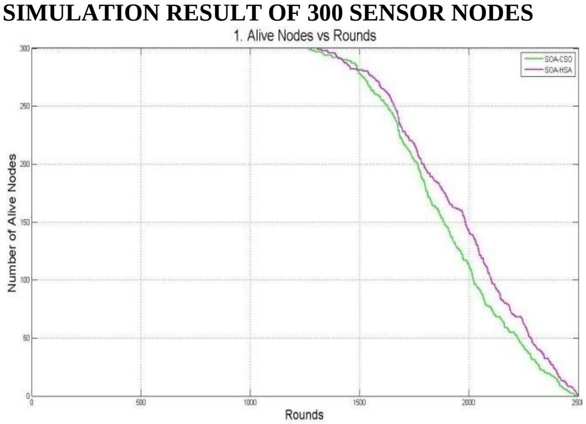


**Figure 14: Alive Nodes vs Rounds**

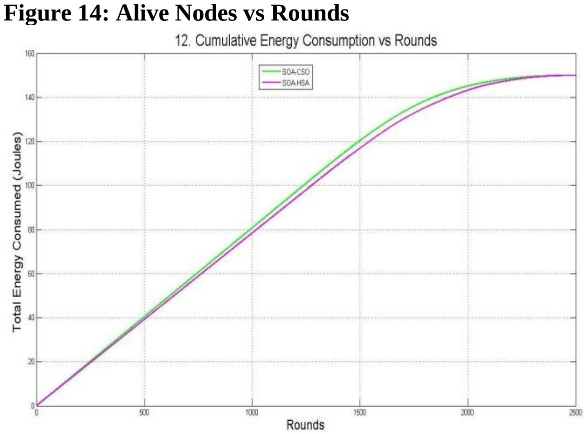


**Figure 15: Cumulative Energy Consumption vs Rounds**

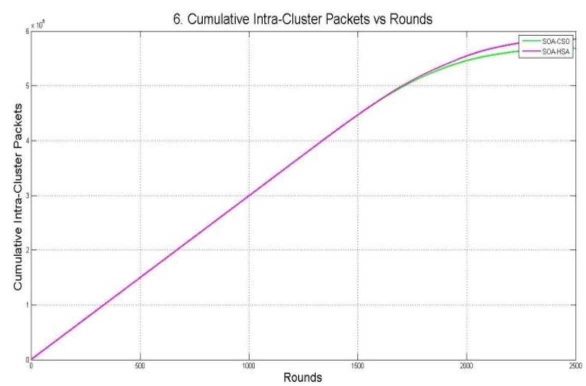


**Figure 16: Overall Cumulative Packets vs Rounds**

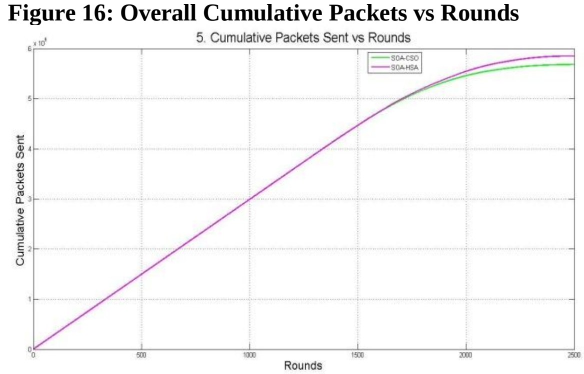


**Figure 17: Overall Cumulative inter-cluster Packets vs Rounds**

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5297-5306

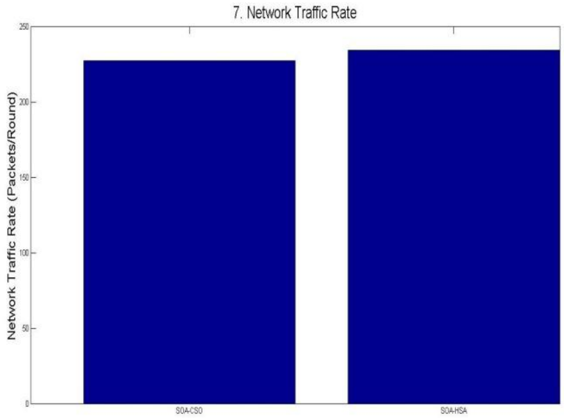


Figure 18: Network Traffic Rate vs Rounds

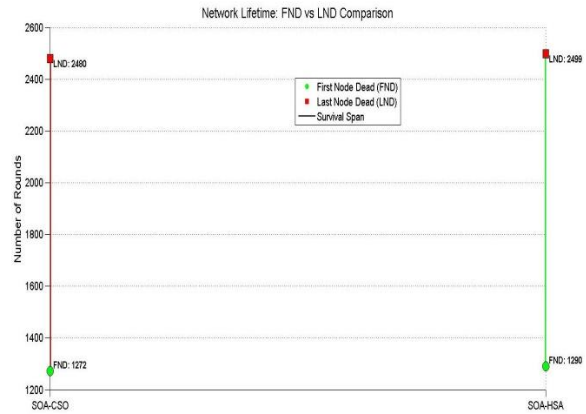


**Figure 19: Network Lifetime Comparison (FND to LND) vs Rounds**

**Table 3: Summary of data for 300 sensor nodes**

| METRIC | HYBRID SOA-CSO | HYBRID SOA-HSA |
|---|---|---|
| Total Rounds (All Dead) | 2495 | 2499 |
| First Node Dead | 1272 | 1290 |
| Last Node Dead | 2480 | 2499 |
| Network Traffic Rate (pkt/round) | 231.13 | 230.27 |
| Cumulative Intra-Cluster Packets | 576451 | 585533 |
| Cumulative Inter-Cluster Packets | 2493 | 2698 |

The performance of the Hybrid SOA-CSO and Hybrid SOA-HSA algorithms was evaluated until full sensor node depletion, with the simulation spanning a maximum duration of 2,499 rounds of 300 sensor nodes. The comparative analysis reveals that Hybrid SOA-HSA demonstrates superior network stability and higher cumulative throughput compared to Hybrid SOA-CSO. In terms of network stability, the First Node Death (FND) in Hybrid SOA-HSA occurred at round 1290, representing a 1.42% improvement over Hybrid SOA-CSO, which reached FND at round 1272.

Additionally, the Last Node Death (LND) was extended from 2480 rounds in Hybrid SOA-CSO to 2499 rounds in Hybrid SOA-HSA, yielding a 0.77% enhancement in the total functional network lifetime.

While the network traffic rate was slightly higher in the Hybrid SOA-CSO model at 231.13 compared to 230.27 packets per round, the Hybrid SOA-HSA algorithm achieved better cumulative data delivery over its extended operational life. Cumulative intra-cluster packet transmissions rose from 576,451 to 585,533 packets, marking a 1.58% gain, while inter-cluster transmissions increased from 2,493 to 2,698 packets, an 8.22% improvement.

Overall, these results confirm that Hybrid SOA-HSA provides a more robust energy balance and a longer stability period, making it a highly reliable solution for maintaining full node coverage and maximizing data integrity in energy-constrained wireless sensor network environments.

## .5. CONCLUSION

Through simulations on networks of 100, 200, and 300 nodes, the proposed Hybrid SOA-HSA algorithm consistently outperformed the Hybrid SOA-CSO of 2500 rounds. The number of alive nodes remained higher throughout the network operation under the proposed Hybrid SOA-HSA algorithm, confirming its enhanced stability compared to the SOA-CSO algorithm. Significant improvements were observed across all evaluated performance metrics as the network size increased. The First Node Dead (FND) metric, which signifies the stability period, showed improvements of 5.19%, 3.52%, and 1.42% for 100, 200, and 300 nodes, respectively. This resulted in an average improvement of 3.38%, highlighting a prolonged stability period and improved energy balancing among sensor nodes. Similarly, the Last Node Dead (LND) metric improved by 0.28%, 0.28%, and 0.77%, yielding an average improvement of 0.44%. This confirms an improved overall network lifetime and maximum utilization of energy before total depletion. Furthermore, the integration of Sandpiper Optimization and the Harmony Search Algorithm led to a noticeable increase in network traffic handling and data transmission efficiency. In terms of data transmission, the cumulative intra-cluster packet transmissions increased by 3.04%, 1.48%, and 1.58% for the respective node densities, with an average improvement of 2.03%, demonstrating efficient data aggregation within clusters. Additionally, the cumulative inter-cluster packet transmissions improved by 8.35%, 8.31%, and 8.22%, achieving a significant average gain of 8.29%. This indicates highly effective cluster head selection and balanced inter-cluster communication, even at higher node densities. Overall, the experimental results prove that the Hybrid SOA-HSA algorithm delivers superior network stability, prolonged lifetime, improved communication efficiency, and enhanced energy utilization compared to SOA-CSO. These results demonstrate the scalability and robustness of the proposed approach for energy-constrained wireless sensor networks and smart IoT applications.

## 6. REFERENCES

[1] A. Patel, R. Mehra, and V. Singh, "Wireless Sensor Networks for Smart City and IoT Applications: A Comprehensive Review," IEEE IoT Journal, vol. 7, no. 6, pp. 5624–5635, 2020.
[2] P. Kumar, S. Ranjan, and D. Roy, "Energy Depletion Challenges in WSN and Lifetime Optimization Techniques," IETE Technical Review, vol. 38, no. 2, pp. 178–190, 2021.
[3] M. S. Reddy, "Clustering Models for Energy Conservation in Wireless Sensor Networks: A Survey," Journal of Communications and Networks, vol. 22, no. 4, pp. 314–329, 2020.
[4] B. Thomas, "Limitations of Conventional CHS Schemes in WSNs: A Performance Study," International Journal of Wireless and Mobile Computing, vol. 15, no. 1, pp. 25–36, 2021.
[5] N. Gupta, S. Banerjee, "Meta-Heuristic Approaches for Cluster Optimization in IoT-Enabled Sensor Networks: Review and Challenges," Ad Hoc Networks, vol. 123, pp. 102–113, 2022.
[6] D. Varma and H. Lakshman, "Balancing Exploration and Exploitation in Swarm-Based Optimization Algorithms," Applied Soft Computing, vol. 111, pp. 107–121, 2021.
[7] A. Das, "Stagnation Issues in PSO, ACO & and GA-Based Routing for WSNs: A Critical Analysis," International Journal of Intelligent Systems and Applications, vol. 13, no. 5, pp. 67–79, 2021.
[8] R. Sharma, "Hybrid Meta-Heuristic Frameworks for Optimized Communication in WSNs" Journal of Ambient Intelligence and Humanized Computing, vol. 14, no.7, pp. 8991–9005, 2023.
[9] K. R. Iyer "Sandpiper Optimization Algorithm for Global Search in WS Routing," International Journal of Computational Intelligence and IoT, vol. 4, no.3, pp. 101–112, 2022.
[10] S. Ahmed, K. K. Nair, and P. Shetty, "Competitive Swarm Optimization for Local Refinement in Large-Scale Sensor Networks," IEEE Access, vol. 10, pp. 76134–76145, 2022.
[11] Raghavan, K., "Sandpiper Optimization-Based Energy-Aware Clustering for IoT-Enabled WSNs," International Journal of Sensor Technologies, vol. 10, no. 2, pp. 45–58, 2020.
[12] Shastri, "A Hybrid Sandpiper–CSO Method for CHS in Smart WSN Environments," Journal of Network Intelligence and Wireless Systems, vol. 5, no. 3, pp. 112–126, 2021.
[13] Vinothkumar, "Enhanced Harmony-Integrated Sandpiper Optimization for Energy-Balanced Clustering in WSNs," IETE Journal of Research, vol. 68, no. 6, pp. 987–999, 2022.
[14] Prabhu, "Multi-Objective Hybrid SOA–CSO Framework for Lifetime-Aware Cluster Formation in WSNs," Journal of Communications and Distributed Systems, vol. 14, no. 4, pp. 301–317, 2023.
[15] Karthikeyan, "A Triple-Hybrid SOA–HSA–PSO meta-heuristic for Optimized CH Allocation in Smart City Sensor Networks," International Journal of Computational Intelligence and Wireless Networks, vol. 9, no. 1, pp. 25–41, 2023.
[16] Devi, R., "Fast-Converging SOA-CSO Model for Secure Data Aggregation in Dense IoT SNs," Ad Hoc and Ubiquitous Computing Journal, vol. 11, no. 2, pp. 140–154, 2024.
[17] Murugan, P, "QoS-Driven Hybrid SOA–Harmony Search Algorithm for Industrial IoT Cluster Management," IEEE Sensors Letters, vol. 8, no. 7, pp. 1–4, 2024.
[18] Sridharan, "Lightweight Sandpiper–Competitive Swarm Optimization Algorithm for Long-Life WSNs," Journal of Ambient Intelligence and Humanized Computing, vol. 16, no. 5, pp. 2251–2265, 2025.