Energy-Efficient Cluster Head Selection Using Hybrid Sandpiper Competitive Swarm Optimization In Wireless Sensor Networks

[1]* S. Mageshwaran, [2] P. Sundareswaran,

[1]Research Scholar Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli, Tamilnadu, India. mca.magesh@gmail.com
[2]Assistant Professor Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli, Tamilnadu, India · psundareswaran@msuniv.ac.in
* Corresponding Author [1, 2] Department of Computer Science and Engineering

ABSTRACT
Wireless Sensor Networks (WSNs) consist of numerous low-power sensor nodes deployed to monitor and collect environmental data. Energy conservation and improving the network life remain significant challenges due to limited battery capacity and high communication overhead. Clustering techniques, when combined with intelligent optimization algorithms, can significantly reduce energy consumption. However, conventional optimization methods often struggle to balance exploration and exploitation phases effectively. To address this limitation, this paper proposes a hybrid Sandpiper Optimization Algorithm–Competitive Swarm Optimization (SOA-CSO) technique for efficient Cluster Head (CH) selection. The hybrid algorithm leverages the global search capability of Sandpiper Optimization Algorithm and the competitive learning dynamics of Competitive Swarm Optimization to achieve optimal Cluster Head selection. Simulation results show that the proposed SOA-CSO achieves significant improvement in network life time, throughput, packet delivery ratio, load balance and network stability compared to the other algorithm.

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

1. INTRODUCTION

Wireless Sensor Networks (WSNs) play an important role in Internet of Things (IoT) applications such as smart cities, precision agriculture, environmental monitoring, and healthcare systems [1]. Each sensor node in a WSN is a compact device equipped with sensing, processing, and communication capabilities. However, due to their battery-operated nature, energy depletion remains the most critical concern affecting network lifetime [2]. Efficient management of energy consumption and communication overhead is, also crucial for sustainable WSN operations. Clustering has been widely accepted as an effective energy conservation strategy [3]. In clustering-based protocols, sensor nodes are grouped, and each group elects a Cluster Head (CH) responsible for aggregating and forwarding data to the sink node. The optimal selection of CHs ensures energy-balanced communication and minimizes redundancy. However, traditional CH selection methods often result in uneven energy distribution and increased packet loss, leading to a shorter network lifespan [4].

Optimization algorithms inspired by natural processes such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), and Genetic Algorithms (GA) have been used in CH selection [5], [6]. Despite their merits, these algorithms often face convergence stagnation and poor balance between exploration (searching new solutions) and exploitation (refining existing ones) [7]. Hence, hybrid meta-heuristic algorithms have recently been explored to overcome these limitations [8].

The Sandpiper Optimization Algorithm (SOA), inspired by sandpipers' foraging behavior, offers strong global search ability but limited fine-tuning precision. Meanwhile, the Competitive Swarm Optimization (CSO) introduces population competition dynamics that improve local search accuracy [9], [10]. By combining SOA's exploration with CSO's exploitation capabilities, this manuscript proposes a hybrid SOA-CSO framework to optimize CH selection in WSNs for improved energy efficiency and network lifetime.

1.1. MOTIVATION

The primary motivation for this research work is to improve the energy efficiency and reliability of WSNs through intelligent CH selection. The conventional clustering algorithms have a dynamic energy imbalance and early node death, which significantly reduce network lifetime. The meta-heuristic algorithms can mitigate these limitations but require an improved balance between exploration and exploitation to effectively adapt to network topology changes. So, combining SOA and CSO aims to deliver a robust hybrid framework capable of maintaining energy uniformity, prolonging network lifetime, and improving communication stability.

1.2. CONTRIBUTION

This research presents the following key contributions:

1. Hybrid Optimization Framework: A novel SOA-CSO hybrid model for CH selection that effectively balances exploration and exploitation phases.
2. Enhanced Search Efficiency: The integration improves global search capability (SOA) and local convergence accuracy (CSO).
3. Performance Evaluation: Comparative analysis with FA-ROA demonstrates superior network lifetime, stability, and energy distribution.
4. IoT Application Relevance: Designed for scalable IoT-based WSNs, suitable for smart city and environmental monitoring scenarios.

2. RELATED WORKS

Yadav et al. [8] proposed a hybrid algorithm combining Particle Swarm Optimization (PSO), fuzzy logic, and Competitive Swarm Optimization (CSO) for cluster head selection in heterogeneous IoT networks. The study compared the hybrid with standard PSO, fuzzy-only, and CSO-based methods. The simulation involved 100–300 nodes with heterogeneous energy distributions, and the fitness function considered residual energy, cluster distance, and latency over 1000 rounds. The hybrid outperformed traditional algorithms, showing significant improvement in energy efficiency and reduction in latency while maintaining more alive nodes over time. The advantages of this approach include flexible integration of fuzzy logic with swarm intelligence and effective balancing of exploration and exploitation. However, the design complexity and sensitivity to parameter tuning create challenges for deployment in resource-constrained IoT devices.
Sankar et al. [12] proposed the Sandpiper Optimization Algorithm (SOA) for cluster head (CH) selection in IoT networks. The algorithm is inspired by sandpiper foraging behavior, where each node evaluates residual energy and spatial position to determine CH candidate solutions. The nodes are dynamically adjusted to balance energy consumption among the clusters. The study compared SOA with traditional methods such as LEACH and HEED in networks of 100 to 300 nodes over 1000 rounds, considering metrics such as network lifetime, energy consumption, and load distribution. The SOA outperformed traditional algorithms, extending network lifetime and achieving more balanced energy usage. Advantages include effective load balancing

and energy efficiency through dynamic role adjustment, while limitations involve sensitivity to parameter tuning, particularly in large-scale networks.

Patel et al. [13] developed Chaotic Sand Cat Swarm Optimization (CSCSO), which integrates chaotic maps into standard Sand Cat Swarm Optimization to enhance global search and avoid local optima. The nodes positions are updated using a combination of swarm intelligence and chaotic perturbations. The algorithm was compared against PSO, SCA, and standard SCSO on networks of 100 to 300 nodes, with fitness functions based on residual energy, cluster distance, and network lifetime over 1000 rounds. The CSCSO improved energy efficiency and showed faster convergence. Its advantages include enhanced exploration-exploitation balance and high-quality CH selection, whereas limitations involve higher computational overhead and sensitivity to chaotic parameter selection.

Somula [14] proposed EACH-COA, a hybrid approach combining energy awareness with the Coati Optimization Algorithm for CH selection. The node fitness was calculated using residual energy, distance to the sink, and intra-cluster distances. The simulation involved networks of 100 to 300 nodes over 1000 rounds. It is compared to LEACH and HEED, EACH-COA improved network lifetime while maintaining more uniform energy distribution across clusters. Advantages include balanced energy consumption and improved intra-cluster communication, whereas limitations include reduced performance in highly dynamic networks with mobile nodes.

Rajesh Kumar et al. [15] introduced an enhanced security based energy aware Routing protocol for RPL, which integrates energy-aware CH selection with trust evaluation. The nodes are ranked based on residual energy and reliability to prevent malicious nodes from becoming CHs. This study compared the protocol with standard RPL and LEACH in 100 to 300 node networks, using metrics such as network lifetime, energy efficiency, and trust levels over 1000 rounds. The hybrid improved energy efficiency and enhanced network security. Advantages include secure CH selection and extended network lifetime, while limitations are increased protocol complexity and higher computational overhead.

Yang et al. [16] proposed a hybrid Multi-Strategy Fusion Snake Optimizer combined with Minimum Spanning Tree (MST). The nodes were calculated based on residual energy, connectivity, and load, and clusters were formed using MST to ensure optimal connectivity. Simulations with 100 to 300 nodes over 1000 rounds showed significant improvement in throughput and better load balancing than LEACH and HEED. Advantages include multi-objective optimization for energy and connectivity, while limitations involve complexity in fine-tuning multiple strategies.

Gupta et al. [17] proposed a hybrid method combining SOA-based CH selection with cosine similarity-based cross-layer routing, allowing simultaneous optimization of CH selection and routing paths. The networks of 100 to 300 nodes were simulated over 1000 rounds, evaluating energy efficiency, packet delivery, and network lifetime. The hybrid improved both network lifetime and data delivery reliability. Advantages include simultaneous optimization of clustering and routing, while limitations are additional computational complexity, which can affect real-time operation in constrained networks.

Nirmala et al. [18] proposed the Optimized Evaporation Rate Water-Cycle Algorithm (OERWCA), inspired by the natural water cycle. The node fitness was calculated using residual energy, cluster distribution, and distance to the sink, with evaporation, condensation, and flow mechanisms guiding CH selection. Simulations on 100 to 300 node networks over 1000 rounds showed significant improvement in network lifetime over LEACH. Advantages include balanced energy consumption and improved network

lifetime, while limitations involve sensitivity to environmental parameters and the need for careful tuning in dynamic IoT networks.

Despite these significant advances, several research gaps remain. The most existing methods focus either on CH selection or routing optimization individually, often failing to maintain an optimal balance between exploration and exploitation. Many approaches also suffer from uneven load distribution, premature convergence, and increased computational overhead when scaled to large IoT networks.

To address these challenges, a hybrid Sandpiper Optimization Algorithm integrated with Competitive Swarm Optimization (SOA-CSO) for CH selection**.** By leveraging SOA's effective exploration capability and CSO's strong exploitation mechanism, the proposed approach identifies energy-efficient and well-distributed CHs while reducing energy consumption and balancing cluster loads. Consequently, SOA-CSO not only improves network lifetime and throughput but also overcomes the limitations of traditional and existing hybrid algorithms, making it highly suitable for large-scale WSN and IoT environments.

3. PROPOSED TECHNIQUE: HYBRID SOA–CSO OPTIMIZATION

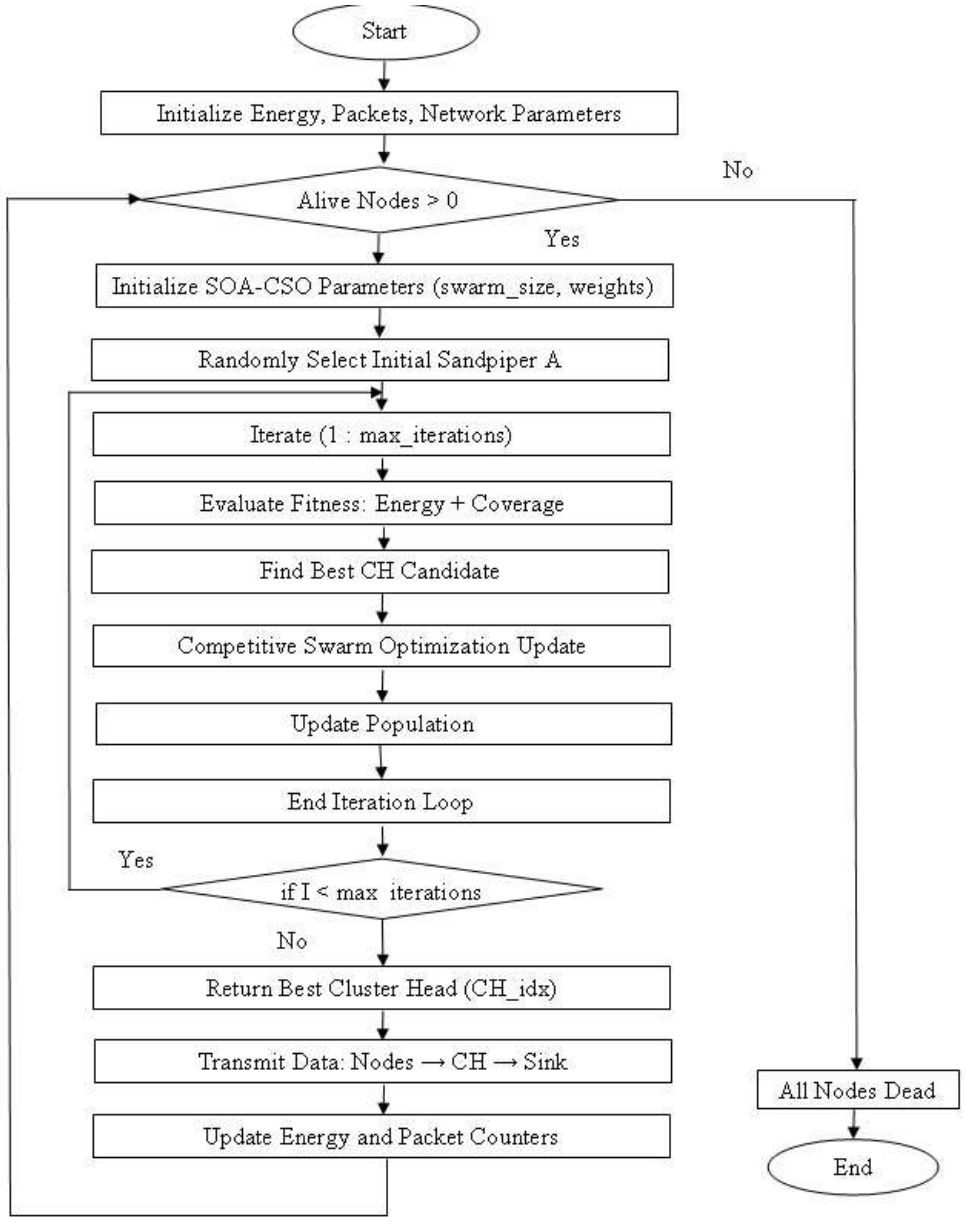
Traditional cluster head (CH) selection methods like LEACH, HEED, and DEEC often rely on random probabilities or fixed thresholds to select cluster heads. While these traditional approaches are simple, the approaches are likely to create uneven energy usage among nodes, redundant cluster heads, and limited adaptability as network conditions change. But the decisions are made locally without considering the overall network. So, these approaches easily choose suboptimal CHs, causing early node failures and reducing network lifetimes. To overcome these issues, the meta-heuristic algorithms are used because it can intelligently explore large solution spaces and adapt to changing environments.

In the proposed approach, the Sandpiper Optimization Algorithm (SOA) is used to identify the most suitable nodes to act as cluster head candidates. The SOA is inspired by the foraging and migration behavior of sandpiper birds. Here, each sandpiper represents a possible CH configuration. During the foraging phase, the algorithm explores the network widely to locate nodes with higher residual energy, shorter distance to the sink, and balanced connectivity. In the migration phase, the candidates move toward optimal positions that minimize communication distance and energy use. Once the potential CHs are identified by the SOA, the Competitive Swarm Optimization (CSO) algorithm steps in to refine them further. The CSO works through a winner–loser competition mechanism, where stronger candidates (those with better energy and position) guide the weaker ones to improve. Over time, this competition helps fine-tune CH selection, ensuring the best possible nodes elect CH roles.

By combining the SOA's strong exploration (searching new solutions) with the CSO's exploitation (refining promising ones) focused local refinement, the hybrid SOA–CSO method ensures that cluster heads are selected intelligently and efficiently. This balance leads to even energy consumption across nodes, reduced communication overhead, and a significantly improved network lifetime in Wireless Sensor Networks.

The Hybrid Sandpiper–Competitive Swarm Optimization (SOA–CSO) algorithm aims to optimize CH selection in each round, maintaining balanced energy consumption and maximizing network lifetime. The algorithm operates in the following phases. They are as follows: network model and energy formation, fitness function formulation, the SOA exploration, the CSO exploitation, CH formation, energy update and transmission model, and Convergence calculation, The flowchart is as follows.

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



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, ε_{fs} and ε_{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 FORMULATION

The fitness function determines the suitability of node i to become a cluster head by combining two key factors namely residual energy and connectivity. The fitness equation supports an adaptive mechanism for selecting cluster heads, promoting improved network lifetime, balanced energy consumption, and improved clustering stability. Each candidate solution represents a possible CH configuration. The fitness of each candidate is evaluated based on residual energy and coverage efficiency to ensure energy-efficient and spatially uniform cluster formation.

$$F_i = \omega_1 \left(\frac{E_{res,i}}{E_{init}}\right) + \omega_2 \left(\frac{C_i}{c_{max}}\right) \quad (3)$$

where $E_{res,i}$ is the average residual energy of nodes connected to the candidate CH, C_i is the sensing coverage ratio, ω_1, $\omega_2 \in [0,1]$ are weighting coefficients , and $\omega_1 + \omega_2 = 1$, Higher F_i indicates a energy efficient CH configuration

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 $X_j = \left[x_{j1}, x_{j2}, \ldots, x_{jD}\right]$ 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 updates 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, $\in [0,1]$ 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 COMPETITIVE SWARM OPTIMIZATION STAGE (EXPLOITATION PHASE)

In the exploitation phase, the Competitive Swarm Optimization (CSO) mechanism is used to refine and search around the most efficient cluster-head (CH) candidates generated during SOA exploration. The CSO focuses on local improvement. During each CSO cycle, the population is randomly divided into pairs. Within every pair, the fitness of two CH candidates is compared based on key WSN parameters such as residual energy, node centrality, coverage efficiency, and distance cost. The candidate with the higher fitness is declared the winner, and the weaker candidate becomes the loser. The

loser then updates its position by learning from both the winner's behavior and the global mean of the population. The CSO model imitates competitive learning, where solutions select in pair-wise competitions, and the winners guide the losers toward better positions. This ensures that the population moves toward higher-fitness CH candidates while reducing the likelihood of premature convergence.
After the SOA stage converges toward promising CH regions, Competitive Swarm Optimization (CSO) refines the solutions via pair wise competition between agents.

(a) Competition Process
For each random pair (X_i, X_j):

- The agent with a higher fitness value becomes the winner.
- The one with a lower fitness becomes the loser.

(b) Velocity and Position Update
The loser updates its velocity and position as follows:

$$V_j^{t+1} = r_1 V_j^t + r_2 (X_i^t - X_j^t) + r_3 (X_{mean}^t - X_j^t) \quad (5)$$

$$X_j^{t+1} = X_j^t r_1 + V_j^{t+1} \quad (6)$$

where $X_{mean}^t = \frac{1}{N_p} \sum_{k=1}^{N_p} X_j^t$ represents the mean position of the swarm, N_p is the number of agents, and $r_1, r_2, r_3, \in [0,1]$ are random parameters controlling memory, competition, and cooperation levels respectively.
This refinement enhances local exploitation around efficient CH candidates, improving convergence rate and stability.

3.5 CLUSTER HEAD FORMATION
After completing max_iterations of the hybrid SOA–CSO 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 (7)
After T_{max} iterations, the best position vector $X_{best}^{T_{max}}$ corresponds to the optimal CH indices:

$$CH^* = \{ i \mid X_{best}^{T_{max}}(i) = 1 \quad (7)$$

Once the optimal CH is selected, each remaining sensor node n joins the clusters formed by the nearest CH, ensuring minimum communication energy consumption. The task is based on the Euclidean distance between node n and each candidate CH.
Each normal node n associates with the nearest CH based on the Euclidean distance:

$$CH(n) = arg_{k \in CH^*}^{min} \sqrt{(x_n - x_k)^2 + (y_n - y_k)^2} \quad (8)$$

3.6 ENERGY UPDATE AND TRANSMISSION MODEL
After cluster formation, data transmission occurs in two phases:

1. Intra-cluster communication (node → CH)
2. Inter-cluster communication (CH → Sink)

During 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 occurs 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. The Efficient intra-cluster communication helps maintain balanced energy usage and prolongs the stability period of the network by reducing premature energy depletion among member nodes.

While the inter-cluster communication stage is executed, 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–CSO optimization framework ensures that nodes with sufficient residual energy and good topological position are selected as CHs, thereby maintaining energy balance and prolonging overall network lifetime.

For a member node i transmit to its CH:

$$E_i^{r+1} = E_i^r - E_{tx}(k, d_{i,CH}) \quad (9)$$

For a CH transmit aggregated data to the sink:

$$E_{CH}^{r+1} = E_{CH}^r - [k\, E_{elec}\, (n_{mem} + 1)\, k\, E_{DA^n\, mem} + E_{tx}\left(k, d_{CH,s}\right)] \quad (10)$$

where 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–CSO 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 small, indicating that further iterations will not create 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.

$$\left| \frac{F_{best}^{r+1} - F_{best}^{t}}{F_{best}^{t}} < \varepsilon \right| \quad (11)$$

This condition ensures stable convergence and computational efficiency. This mechanism prevents unnecessary computation, reduces algorithmic overhead, and ensures that the final cluster-head selection is both efficient and robust.

4. SIMULATION AND DISCUSSION

The performance of the proposed hybrid SOA-CSO technique is evaluated using MATLAB 2013a simulation tool. The Simulation parameters include increasing number of sensor nodes ranging from 100, 200 and 300. The area of the nodes is 100×100 m^2. 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 / m^2 (short range) and E_{amp} = 0.0013 p J / bit / m^2 (long range). The packet size is 4000 bits. The base station of the network is located at (50, 50). The simulation runs for 3000 rounds.

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

In the Fitness Averaged Rider Optimization Algorithm (FA-ROA), solutions are computed and split into two groups based on fitness. Better solutions are updated using the average behavior of bypass and follower riders, while the others are updated using attacker and over-taker riders. This approach, called FA-ROA, balances exploration and exploitation and helps the algorithm reach optimal solutions more efficiently.
In the hybrid Sandpiper Optimization Algorithm is integrated with Competitive Swarm Optimization (SOA-CSO) to improve clustering efficiency. It works with a swarm size of 20 individuals and is executed for 50 iterations to ensure stable convergence. The fitness function is computed to do dual objectives: minimize the overall energy consumption of the network and maximize improving cluster head coverage. This combination yields the selection of energy-efficient and equally-distributed cluster heads.

SIMULATION OUTCOME OF 100 SENSOR NODES

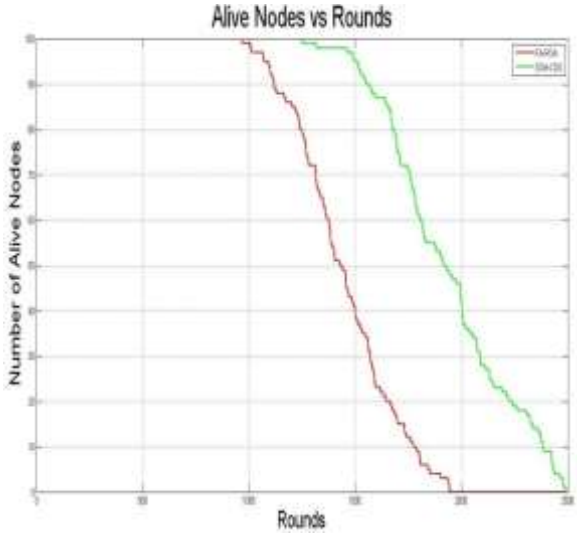


Figure 2: Alive Nodes vs Rounds

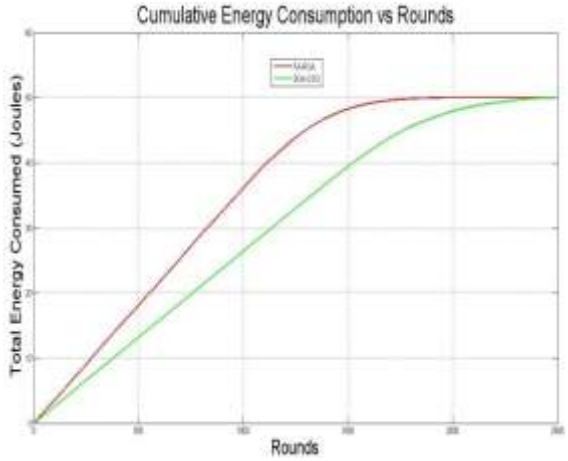


Figure 3: Cumulative Energy Consumption vs Rounds

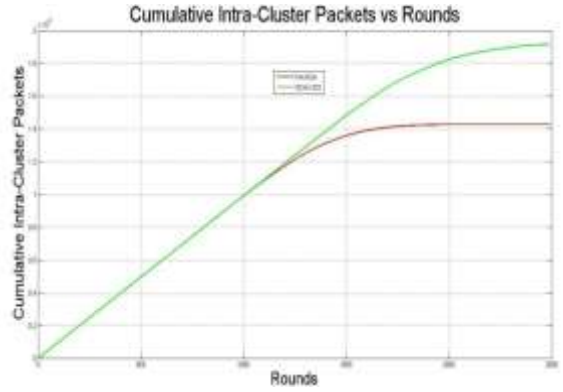


Figure 4: Overall Cumulative Packets vs Rounds

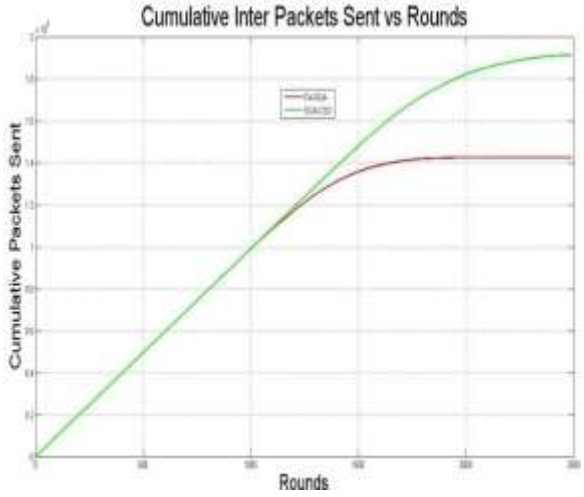


Figure 5: Overall Cumulative inter-cluster Packets vs Rounds

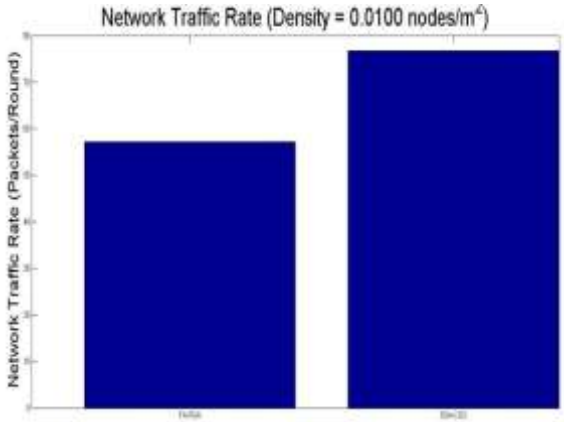


Figure 6: Network Traffic Rate vs Rounds

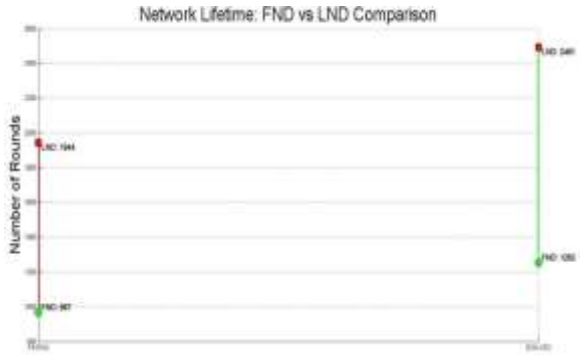


Figure 7: Network Lifetime Comparison (FND to LND) vs Rounds

Table 1: Summary of Collected Data for 100 sensor nodes

METRIC	FA-ROA	HYBRID SOA-CSO	IMPROVEMENT PERCENTAGE
Total Rounds (All Dead)	2491	2491	
First Node Dead	967	1252	(+29.47)
Last Node Dead	1944	2491	(+28.14)
Network Traffic Rate (pkt/round)	57.16	76.78	(+34.33)
Cumulative Intra-Cluster Packets	142410	191260	(+34.30)
Cumulative Inter-Cluster Packets	1939	2490	(+28.42)

The performance of the FA-ROA and HYBRID SOA-CSO algorithms was evaluated until all sensor nodes were depleted, with both techniques completing 2,491 rounds. The comparative analysis showed that the HYBRID SOA-CSO algorithm consistently outperforms FA-ROA across all primary network performance metrics.

In terms of network stability, the first node death (FND) in HYBRID SOA-CSO occurred at round 1,252, which represents a 29.47% improvement over FA-ROA, where the first node died at round 967. Furthermore, the last node death (LND) was significantly delayed from 1,944 rounds in FA-ROA to 2,491 rounds in HYBRID SOA-CSO, achieving a 28.14% enhancement in the operational network lifetime.

The HYBRID SOA-CSO also showed superior data transmission capabilities. The network traffic rate increased from 57.16 packets per round in FA-ROA to 76.78 packets per round, yielding a 34.33% improvement. Similarly, the cumulative intra-cluster packet transmission rose from 142,410 to 191,260 packets, reflecting a 34.30% gain. Additionally, inter-cluster packet transmissions increased from 1,939 to 2,490 packets, corresponding to a 28.42% improvement. This substantial increase in packet throughput indicates a more effective cluster head selection process and optimized inter-cluster communication.

Overall, the results confirm that the HYBRID SOA-CSO algorithm achieves better energy utilization, improved traffic handling, and an extended stability period compared to FA-ROA, making it a more efficient solution for energy-constrained smart IoT and wireless sensor network environments.

SIMULATION OUTCOME OF 200 SENSOR NODES

Figure 8: Alive Nodes vs Rounds

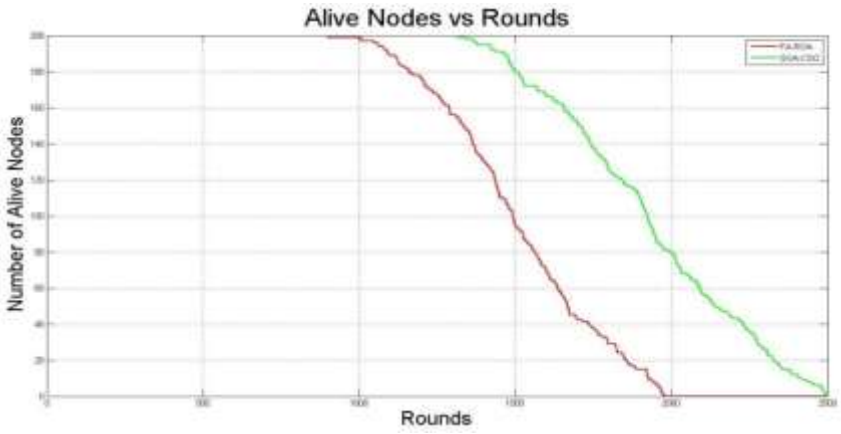


Figure 9: Cumulative Energy Consumption vs Rounds

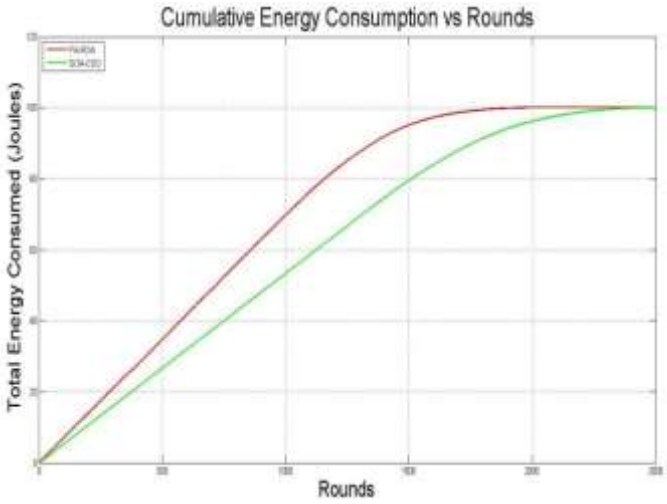


Figure 10: Overall Cumulative Packets vs Rounds

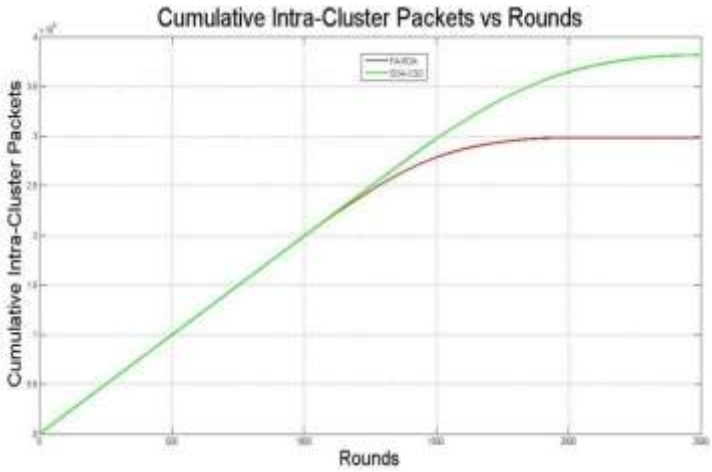


Figure 11: Overall Cumulative inter-cluster Packets vs Rounds

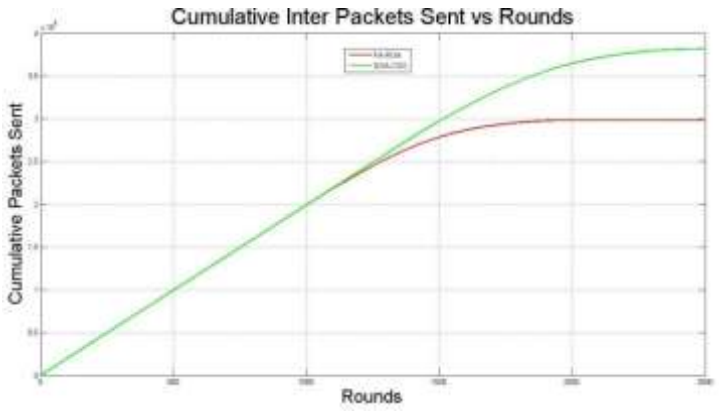


Figure 12: Network Traffic Rate vs Rounds

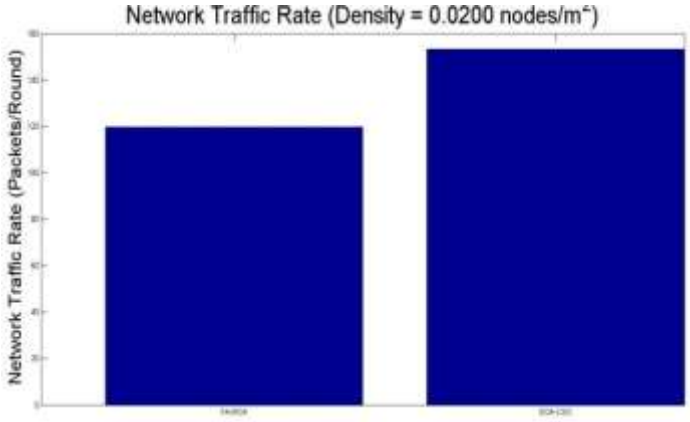


Figure 13: Network Lifetime Comparison (FND to LND) vs Rounds

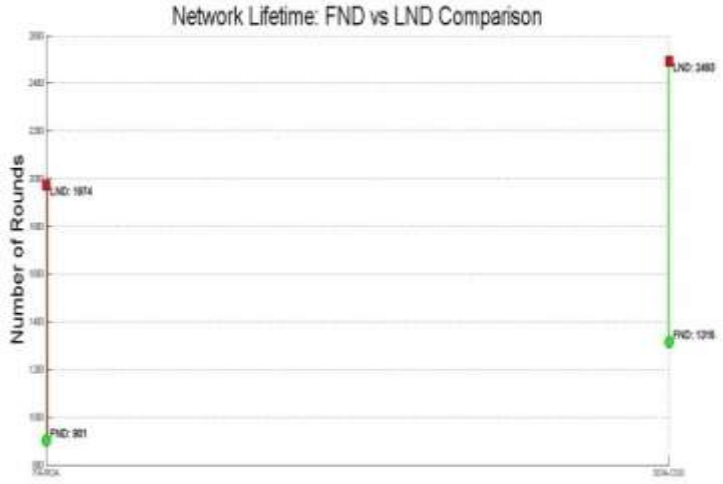


Table 2: Summary of Collected Data for 200 sensor nodes

METRIC	FA-ROA	HYBRID SOA-CSO	IMPROVEMENT PERCENTAGE
Total Rounds (All Dead)	2493	2493	-
First Node Dead	901	1315	(+45.95)
Last Node Dead	1974	2493	(+26.29)
Network Traffic Rate (pkt/round)	119.65	153.11	(+27.96)
Cumulative Intra-Cluster Packets	298289	381706	(+27.96)
Cumulative Inter-Cluster Packets	1969	2492	(+26.56)

The performance of the FA-ROA and HYBRID SOA-CSO algorithms was evaluated until all sensor nodes were depleted, with both techniques completing 2,493 rounds. In terms of network stability, the first node death (FND) in HYBRID SOA-CSO occurred at round 1,315, which represents a significant 45.95% improvement over FA-ROA, where the first node died at round 901. Furthermore, the last node death (LND) was delayed from 1,974 rounds in FA-ROA to 2,493 rounds in HYBRID SOA-CSO, achieving a 26.29% enhancement in the operational network lifetime.

The HYBRID SOA-CSO also demonstrated superior data transmission capabilities. The network traffic rate increased from 119.65 packets per round in FA-ROA to 153.11 packets per round, yielding a 27.96% improvement. Similarly, the cumulative intra-cluster packet transmission rose from 298,289 to 381,706 packets, reflecting the same 27.96% gain. Additionally, inter-cluster packet transmissions increased from 1,969 to 2,492 packets, corresponding to a 26.56% improvement. This significant increase in packet throughput indicates that the hybrid optimization effectively selects Cluster Heads (CHs) that balance energy consumption and data routing efficiency.

Overall, the results confirm that the HYBRID SOA-CSO algorithm achieves better energy utilization, improved traffic handling, and an extended stability period compared to FA-ROA, making it a more robust solution for energy-constrained smart IoT and wireless sensor network environments.

SIMULATION OUTCOME OF 300 SENSOR NODES

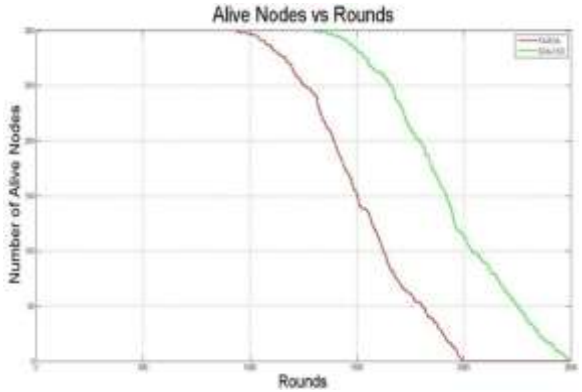


Figure 14: Alive Nodes vs Rounds

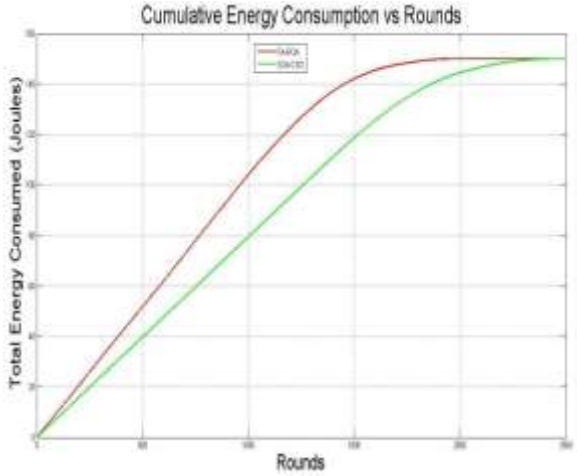


Figure 15: Cumulative Energy Consumption vs Rounds

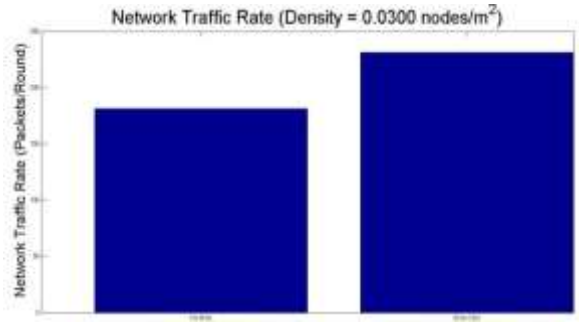


Figure 18: Network Traffic Rate vs Rounds

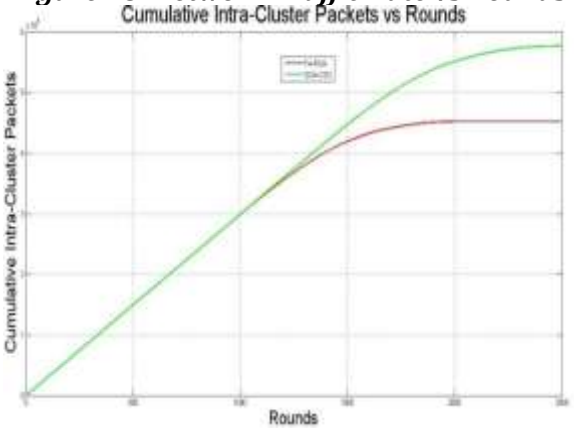


Figure 16: Overall Cumulative Packets vs Rounds

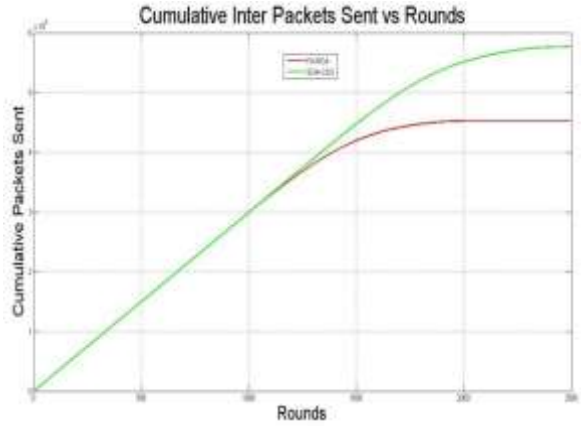


Figure 17: Overall Cumulative inter-cluster Packets vs Rounds

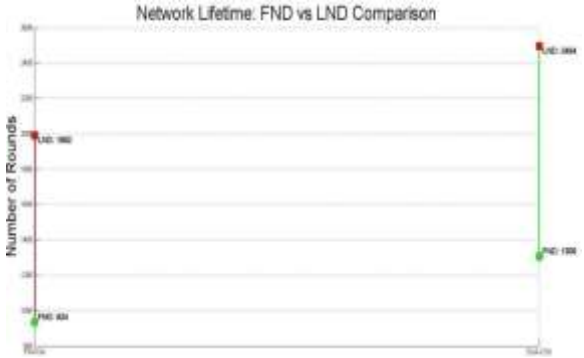


Figure 19: Network Lifetime Comparison (FND to LND) vs Rounds

Table 3: Summary of Collected Data for 300 sensor nodes

METRIC	FA-ROA	HYBRID SOA-CSO	IMPROVEMENT %
Total Rounds (All Dead)	2495	2495	-
First Node Dead	934	1306	(+39.83)
Last Node Dead	1992	2494	(+25.20)
Network Traffic Rate (pkt/round)	181.21	231.13	(+27.55)
Cumulative Intra-Cluster Packets	451945	576451	(+27.55)
Cumulative Inter-Cluster Packets	1986	2493	(+25.53)

Table 4: Summary of average improvement of metric sensor nodes (100,200 and 300)

METRIC	100 NODES	200 NODES	300 NODES	AVERAGE IMPROVEMENT
First Node Dead	(+29.47)	(+45.95)	(+39.83)	(+38.42)
Last Node Dead	(+28.14)	(+26.29)	(+25.20)	(+26.54)
Network Traffic Rate (pkt/round)	(+34.33)	(+27.96)	(+27.55)	(+29.95)
Cumulative Intra-Cluster Packets	(+34.30)	(+27.96)	(+27.55)	(+29.94)

Cumulative Inter-Cluster Packets	(+28.42)	(+26.56)	(+25.53)	(+26.84)

The performance of the FA-ROA and HYBRID SOA-CSO algorithms was evaluated until the total depletion of a maximum of 2,495 rounds. The First Node Dead (FND) for HYBRID SOA-CSO occurred at round 1,306, marking a significant 39.83% improvement over FA-ROA, which experienced its first failure at round 934.Furthermore, the Last Node Dead (LND) was improved from 1,992 rounds in FA-ROA to 2,494 rounds in HYBRID SOA-CSO, reflecting a 25.20% enhancement in the overall operational lifetime. The Network Traffic Rate increased from 181.21 packets per round in FA-ROA to 231.13 packets per round, representing a 27.55% improvement. Consequently, the Cumulative Intra-Cluster Packets rose from 451,945 to 576,451, matching the overall traffic improvement. Efficiency in data communication was also evidenced by a 25.53% improvement in Cumulative Inter-Cluster Packets, which rose from 1,986 to 2,493. Overall, these results confirm that the HYBRID SOA-CSO algorithm achieves a more robust balanced between energy utilization and data reliability, establishing it as a very efficient solution for energy-constrained smart IoT environments.

5. CONCLUSION

Through simulations on networks of 100, 200, and 300 nodes, the proposed Hybrid SOA-CSO approach consistently outperformed the FA-ROA. The number of alive nodes remained consistently higher throughout the network operation under the proposed Hybrid SOA-CSO scheme, confirming its enhanced stability compared to FA-ROA. Significant improvements were observed across all evaluated performance metrics as the network size increased from 100 to 300 nodes. The First Node Dead (FND) metric shows significant improvements of +29.47%, +45.95%, and 39.83% for 100, 200, and 300 nodes, respectively, resulting in an average improvement of 38.42%, which highlights a prolonged stability period and improved energy balancing among sensor nodes. Similarly, the Last Node Dead (LND) metric improved by 28.14%, 26.29%, and 25.20%, yielding an average enhancement of 26.54%, thereby confirming an improved overall network lifetime. Furthermore, the integration of Sandpiper and Competitive Swarm optimization techniques led to a 29.95% average increase in network traffic handling and data transmission efficiency. In terms of data transmission efficiency, the cumulative intra-cluster packet transmission increased by 34.30%, 27.96%, and 27.55%, with an average improvement of 29.94%, demonstrating efficient data aggregation within clusters. Additionally, the cumulative inter-cluster packet transmission improved by 28.42%, 26.56%, and 25.53%, achieving an average gain of 26.84%, which indicates effective cluster head selection and balanced inter-cluster communication. Overall, the experimental results proved that the Hybrid SOA-CSO algorithm delivers superior network stability, prolonged lifetime, improved communication efficiency, and enhanced energy utilization compared to FA-ROA. These show the scalability and robustness of the proposed approach for energy-constrained wireless sensor network and smart IoT applications.

6. REFERENCES

1. M. Musa, "WSNs for Precision Agriculture," Sensors, vol. 24, p. 51, 2023.
2. S. Tabatabaei, "New Energy Efficient Management Approach for Wireless Sensor Networks," ScienceDirect, 2025.
3. T.A. Abose, "Improving Wireless Sensor Network Lifespan with Optimized Clustering," ScienceDirect, 2024.

4. Y. Qu, "Intelligent Unequal Clustering in Wireless Sensor Networks," Nature Communications, 2025.
5. M.A. Alqarni, "Improved Wireless Sensor Network Data Collection Using Optimization Algorithms," ScienceDirect, 2023.
6. H. Khujamatov, "Clustered Routing Using Chaotic Genetic Algorithm with Grey Wolf Optimizer," Sensors, vol. 24, no. 13, p. 4406, 2024.
7. M.K. Roberts, "An Improved Dual-Phased Meta-Heuristic Optimization for Energy-Efficient Routing in Wireless Sensor Networks," ScienceDirect, 2024.
8. Yadav, R.K., Mahapatra, R.P., & Sahoo, S.K. "Hybrid Metaheuristic Algorithm for Optimal Cluster Head Selection in WSNs," Pervasive and Mobile Computing, 2022.
9. J. Pan, "Surrogate-Assisted Hybrid Meta-Heuristic Algorithm with Gannet Optimization and Differential Evolution," MDPI, 2023.
10. S. Zhang, "Improving the Functionality of Wireless Sensor Networks Using Meta-Heuristic Algorithms," Nature Communications, 2025.
11. Kumar, S., Kumar, R., & Kumar, V. "Optimal cluster head selection for energy efficient wireless sensor network using hybrid competitive swarm optimization and harmony search algorithm." Sustainable Energy Technologies and Assessments, 52, 102243, 2022.
12. Sankar, S., Ramasubbareddy, S., & Dhanaraj, R.K. "Cluster head selection for the Internet of Things using a Sandpiper Optimization Algorithm." Journal of Sensors, 2023.
13. Patel, F., & Kiani, F. "Chaotic Sand Cat Swarm Optimization: A new hybrid metaheuristic algorithm for constrained and complex optimization problems." Mathematics, 11(5), 2023.
14. Somula, R., Cho, Y., & Mohanta, B.K. "EACH-COA: An energy-aware cluster head selection for the Internet of Things using the Coati Optimization Algorithm." 2023.
15. Rajesh Kumar, R., & Dhanaraj, R.K. "Enhanced security-based energy-aware routing for RPL in IoT network." Manipal University, 2024.
16. Yang, L., Zhang, S., & Wang, X. "Energy efficient cluster-based routing protocol for WSN using multi-strategy fusion snake optimizer and minimum spanning tree." Scientific Reports, 14, 2024.
17. Gupta, A., & Ramasubbareddy, S. "Sandpiper Optimization Algorithm with cosine similarity-based cross-layer routing protocol for smart agriculture in WSN assisted Internet of Things systems." 2025.
18. Nirmala, S., & Dhanaraj, R.K. "Energy-efficient cluster head selection in Internet of Things networks using an optimized evaporation rate Water-Cycle Algorithm." Springer Open Journal of Electrical Engineering & Technology, 2025.