A Hybrid Optimization Algorithm for Enhanced Coverage and Prolonged Lifetime in Integrated Static and Movable Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) are critical in monitoring and collecting data across diverse applications such as environmental surveillance, disaster response, and smart infrastructure. However, the dual challenge of maximizing network coverage and prolonging operational lifetime persists due to constraints on sensor energy and dynamic environmental conditions. To improve WSN performance, this research proposes hybrid optimization strategy that includes static and fixed sensor nodes while employing single-hop and multi-hop communication strategies. We have suggested an integrated stable deployment of static nodes with the adaptability of movable nodes to dynamically address coverage gaps and balance energy consumption. Static node placement, movable node movement patterns, and effective routing protocols are all determined through advanced optimization techniques. In comparison to traditional WSN configurations, simulation results indicate that proposed hybrid approach substantially improves network coverage that extends lifetime. By bridging the strengths of static and movable nodes and leveraging single-hop and multi-hop communication, this study offers a robust and energy-efficient solution to the critical challenges faced by WSNs. The findings have significant implications for the deployment of WSNs in dynamic and resource-constrained environments, paving the way for more resilient and adaptive sensing networks.

Keywords: Coverage area, gray wolf optimization (GWO), Horse herd optimization (HHO), Hybrid horse herd whale optimization (HHHWHO), Lifetime of network, Particle swarm optimization, (PSO), Whale optimization (WHO)

1. Introduction

WSNs have become an essential technology in several domains that include environmental monitoring, military surveillance, smart agriculture, and disaster management. Spatial sensor nodes that may monitor environmental conditions while transmitting information collected to a central node or base station constitute these networks. Despite their widespread applications, achieving optimal coverage and prolonged network lifetime remains a critical challenge, particularly in resource-constrained environments.

Traditional WSNs typically rely on either static or movable sensor nodes. Static sensor nodes are permanently deployed and are limited in their ability to adapt to changing coverage requirements. In contrast, movable sensor nodes introduce dynamic repositioning capabilities, allowing them to adjust their locations to enhance coverage and reduce communication overhead. But depending only on static or fixed nodes may result in inadequate coverage, energy efficiency, or deployment cost.

To address these challenges, a hybrid approach that integrates both static and movable sensor nodes is proposed. This combination leverages the strengths of static nodes for cost-effective and stable deployment while utilizing the adaptability of movable nodes to dynamically enhance coverage and balance energy consumption. Furthermore, employing single-hop and multi-hop communication strategies can optimize data transmission efficiency, reduce latency, and mitigate energy depletion in sensor nodes.

Developing hybrid optimization approach that extends WSN's lifetime and maximizes network coverage is the objective of this research. The proposed algorithm employs advanced hybrid optimization technique hybrid horse herd whale optimization algorithm (HHHWHO) to determine the optimal placement of static nodes, dynamic movement of movable nodes, and efficient routing strategies for both single-hop and multi-hop communication. By addressing these interdependent factors, the algorithm aims to overcome the limitations of existing WSN architectures and deliver robust, energy-efficient performance.

Structure of this document is as follows: Relevant literature on WSN optimization for energy efficiency and coverage is reviewed in Sec. 2. Sec. 3 displays problem formulation and proposed hybrid optimization framework. Setup and results of simulation have been addressed in Sec. 4. Sec. 5 draws the research to a conclusion while suggesting potential directions for further investigation.

2. Background

To increase network lifetime while addressing challenges of deterministic and grid-based deployment, X. Liu [1] developed three deployment techniques. Algorithm 1 assigns nodes to several groups that are connected by shortest paths. Second, is a delay-based deployment method that significantly reduces transmission path length and transmission delay by evaluating deployment cost profit and transmission delay loss. Third, actual demand levels determine allocation of nodes, thus extra nodes are only deployed when required. Network lifetime is greatly increased as a result. To evaluate and confirm efficacy and superiority of results, authors employed advanced simulations.

[2] Following their initial deployment of stationary nodes, Younis et al. devised an algorithm that identifies ideal number and placement of mobile nodes that should be included. Their genetic algorithm had been assessed based on several metrics. Results of simulation demonstrated that suggested algorithm optimized network coverage.

[3] To expand GWO's capacity for global exploration, authors suggested an enhanced position-updating equation for enhancing leadership of high-ranking wolves. The objective of leading wolves about dominant wolves is for maintaining optimum ratio of exploration to exploitation. This approach is employed for addressing WSN coverage optimization problem, experimental results demonstrate that GWO-EH is applicable and valid.

[4] M. Mousavirad explored Harris Hawks Optimization (HHO) algorithm for sensor node localization and compared its performance with other optimization algorithms such as SSA, EO, and GWO. Implemented proposed work using the MATLAB tool and various parameters are analyzed, including mean localization error, computational cost, and the number of localized sensor nodes. HHO algorithm was evaluated against other algorithms (SSA, EO, GWO) for its effectiveness in sensor node localization.

[5] Current study proposes Whale Optimization Algorithm (WOA), a nature-inspired meta-heuristic optimization algorithm. It resembles humpback whale social behavior. Algorithm has been modeled after bubble-net hunting approach. 6 structural design difficulties and 29 mathematical optimization tasks have been employed to test WOA. According to optimization results, WOA algorithm outperforms conventional techniques and most advanced meta-heuristic algorithms.

[6] The paper by Sharma and R. K. Gupta presents a hybrid algorithm that combines HHO and WOA to optimize WSN lifetime. Hybrid algorithm efficiently combines HHO and WOA strengths, leading to improved optimization performance compared to using either algorithm alone and proposed algorithm significantly extends the network's operational lifetime.

[7] The genetic algorithm proposed by the authors effectively determines optimal positions for mobile sensor nodes to enhance the coverage of WSN. This algorithm reduces the need for additional mobile nodes, ensuring efficient resource utilization. Algorithm significantly improves the overall coverage of the network by filling coverage gaps left by the initial random deployment of static nodes. Results demonstrate that the genetic algorithm outperforms other traditional deployment methods.

[8] T.S. Raut et al focused on using GWO algorithm to enhance both coverage and energy management in WSNs.GWO algorithm effectively improves coverage of the sensor network by optimizing the placement of sensor nodes, ensuring better

monitoring of the target area. The algorithm also addresses energy efficiency by optimizing the energy consumption of the sensor nodes, thereby prolonging network's operational lifetime. The paper evaluates the performance of GWO algorithm using various metrics and demonstrates its superiority over other optimization techniques in terms of both coverage and energy efficiency.

[9] M. Mousavirad et al introduced HHO algorithm which enhances the accuracy of node localization by effectively determining the positions of sensor nodes within the network. Proposed approach optimizes energy consumption, which is crucial for prolonging the operational lifetime of sensor network. Research paper compares HHO algorithm performance with other existing algorithms hence, demonstrating its superiority concerning localization accuracy and energy efficiency.

[10] Seyedali Mirjalili published HHO algorithm and explores its applications. HHO algorithm is inspired by the cooperative behavior and chasing style of Harris' hawks in nature, known as surprise pounce. The algorithm mimics these behaviors to solve optimization problems. Research paper demonstrated efficacy of HHO algorithm on various benchmark problems and real-world engineering applications, showing promising results compared to other metaheuristic techniques.

[11] Authors utilized hybrid GWO and Particle Swarm Optimization (PSO) to arrange and size numerous distributed generations in distribution system. Improve voltage profiles while reducing power loss in electrical systems.

[12] Y. Zhang et al enhanced the performance of traditional PSO by addressing challenges that includes local optima entrapment and slow convergence. HSPSO demonstrated superior performance over standard PSO and other optimization algorithms like Butterfly Optimization Algorithm, Hummingbird Flight patterns PSO, Ant Colony Optimization, Dynamic Adaptive Inertia Weight PSO, and Firefly Algorithm regarding best, and average fitness, along with stability.

[13] M. A. Abido developed a novel hybrid algorithm that combines PSO and Genetic Algorithm (GA) for resolving optimization problems more effectively. Hybrid algorithm integrates the exploration capabilities of PSO with GA exploitation strengths. The algorithm uses adaptive weight adjustment to balance exploration and exploitation. These techniques are incorporated for preventing local optima while enhancing convergence speed. Hybrid PSO-GA algorithm demonstrated superior performance compared to standard PSO and GA algorithms.

[14] X. Li et al discussed an enhanced version of PSO and GWO algorithms. Authors addressed issues including premature convergence, poor global search ability, and tendency to fall into local optima in traditional PSO algorithms. The algorithm uses chaos theory for initializing speed and position of particles, increasing diversity in addition to reducing premature convergence. To increase convergence speed and global search capabilities, an innovative adaptive inertial weight has been developed. Improved algorithm was tested on ten benchmark functions, showing better performance compared to traditional PSO-GWO methods.

[15] Das, S. introduced a novel hybrid algorithm that combines Heterogeneous Improved Dynamic Multi-Swarm Particle Swarm Optimization (HIDMS-PSO) with GA. This enhanced the performance of optimization algorithms by leveraging the strengths of HIDMS-PSO and GA to maintain diversity and improve convergence.GA-HIDMS-PSO algorithm outperformed 24 comparison algorithms, including 12 state-of-the-art PSO variants and 12 other metaheuristics, on both 30 and 50-dimensional CEC test suites. The hybrid approach effectively maintained diversity and improved convergence speed.

[16] M. S. Sayed, A. E. Hassanien, and S. H. Ahmed presented a hybrid algorithm that combines WOA and PSO for clustering tasks. By utilizing WOA and PSO's advantages, objective is to improve clustering performance by increasing convergence speed and global search capability. Algorithm combines PSO's strengths in exploitation with WOA's exploratory capabilities. Hybrid algorithm is applied to clustering tasks, aiming to find optimal cluster centers and improve clustering accuracy.

[17] S. Emary et al presented a hybrid algorithm combining Harris Hawk Optimization and Whale optimization algorithm for feature selection. The algorithm integrates exploration capabilities of Harris hawk optimisation with Whale optimization algorithm's exploitation strengths. Hybrid algorithm is applied to select a subset of relevant features from a larger set, reducing dimensionality and superior performance compared to using standalone algorithm in feature selection tasks.

[18] This paper presents a hybrid bio inspired algorithm which extended the network lifetime in IoT enabled Wireless Sensor Networks (WSNs). This is achieved by optimizing the node placement and energy consumption of nodes. Authors hybridized the Whale optimization algorithm with flower pollination algorithm. Authors claimed 25-30 % improvement in coverage area as compared with PSO and FPA.

[19] Authors introduced a novel meta-heuristic known as Improved Flower pollination algorithm draws inspiration from flower pollination algorithm. This approach improves the coverage area and connectivity in WSNs having heterogeneous nodes. The algorithm is compared with PSO and GA and provided 15% more improvement in coverage area.

3. Problem Formulation

The nodes communicate with a base station (sink) to relay the collected information. Given limited energy resources accessible to each sensor node, maximizing coverage area when extending network's lifetime is major challenge in WSNs. Here we have assumed the following network model aimed at addressing this challenge.

Grid Area: The WSN is deployed over a predefined grid area of dimensions (100 by 100) meters.

Sensor Nodes: There are 100 sensor nodes in all. Randomly distributed within the grid. Each node has a fixed sensing radius of (0.5) meters.

Base Station: A single base station is located at a fixed position within the grid, responsible for collecting data from sensor nodes.

Communication Model: Depending on their distance from the base station, sensor nodes can link to it directly or through multi-hop routing. Depending on how far away they're from the base station, sensor nodes can either connect directly with it or use multi-hop routing. Here we have used Rayleigh path loss model with path loss exponent of 7.5 for harsh urban environment.

Initial Energy: Sensor nodes are given an initial energy of 1000 units.
Energy Consumption: Energy usage of sensor nodes is influenced by sensing and communication processes.

Sensing Energy Consumption: Energy consumed for sensing the environment within the sensing radius.

Coverage area calculation: The coverage area is defined as the total area within the grid that is monitored by at least 1 sensor node. The objective is to maximize this area. Coverage is calculated based on sensing radius of each node and their positions within grid.

Network Lifetime Calculation: Amount of time before the first sensor node runs out of power and also stops operating. The aim is to prolong this period as much as feasible. The lifespan is determined by consistently tracking the sensor nodes' energy levels while determining the moment when the first node depletes its energy.

4. Methodology

WSNs are comprised of several sensor nodes which communicate wirelessly to observe and gather information from the surroundings. These nodes typically have limited energy resources, making efficient energy management critical for the network's performance and lifetime. Optimization plays a vital role in WSNs by addressing various challenges. Optimization is a mathematical and computational discipline focused on identifying the optimal solution to an issue while adhering to specific limitations and requirements. It involves selecting the most efficient, effective, or functional solution from a range of possible options. Optimization techniques are widely used in enhancing wireless sensor network performance.

The main goal of the optimization is twofold first maximum possible area within the grid is covered by the sensor nodes, thereby improving the effectiveness of WSN and efficiently managing sensor nodes' energy usage to extend network's overall operating time. The Optimization is affected by Energy Constraints and Coverage Constraints. Combining the HHOA and WOA for WSNs can significantly improve coverage area and network lifetime due to the complementary strengths of both algorithms.

Exploration: HHOA is known for its strong exploration capabilities, which help in searching a wide area of the solution space. Diversity Maintenance**:** It maintains diversity among solutions, preventing premature convergence to local optima.

Exploitation: WOA excels in exploitation, fine-tuning solutions to reach the global optimum.

Convergence Speed: It has a faster convergence speed, which helps in quickly finding optimal solutions.

Enhanced Coverage: By combining HHOA's exploration with WOA's exploitation, the hybrid algorithm can effectively search for and fine-tune optimal sensor placements, leading to improved coverage.

Extended Lifetime: The improved coverage ensures that fewer sensors are required to cover same area, reducing energy consumption and extending network's lifetime
Fitness (Objective) Function

Objective function aims at maximizing total coverage area C along with cutting down on the amount of energy used. It can be formulated as follows:

This objective function for coverage area can be represented as:
Maximize $C = \sum_{i}^{N} A(xi, yi, r)$ (1)

C is the coverage area, which results from the sensor positions
Let N be the sum of all the sensor nodes.
xi and yi be the i-th sensor node's coordinates
r be the radius of detection for every sensor node

Objective function aims for minimizing energy consumption. It could be formulated as given below:
Ei is the energy consumption for sensor node i, where N represents total number of sensor nodes Einitial is each sensor node's starting energy T be network lifetime
Objective function could be represented as:
Maximize T=min[(Einitial-Ei) / Einitial](2)

The goal is to maximize the minimum remaining sensor nodes energy, which indirectly maximizes the lifetime of the network.
The combined objective function can be represented as:
$O\_T = Kc \times \left(\frac{C}{Cmax}\right) + Kl \times \left(\frac{T}{Tmax}\right)$(3)
Where,
C max is the maximum possible coverage are T max is the maximum possible network lifetime. In this function:
Kc and Kl are weights that, respectively, indicate how important coverage area along with network lifetime. Depending on particular needs or design considerations for the wireless sensor network, these weights can be changed by wireless network designer.

5. Hybrid Algorithm Design: Horse Herd and Whale Optimization

5.1. Initialization

- Population Initialization: Randomly initialize the positions of the agents (nodes) within the grid. Each agent represents a potential solution with coordinates determining the positions of sensor nodes.
- Parameters Setup: Define the parameters for HHO and WHO. HHO Parameters: Number of horses, number of iterations, step sizes, and randomization factors. WHO Parameters: Initial population, parameters A and C, no of iterations

5.2. Fitness Evaluation

Fitness Function: Define a fitness function to evaluate each agent's performance based on

Coverage Area: The total area covered by sensor nodes.
Energy Consumption: Energy levels of the nodes, impacting network lifetime.
Initial Evaluation: Calculate the initial fitness of each agent based on their positions.

5.3. Algorithm Execution

Hybrid Approach: Combining HHOA and WOA could significantly enhance WSNs performance in terms of coverage area and network lifetime.

Initialization: The algorithm starts by initializing a population of solutions using HHOA, which ensures a diverse set of initial positions.

Exploration: HHOA's exploration capabilities help in searching a wide area of the solution space, avoiding local optima.

Exploitation: WOA's exploitation strengths fine-tune the solutions for attaining global optimum. For HHOA algorithm implementation the movement of horses in a herd is modeled mathematically to simulate exploration. Based on their interactions and the leader horse's effect, the horses' positions are updated.
Mathematically,

For each iteration the m th horse position is updated by equation (4)

$$P_m^{iter,age} = Vel_m^{iter,age} + Vel_m^{(iter-1),age} \quad (4)$$

The formula determines a horse's current position by summing its past position and current velocity.
The velocity of α,β,γ, horse is governed by equations (5), (6), (7) and (8)

$$Vel_m^{Iter,\alpha} = Gra_m^{Iter,\alpha} + DefMec_m^{Iter,\alpha} \quad (5)$$

$$Vel_m^{Iter,\beta} = Gra_m^{Iter,\beta} + H_m^{Iter,\beta} + Soc_m^{Iter,\beta} + DefMec_m^{Iter,\beta} \quad (6)$$

$Vel_m^{Iter,\gamma} = Gra_m^{Iter,\gamma} + H_m^{Iter,\gamma} + Soc_m^{Iter,\gamma} + Imt_m^{Iter,\gamma} + Ro_m^{Iter,\gamma} + DefMec_m^{Iter,\gamma}$(7)
$Vel_m^{Iter,\delta} = Gra_m^{Iter,\delta} + Imt_m^{Iter,\delta} + Ro_m^{Iter,\delta}$(8)

Where,
H iter,age m illustrates the location of the best horse with the variable of velocity.
$P_m^{iter,age}$: Represents the position of the mth horse.

Age: Defines the range of each horse, with possible values of α, β, γ, and δ.
Iter: Indicates the current number of iterations.
$Vel_m^{iter,age}$: Represents the velocity vector of the mth horse.
Soc_m^{Iter}: describes the vector of social motion that is presented by the ith horse
$Imt_m^{Iter,\delta}$: expresses the vector of motion that represents the ith horse around the average of the best horse at P position.
$DefMec_m^{Iter,\gamma}$: describes the escape vector of the ith horse, based around the average position of a horse in the worst P position
$Ro_m^{Iter,\gamma}$: is the arbitrary velocity vector of the ith horse for just a local area search and an escape from local minima.
In whale optimization algorithm the movement of whales is modeled mathematically by equations (9) and (10) to simulate exploitation. Positions of whales are updated depending upon their social behaviors, that includes encircling prey and bubble-net feeding.
Mathematically the position update mechanism in WOA is given by:
$\vec{D} = \left|\vec{C}\,.\overrightarrow{X^*(t)} - \overrightarrow{X(t)}\right|$(9)
$\vec{X}(t+1) = X^*(t) - \vec{A}\,.\,\vec{D}$(10)

Where ,
$\vec{A}$ & $\vec{C}$ are coefficient vectors.
The vectors are calculated as,
$\vec{A} = 2\vec{a}\,.\vec{r} - \vec{a}$
$\vec{C} = 2.\vec{r}$

Where $\vec{a}$ is linear reduced from 2 to 0 and $\vec{r}$is random vector between [0,1]
The overall equation for Whale Optimization algorithm will be,
$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*(t)} - \vec{A}\,.\vec{D} & if\ p < 0.5 \\ \vec{D}\,.\,e^{bl}\cdot cos(2\pi l) + \overrightarrow{X^*(t)} & if\ p > 0.5 \end{cases} \quad (11)$$
Where p is a random number between [0,1]
X(t): Current position
A and C: Coefficients controlling the encircling behavior.
b and l: Constants defining the shape of the spiral.

The whole algorithm is represented by following flowchart as shown in figure 1.

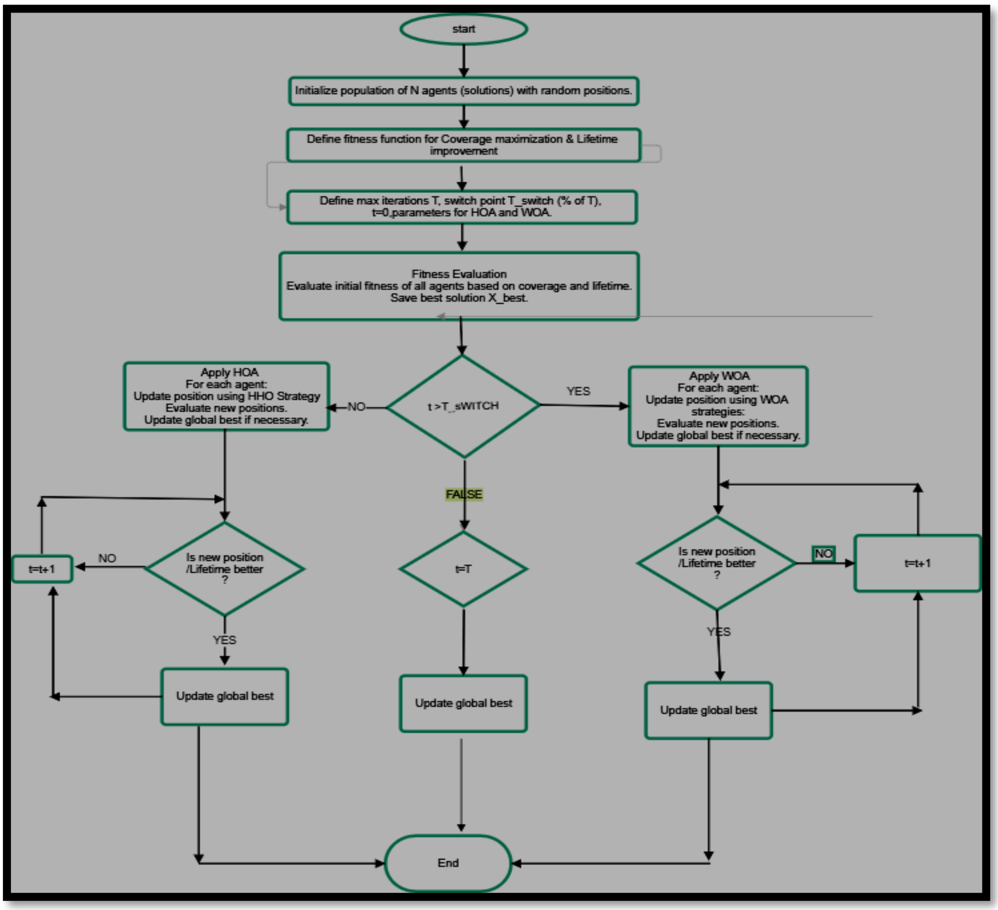

Figure1: Flowchart of proposed HHHWHO algorithm

6. Results and Discussions

We have compared our proposed algorithm with PSO,GA,GWO,HHO and WHO .For performance evaluation of our proposed HHHWHO the algorithm continuously monitors the solutions for maximum coverage area and network lifetime from the search space. The experiments were performed on a desktop PC, Intel Duo Core i3-713OU CPU @ 2.7 Ghz, 4GB RAM, running Windows 10. The algorithm was implemented in MATLAB 2022 b with populations sizes of 10 and 50 and number of iterations varying from 10, 20, 100, 1000.The following table 1 and table 2 presents the percentage improvement in coverage area and network lifetime achieved by the HHHWHO algorithm respectively.

Table 1: Comparison of Coverage Area of WSN for various algorithms with proposed HHHWHO algorithm

Number of Nodes	Coverage Area of WSN in Percentage (%)					
	PSO	**GA**	**GWO**	**HHO**	**WHO**	**HHHWHO (Proposed)**
25	74.2	70.8	72.4	76.5	78.1	80.4
50	80.2	76.3	78.9	83	84.7	86.9
75	83.5	79.2	81.3	86.2	87.8	89.3
100	87.6	82.8	85.2	89.3	90.5	92.7
125	89.7	85.4	87.0	91.1	92.6	94.2
150	91.8	87.9	89.1	93.3	94.5	96.0

Table 2: Comparison of Coverage Area of WSN for various algorithms with proposed HHHWHO algorithm

Number of Nodes	Lifetime of WSN in Minutes					
	PSO	**GA**	**GWO**	**HHO**	**WHO**	**HHHWHO (Proposed)**
25	520.56	470.65	500.51	540.26	560.19	580.73
50	750.92	680.79	720.65	770.51	800.21	820.53
75	970.73	910.38	950.72	990.09	1020.42	1050.52
100	1220.02	1150.67	1200.65	1240.73	1280.31	1310.78
125	1470.37	1400.54	1450.34	1490.54	1520.32	1550.93
150	1720.21	1650.89	1700.76	1740.29	1770.71	1800.64

7. Analysis and Comments

7.1 Coverage Area

As expected, coverage area increases as number of nodes increases. Hybrid HHWHO algorithm consistently provides highest coverage across all node scenarios. This is due to the adaptive nature of the hybrid algorithm, that combines HHO exploration power and local search optimization capabilities of WHO.

PSO and GWO perform similarly, with PSO showing slightly better performance in the lower node densities but trailing behind as the node count increases. GA performs relatively lower than PSO and GWO across all scenarios, likely due to its less effective search strategy in a high-density WSN.WHO and HHO have higher coverage percentages than PSO and GA, but they still lag behind the Hybrid HHHWHO approach, which integrates the strengths of both algorithms. The results are depicted in Figure (2).

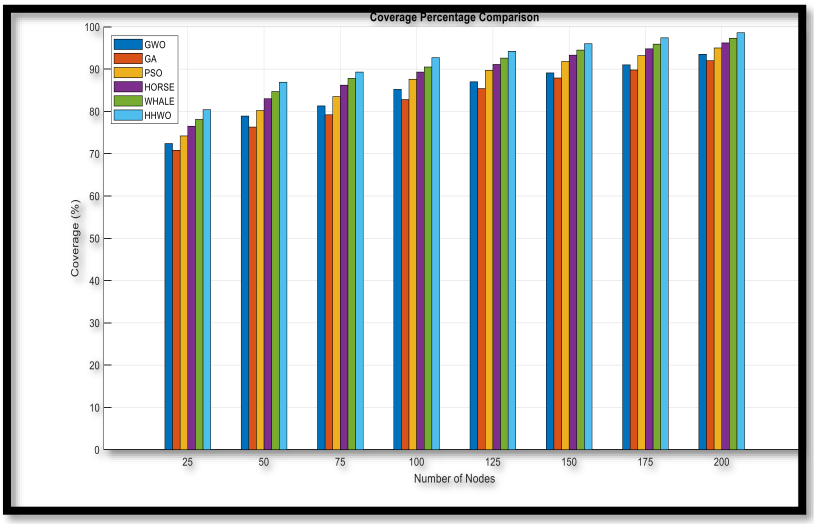

Figure 2: Coverage percentage comparison of PSO, GA, GWO, WHO, HHO, HHHWHO

7.2 Network Lifetime

Figure (3) shows that, Hybrid HHWHO also leads in improvement in network lifetime across all node scenarios. This indicates that the hybrid approach is better at minimizing energy consumption while maintaining coverage, likely due to more effective exploration-exploitation balance.

PSO, GA, and GWO show similar results in network lifetime, with GWO slightly outperforming PSO and GA. However, all three show diminishing performance as the node count increases.

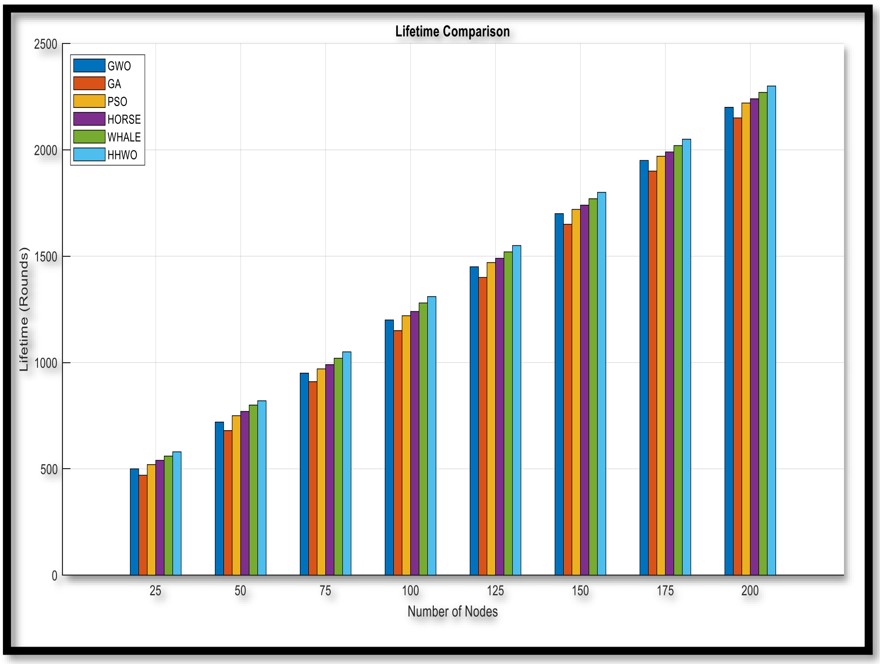

Figure 3: Network Lifetime comparison of PSO, GA, GWO, WHO, HHO, HHHWHO

Figure 3 shows that, HHO and WHO show a better lifetime than PSO and GA, with WHO performing slightly better than HHO in most scenarios due to its better global search and exploitation ability.

7.3 Scalability

The Hybrid HHHWHO algorithm scales exceptionally well with an increasing number of nodes. Both coverage and lifetime metrics improve significantly as the node count rises, indicating its robustness in large-scale networks.PSO and GWO show diminishing returns in coverage and lifetime as the number of nodes increases. The performance of GA remains relatively stable but does not scale as effectively as the other algorithms.

7.4 Convergence and Efficiency

The Hybrid HHHWHO algorithm is the most efficient in terms of coverage and lifetime, owing to its ability to adaptively switch between exploration and exploitation, ensuring the network operates optimally.

PSO and GA exhibit relatively slower convergence when compared to WHO and HHO, especially in larger node scenarios, possibly due to their tendency to get stuck in local optima in highly complex WSN environments.

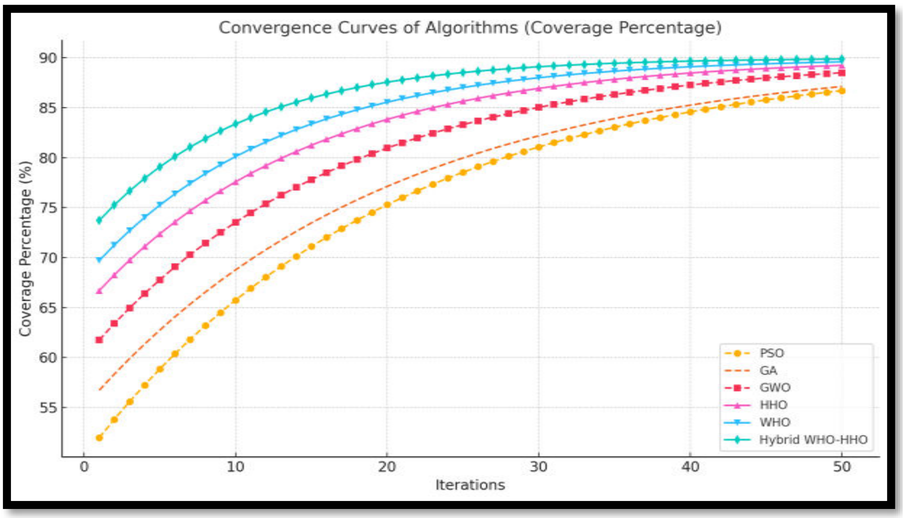

Figure 4: Comparison of convergence for PSO, GA, GWO, WHO, HHO, HHHWHO

Figure 4 states that, WHO and HHO both show relatively quick convergence with high-quality solutions in moderate to large-scale networks, but WHO outperforms HHO slightly in terms of lifetime.

Results demonstrate that, for all evaluated node densities, Hybrid WHOHHO/HHHWHO performs significantly better compared to alternative algorithms concerning coverage area and network lifetime. Due to algorithm effectively utilizing exploration and exploitation phases. While PSO, GA, and GWO provide decent solutions in low-node density environments, WHO and HHO provide superior results, and the Hybrid WHOHHO/HHHWHO approach further improves the performance, making it highly suitable for large-scale wireless sensor network applications.

Thus, our work focuses on optimization of wireless sensor network having combination of static and movable sensors. We have introduced a hybrid optimization technique in this research that combines the advantages of WOA and HHO. The hybrid approach leverages HHO exploration power and local search optimization capabilities of WOA providing a balanced optimization strategy. Through comprehensive simulations, we demonstrate that the hybrid algorithm significantly outperforms traditional optimization techniques and standalone HHO and WOA. The results show substantial improvements in both coverage area and network lifetime, making this hybrid approach a robust solution for WSN optimization.

8. Conclusion

The integration of horse herd optimization (HHO) algorithm and whale optimization algorithm (WOA) in hybrid optimization mode offers a transformative approach to addressing critical challenges in WSNs. By balancing exploration and exploitation, these techniques improve coverage and extend network lifetime in static and movable, single-hop and multi-hop WSN configurations. Future research should focus on real-world implementation and scalability to further validate the efficacy of these approaches.

Declaration of Interests

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Conflicts Of Interest

The authors declare that we have no conflict of interest.

Competing Interests

The authors declare that we have no competing interest.

Data Availability Statement

All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real world data with appropriate permissions.

Ethics Approval

No ethics approval is required.

Consent to Participate

Not Applicable

Consent for Publication

Not Applicable

Human and Animal Ethics

Not Applicable.

Code Availability

Not Applicable.

Author’s Contributions

Author 1: Performed the Analysis the overall concept, writing and editing.
Author 2: Participated in the methodology and Conceptualization.
Author 3: Participated in Data collection and writing the study.

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