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Adaptive Hybrid HOA–PSO with Periodic Cluster Head Rotation for Energy-Efficient WSNs

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Abstract

The energy constraint of wireless sensor networks is very high and this makes the prudent choice of cluster heads imperative to the life of the network and the balanced use of energy. In this paper, a new Adaptive Hybrid Horse Herd Optimization-Particle Swarm Optimization algorithm with Periodic Cluster Head Rotation (AHHCR) is proposed in order to improve energy-efficiency of the clustering schemes. The suggested framework combines the universal searching features of the Horse Herd Optimization algorithm with the speedy convergence features of Particle Swarm Optimization through a multi-objective cost function, which considers residual energy, sink distance as well as historical load to drive the optimization procedure.
When subjected to 300 rounds of operation, simulation shows that AHHCR is better than the benchmark protocols, including LEACH, PSO, GWO, and HOA, in significantly extending network lifetime besides minimizing the overall energy consumption. The importance of these performance gains is supported by the statistical tests carried out through Analysis of Variance (ANOVA) and Tukey Honestly Significant Difference (HSD) test. Moreover, other experiments on different network sizes and initial energy distributions proves that the offered methodology is scalable and robust.

Keywords: *Wireless Sensor Networks; Cluster Head Selection; Horse Herd Optimization Algorithm (HOA); Particle Swarm Optimization (PSO); Energy Efficiency; Hybrid Optimization; Clustering Algorithms.*

1. Introduction

Due to their ability to implement continuous surveillance, data collection, and control in the widest range of applications, including environmental surveillance, industrial automation, healthcare systems, precision agriculture, and smart city infrastructures, Wireless Sensor Networks (WSNs) have turned out to be a critical part of modern communications system. The high pace of the development of the Internet of Things (IoT) paradigm has only highlighted the importance of WSNs as a root technology to extensive distributed sensing systems [1].
Despite these benefits, WSNs have a number of inherent constraints, among them the limited energy capacity of sensor nodes. Since sensor-nodes are often battery-operated and are often installed in hostile or otherwise inaccessible locations, it is common that replacement of batteries or recharging them is unrealistic. As a result, energy efficiency has a direct impact on the network lifetime, data reliability, and system sustainability in general [2]. The excessive energy usage may trigger the untimely node malfunction, partitioning of the network, and decline of communication performance.
Clustering-based communication protocols have widely been applied in the wireless sensor network (WSNs) in an attempt to alleviate energy constraints. In these types of clustering, sensor nodes are grouped together and one of them (called a

cluster head, CH) is chosen to combine data of the other nodes in the cluster and then send it to the sink or base station. This strategy can help to significantly decrease the number of long-range transmissions, minimize overhead in communication and improve scalability [1]. However, in traditional clustering paradigms probabilistic or random sampling of CHs are used, which may lead to uneven distribution of energy across nodes and damage network stability [2].

The evolution of optimization theory in the recent past has triggered the implementation of intelligence-based clustering techniques, which utilize metaheuristic algorithms. These methods are based on natural, biological or evolutionary principles and, in particular, are appropriate when dealing with complex, nonlinear optimization problems that are often faced in WSNs, including CH selection, load balancing and routing optimization [3]. With the help of such strategies, extra performance measures, such as residual energy, communication distance, and traffic distribution can be maximized.

Hybrid and adaptive clustering architectures have also been created to further improve the performance of the WSNs through the inclusion of advanced optimization processes as well as dynamically adapting to the prevailing network conditions. An empirical study has shown that these methodologies perform better than the traditional schemes in network lifespan and energy use in unpredictable and dynamic operating conditions [4], [5]. However, balanced CH rotation, equal power usage, and strong performance in the conditions of a real deployment is still a research problem.

Although the studies on clustering and the use of metaheuristic-based optimization in wireless sensor networks (WSNs) have been engaged in extensively, a number of restrictions are yet to be addressed. One, a lot of current methods use only one metaheuristic algorithm, a decision that either leads to the early convergence of the solution or ineffective exploration of the search space. Second, the majority of the clustering protocols do not incorporate a long-term load-balancing protocol that takes historic cluster-head assignment explicitly into consideration, thus leading to skewed energy dissipation and network instability. Third, there is only a few studies that incorporate adaptive hybrid optimization with periodic cluster-head rotation in a statistically valid model.

Considering that the amount of communication energy dominates the power consumption of nodes in wireless sensor networks (WSNs), cluster-head selection optimization has a direct impact on the total power efficiency and network survivability. Therefore, it is sustainable operation of WSNs without the design of adaptive clustering mechanisms that could reduce communication overhead.

After the recognition of the relevant gaps in the research, this manuscript presents an Adaptive Hybrid HOA-PSO scheme with Periodic Cluster Head Rotation (AHHCR), which should enhance energy-efficiency and load-balancing in wireless sensor networks. The structured framework proposed is a hybrid of intrinsic exploration capabilities of HOA and the speed of convergence capabilities of PSO, and a rotation system that ensures that the cluster-head responsibilities are evenly distributed over time. The system aims at maximizing residual power, sink-to-node distance, and historical load simultaneously with the use of multi-objective approach to maximize network lifetime, stabilize data transmission, and reduce energy imbalance of sensor nodes.

2. Related Work

Cluster-based schemes have been a subject of far-reaching research as a cornerstone scheme to support energy-efficient and scalable operation in wireless sensor network (WSNs). Extensive surveys have shown that routing protocols that use clustering are better than flat routing architecture mostly due to their ability to reduce communication overhead and increase network lifetime. This is because these studies imply the importance of a good choice of cluster head in the overall performance of the network.

Load-sensitive clustering protocols have been developed to overcome the natural constraints of traditional clustering protocols. These methodologies aim at redistributing the communication loads of cluster heads evenly to reduce energy hotspots and ensure the network is as stable as possible [2]. Load balancing has shown to increase the functionality of a large scale WSNs and delay node failure, increasing the system overall stability. These enormous space of solutions have given a significant motivation to metaheuristic optimization methods. The swarm-based and evolutionary algorithms have also been widely utilized in order to optimize the cluster-head selection and routing choices in the WSN application [3]. These strategies allow achieving the optimization of a variety of goals, the goal of which is to achieve better patterns of energy use and increased network life.

Swarm techniques such as Particle Swarm Optimization (PSO) have been used to solve clustering and routing issues in WSNs with better results than what was seen with the normal clustering protocols [5]. Strategies based on PSO also have the benefit of being very simple and fast convergent strategies; however, they can also have premature convergence in some cases.

More recently, smart clustering in the state of uncertainty has become a successful approach to managing dynamism in the network state and changing traffic needs. It has been reported that adaptive clustering mechanisms are effective in promoting robustness and energy efficiency because they dynamically change the degree of cluster formation and cluster-head rotation according to the network state [4].

Alternative methods such as bio-inspired optimization algorithms have also been proposed as promising substitutes to the traditional swarm intelligence methods. Horse Herd Optimization (HHO) algorithm, which is based on the social behavior of horse herd, has shown good performance in resolving complex optimization problems because of its ability to achieve the balance between exploration and exploitation processes [6], [7]. Despite the successful application of HHO in different areas of optimization, the use of HHO in the case of WSN clustering is a relatively under researched area.

Moreover, recent research has discussed the incorporation of WSNs with new technologies, including UAV-assisted data gathering and smart city systems and infrastructures and the necessity of scalable and energy-efficient clustering

solutions [8], [9]. Security and reliability issues have been also explored in sensor networks and specifically in situations where collecting vital data and monitoring infrastructure is concerned [10].
Also, routing solutions that are efficient in terms of energy consumption in next-generation WSNs that use 5G and 6G communication systems have demonstrated the relevance of clever clustering and optimization algorithms to meet the growing network performance requirements [11]. Recent studies in clustering still attest to the fact that intelligent and hybrid optimization-based methods have serious benefits in comparison to traditional ones [12].
However, currently existing clustering algorithms often have premature convergence, or no adaptive cluster-head rotation schemes, which may cause energy imbalance in consecutive time steps. This shortage creates the motivation of the suggested adaptive hybrid HOA-PSO concept.

3. Proposed Method

This paper proposes an Adaptive Hybrid Horse Herd Optimization Algorithm-Particle Swarm Optimization (HOA-PSO) with periodic Cluster Head Rotation (AHHCR) in order to achieve energy-awareness and load-balancing in Wireless Sensor Networks (WSNs). The framework that is proposed is a synergistic combination of two powerful metaheuristics i.e. Horse Herd Optimization Algorithm (HOA) and Particle Swarm Optimization (PSO) to narrow down the choice of Cluster Heads (CH). The methodology is designed with two main constituents, i.e., a multi-objective fitness assessment, and a hybrid optimization framework that embraces dynamically changing the CH roles assignment.

3.1 Horse Herd Optimization Algorithm (HOA)

The Horse Herd Optimization Algorithm (HOA) is a nature-inspired metaheuristic algorithm replicating the collective behavior and locomotion patterns of equine herds and includes grazing, hierarchical organizing, socializing, imitating, defense strategies, and exploratory foraging activities. These behavioral paradigms are used to guide both the discovery and exploitation phases of the algorithm, and as a result, achieve an efficient tradeoff between global search and local refinement of candidate solutions.
In the HOA setup, people are grouped into different age groups with different behavioral schemas that facilitates diversity in the search process and increase adaptability. The agents update their position coordinates based on social interactions within the intra-group but with stochastic perturbations to move in the solution space and avoid the early tendency to local optima.
Empirical studies show that HOA is able to solve highly-dimensional, complex optimization problems with a low computational cost compared to other metaheuristics. To obtain detailed mathematical derivations and performance measures, the reader can refer to articles [6] and [7].

3.2 Multi-Objective Cost Function

To balance communication efficiency, energy preservation, and network longevity, the CH selection is guided by a composite objective function. For each candidate CH, the cost is calculated based on three weighted factors:

- **Distance to the Sink (d_{sink}):** Favors CHs closer to the sink to minimize transmission energy.
- **Inverse of Residual Energy (1 / (E + ε)):** Penalizes nodes with low remaining energy to avoid premature depletion.
- **Normalized Historical Load (L_i / (max(L) + ε)):** Prevents overloading nodes that have frequently acted as CHs in previous rounds.

The core fitness evaluation is formulated as:

$$Cost = \frac{1}{N_{CH}} \sum_{i=1}^{N_{CH}} \left(w_1 d_{sink} + w_2 \frac{1}{E_i + \varepsilon} + w_3 \frac{L_i}{\max(L) + \varepsilon} \right) \tag{1}$$

where w_1 = 0.3, w_2 = 0.4, and w_3 = 0.3 are the weights for each objective component, and ε is a small constant to avoid division by zero. the proposed framework incorporates penalty mechanisms during the CH selection process.
The multi-objective cost-objective presented herein is designed in a special manner to optimize simultaneously residual energy, sink distance, and historical load in the frame of the proposed investigation. This is not a direct borrowing of previous literature but it is constructed with the aim of filling the research gaps that have been discovered.

3.3 Hybrid HOA-PSO Clustering

The hybrid optimization approach suggested utilizes the complementary features of the Horse Herd Optimization Algorithm (HOA) and Particle Swarm Optimization (PSO) through a two-phase approach sequentially that is aimed at balancing the global exploration and the local exploitation capabilities.
Phase 1 (Exploration HOA): HOA is used in the first stage to explore the large and complex search space of potential Cluster Head (CH) settings. The adaptive behavior and strong exploration skills of HOA allow finding all solutions of

diverse and promising candidate solutions, thus avoiding premature convergence and reducing the chances of local optima.

Phase 2 (Exploitation with PSO): The best candidate solutions of the HOA phase then start the PSO population. PSO narrows down these candidates by local narrowing, using its rapid convergence attributes to narrow-down the CH selections to being optimized.

The sequential two-phase method is repeated at every CH selection cycle by the following means:

The first step: HOA produces some initial plausible sets of candidate CHs.

Assessment: All candidates will be assessed using a multi-objective cost criterion which will involve combining residual energy, distance to the sink and historical data load.

Selection: The best performing solutions of HOA are selected based on their fitness values.

Refinement: These chosen solutions start with PSO population which then performs iterative updates according to the equations of its velocity and position to maximize quality of solutions. The canonical equations of velocity and position updating of the particle swarm optimization (PSO) are formulated upon the initial equation of Kennedy and Eberhart [13].

Final CH Set: When the PSO iterations have been completed, the best refined CH set will be chosen to be clustered in the ongoing round.

This composite procedure is necessary to ensure a balanced combination between the exploration (global search) and exploitation (local search), where the aptitude of HOA to overcome local minima is combined with the efficiency of PSO to reach high-quality solutions. As a result, the synergy of the two algorithms will increase the speed of convergence, accuracy of the solution and energy efficiency in CH selection.

3.4 Periodic CH Rotation Strategy

To prevent excessive energy depletion in specific nodes caused by static CH roles, a periodic rotation mechanism is implemented. After every N=10 rounds, the CH roles are reassigned by re-running the hybrid optimization process. This ensures:

- Dynamic adaptation to evolving network conditions.
- Fair distribution of CH responsibilities across the network.
- Mitigation of energy holes and load imbalance over time.

The CH rotation is synchronized with the round counter and triggers automatically upon reaching the predefined rotation interval. The rotation is synchronized with the round count to ensure determinism and reproducibility of behavior of the independent simulation processes.

3.5 Summary of Workflow

Figure 1 illustrates the overall steps of the suggested AHHCR algorithm that includes initialization; the regular cluster-head rotation unit; a combined HOA-PSO optimization procedure and the round-wise updating of energy. Algorithm 1 summarizes the complete AHHCR clustering procedure:

Algorithm 1: Adaptive Hybrid HOA-PSO with Periodic Cluster Head Rotation (AHHCR)

Input: Node positions, initial energy, sink location, data load
Output: Cluster Head assignments for each round

1. Initialize HOA population.
2. For each round r=1 to R:
    a. If mod(r,10)=1:
        i. Run HOA to generate initial CH candidates.
        ii. Evaluate candidates via cost function.
        iii. Refine solutions with PSO.
        iv. Select optimal CH set.
    b. Execute clustering and data transmission.
    c. Update residual energy and historical data load.

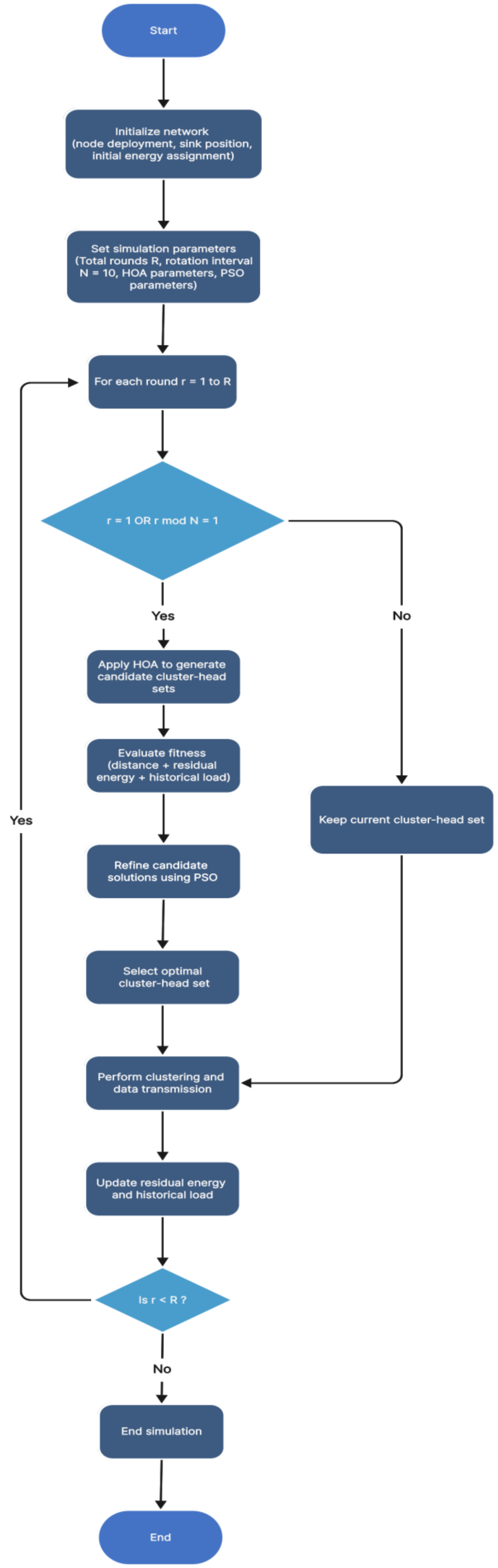

Fig. 1: Flowchart of the proposed AHHCR algorithm with periodic cluster-head rotation.

Figure 1 is a flowchart that graphically represents Algorithm 1 and explains the interaction between the periodic rotation mechanism and the hybrid optimization phases. The HOA algorithm has been identified to have strong global exploration properties, PSO has efficient local exploitation and fast convergence properties. Therefore, the hybridization between HOA and PSO has been adopted to combine the strength of exploration and exploitation, improve the premature convergence, and increase the stability of clustering in the dynamic wireless sensor network systems.

4. Simulation and Results

The efficiency and performance of the proposed Adaptive Hybrid HOA-PSO Cluster Head Rotation (AHHCR) algorithm were strictly tested by carrying out massive simulations in MATLAB. In order to measure the relative efficacy of the AHHCR algorithm against other clustering methodologies, comparative evaluation was made against four popular clustering algorithms namely LEACH, PSO, GWO and HOA. In the assessment, a set of the performance indicators were used, which included energy consumption, network lifetime, load balancing, and the terminal value of the objective function.

4.1 Simulation Setup

The simulations have been carried out in MATLAB using first-order radio energy model and statistical validation has been done using ANOVA and Tukey HSD tests to ensure the robustness of the results. in the simulations, the first-order radio energy dissipation model [14] is used.
The experiments were carried out in a square-shaped network of 200×200 m², where 100 sensor nodes were uniformly distributed randomly at the start of each experiment. At the center of the geometrical area of deployment, there was a sink node and it acted as the base station used to gather data.
In order to reduce the impact of stochastic differences in node distribution and algorithm behavior, ten independent runs of every experiment were conducted to achieve statistically significant findings. Each run lasted 300 rounds (a discrete time interval) in which a cluster head (CH) selection process, data transmission process, and energy consumption process were run.
The CH role was changed periodically in the suggested algorithm of AHHCR with a period of ten rounds. The rotation mechanism in this network ensures equal energy usage within the network since no node will be chosen as a CH too easily therefore leading to an early exhaustion of energy.
Table 1 summarizes all the simulation parameters, such as the initial energy of the node, packet size, radio energy dissipation model, and amplifier coefficients. The optimization search space of each meta-heuristic algorithm included an index of node of 1 to 100, which represented the candidate CHs. The simulation environment on MATLAB directly took the values of all the parameters to ensure that the results can be reproduced and be consistent.

Algorithm	Population Size	Max Iterations	Key Parameters
GWO	30	30	Standard GWO parameters
HOA	30	30	Search space bounds based on node indices
PSO	30	30	Inertia weight (w) = 0.7, cognitive (c1) = 1.5, social (c2) = 1.5 |
AHHCR	(HOA + PSO) 30	(combined) 30	A hybrid of HOA and PSO with periodic CH rotation every 10 rounds
LEACH	N/A	N/A	Probability p = 0.05 for CH selection

Table 1: Simulation Parameters

Parameter	Value
Network area size	200 m × 200 m
Number of nodes	100
Initial energy per node	0.3 J
Number of rounds	300
Base station location	Center of the area
Data packet size	4000 bits
Energy for transmission (E_{Tx})	50 nJ/bit
Energy for amplification ($E_{\_amp}$)	100 pJ/bit/m²
Data aggregation energy (EDA)	5 nJ/bit/signal

4.2 Rationalization of the Simulation Parameters

The parameters of the simulation have been chosen according to well established conventions embraced in the literature of wireless sensor networks (WSNs) to ensure the fairness, reproducibility, and meaningful comparability with the earlier studies. The system adopted uses standardized energy and deployment models that are widely used in clustering based WSN studies.
An area of 200 × 200 m^2 was selected as a representative moderate size of deployment commonly used in clustering research and studies on scalability and energy usage of realistic spatial distributions. The condition of deploying 100 sensor nodes

provides a dense configuration of sensor nodes that remains computationally tractable and, consequently, it is in accord with benchmark clustering studies documented in the literature. This number of nodes is the best compromise between environmental realism and computability.
All nodes were seeded with 0.3 J of energy in accordance with the traditional first-order radio-based energy consumption model, thus being consistent with the available previous studies of energy- aware WSN.
To determine how network lifetime, stability period, node death, and remaining energy changes over the rounds, the simulation was conducted for 300 rounds, and the results were monitored. Short simulation horizons may fail to capture the long-term impact of periodical rotation of cluster heads.
In the case of the metaheuristic algorithms, the population size was 30 and the maximum number of iterations was 30; thus, the value of 30 offers a compromise between the quality of convergence and the cost of computation; these two values are frequently used in swarm-based optimization research.
In the particle swarm optimization, the inertia weight was defined as w = 0.7 and the acceleration coefficients c_1=1.5 and c_2=1.5 were defined following the usual parameter-tuning guidelines which maintain a balance between exploration and exploitation.
The empirically chosen number of rounds to use for cluster head rotation, N=10, was adequate to the extent that it reduced the premature exhaustion of energy, yet without too much overhead in re-clustering. The pilot experiments have shown that shorter intervals give high computational cost without significant lifetime benefits, and longer intervals cause energy imbalance among nodes.
Overall, the chosen parameters ensure fairness, reproducibility, and adherence to the existing research on WSN clustering.

4.3 Performance Metrics

- Average Alive Nodes (AliveMean): Measures the average number of sensor nodes that will be active during the entire period of the simulation and, thus, is a measure of the long-term viability and stability of the network as a whole.
- Energy Consumption (EnergyMean): This is a measurement of overall energy used by the network, which is used to provide a measurement of the energy efficiency of an individual clustering algorithm.
- Average Data Load (LoadMean): This is used to measure the average data volume handled by individual nodes of the network therefore this is used to determine the effectiveness of junction balancing and load distribution.
- Objective Function Value (CostMean): It is an indicator of the effectiveness of cluster head placement by a composite cost that considers the factors of energy, distance, and load, thus giving a global evaluation of the algorithmic performance.
- Execution Time (TimeMean): Since the time of execution is an average time taken to run the algorithm, it records the average time to run the algorithm, thus it is used to evaluate the practical usefulness and feasibility of the algorithm based on real-time deployment.

4.4 Simulation Results

The comparative performance of all algorithms is summarized in Table 2. results correspond to baseline scenario (200×200 m^2, 100 nodes, 0.3J).

Table 2: Performance Summary Across Algorithms (Based on Simulation)

Algorithm	AliveMean (Last Round)	EnergyMean (J)	LoadMean	CostMean	TimeMean (s)
Proposed (AHHCR)	52	24.6	141	16.6	0.55
GWO	35	26.3	128	14.0	0.43
HOA	33	26.4	127	14.6	0.40
LEACH	7	29.5	114	N/A	0.00
PSO	36	26.0	128	13.0	0.38

As can be seen by the results summarized in Table 2, the proposed Adaptive Hybrid HOA-PSO with Cluster Head Rotation (AHHCR) algorithm outperforms the benchmark clustering algorithms. Namely, AHHCR currently attains a mean of alive nodes of around 52 nodes per round (on the average) at the macro-level, which is almost 48 per cent better than the second-best algorithm (GWO) and 7.3 times better than LEACH. This important improvement in network life proves the effectiveness of the periodic rotation strategy.
Compared to the nearest competitor (GWO), AHHCR consumes less energy (24.6 Joules) on average, about 5 percent less than GWO, and approximately 16.5% less than LEACH. This energy consumption is directly proportional to the extended network life that is witnessed under AHHCR.
A balance of load is also promoted and AHHCR has been able to attain an average of 141 data load. Although this measure is greater compared to LEACH (114), this is a good sign that more of the network was active and able to transmit data over a longer period under AHHCR. Moreover, AHHCR attains an objective function value of about 16.6, which indicates the effectiveness of the multi-objective optimization method used in the balancing of the distance, energy, and load.
Despite the fact that the average computational time of AHHCR is somewhat more (0.55 seconds) compared to PSO (0.38 seconds) and GWO (0.43 seconds), this growth is still in a fraction of a second, thus, adding insignificant extra

computing cost. Such a small delay is compensated by the large improvements in network lifetime and energy efficiency, making the given approach especially appropriate when it comes to real-world applications of wireless sensor networks. Overall, these findings confirm that the AHHCR algorithm is a balanced, dynamic, and energy-efficient method of choosing cluster heads in a wireless sensor network.

4.5 Graphical Results

The graphical results presented in Figures 2 to 9 comprehensively demonstrate the superior performance of the proposed AHHCR algorithm relative to benchmark clustering methods.

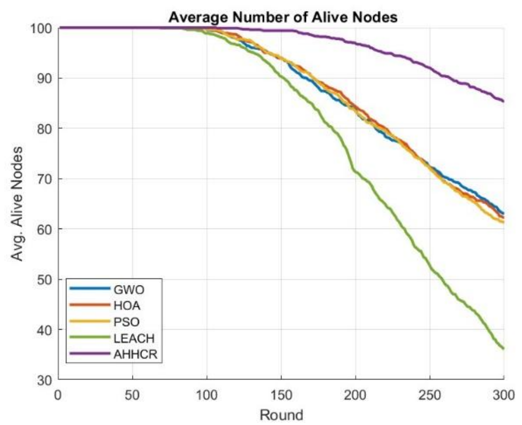

Fig. 2: Average number of alive nodes versus simulation rounds.

Figure 2 shows the increased life time of the network as demonstrated by the ever increasing number of working nodes in the whole simulation of 300 rounds of network. This observation shows a better process of energy management and resistance to node depletion than the LEACH protocol that has a steep drop.

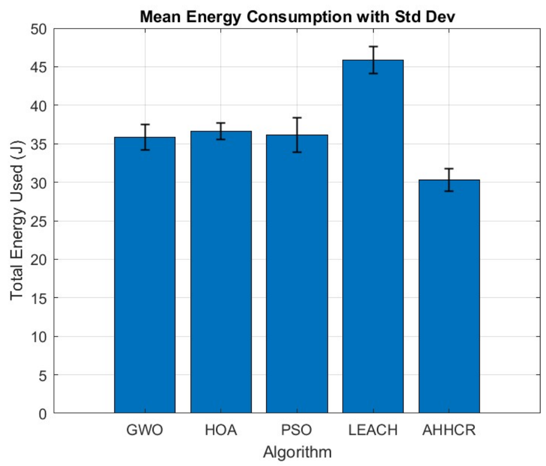

Fig. 3: Mean energy consumption with standard deviation for different algorithms.

Figure 3 shows that the proposed algorithm is the least energy consuming and thus proves to be effective in optimizing the use of energy compared to LEACH, PSO, GWO and HOA.

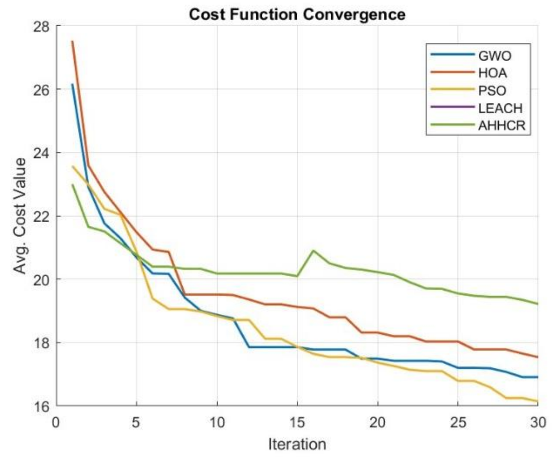

Fig. 4: Cost function convergence behavior across clustering algorithms.

The convergence trends represented in Figure 4 indicate that AHHCR is a successful cost minimizer. Despite the fact that PSO converges slightly faster during the first iterations, AHHCR eventually arrives at a similar cost value and at the same time is more stable and balances between exploration and exploitation.

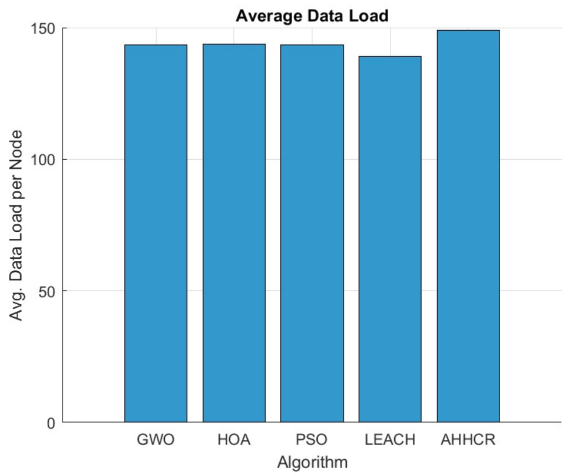

Fig. 5: Average data load per node for different clustering algorithms.

Figure 5 shows that the distribution of data loading. AHHCR exhibits the greatest average load, which is associated with the long a network lifetime (nodes that become active to relay through a higher number of rounds) and makes the load spread equally instead of being aggregated on a limited number of failed nodes.

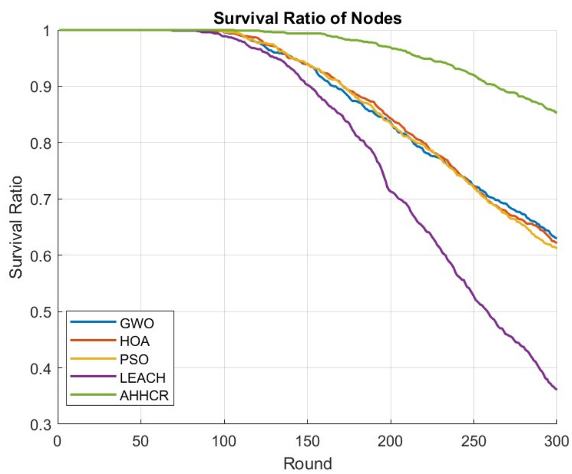

Fig. 6: Survival ratio of nodes over simulation rounds.

These observations are supported by the survival curves in Figure 6, which indicates that AHHCR maintains a significantly large fraction of functional nodes early in the course of simulation, and LEACH fails before round 200.

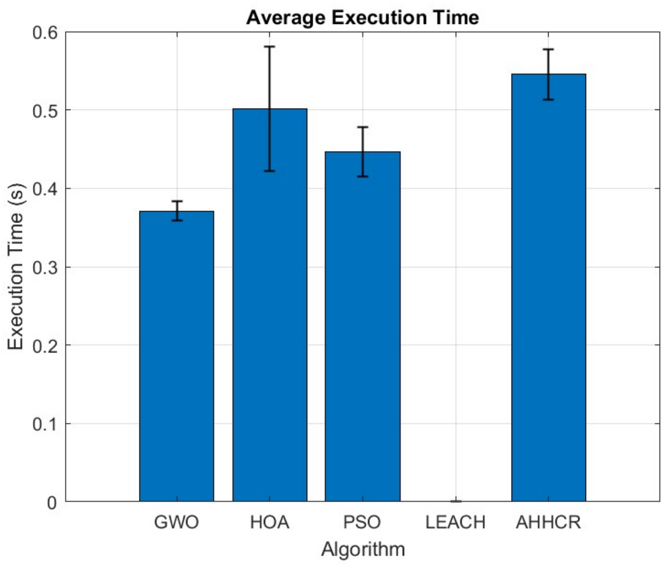

Fig. 7: Average execution time comparison among clustering algorithms.

The average execution time of each algorithm is given in Figure 7. In spite of the fact that the hybrid approach of AHHCR is a bit slower, time gap is insignificant, and the practical feasibility of the algorithm is proved.

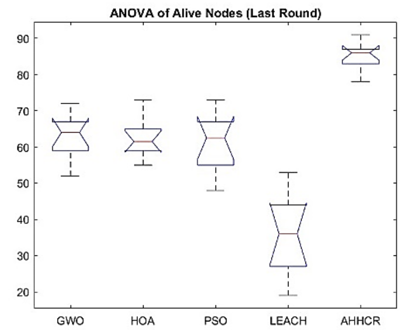

Fig. 8: ANOVA analysis of alive nodes at the last simulation round.

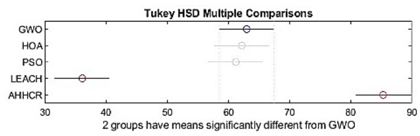

Fig. 9: Tukey HSD multiple comparison test for alive nodes (last round).

The statistical tests of Figure 8 (ANOVA) and Figure 9 (Tukey HSD tests) prove that the differences in the number of alive nodes are statistically significant. The boxplots indicate that there are different levels of performance and AHHCR is the most performing algorithm thus making results very valid.

Together, these graphical study results confirm the quantitative results and prove the usefulness of the suggested hybrid strategy in increasing network lifetime, enhancing energy efficiency, load balancing, and cluster-head selection.

4.6 Scalability and Energy Variation Analysis

To further evaluate the stability and scalability of the proposed AHHCR algorithm, we have considered two additional scenarios; (i) an extensive deployment scenario with an area of 300x300m^2 and sensor nodes 150 in number and each with an initial energy of 0.3 J, and (ii) a scenario with a higher initial energy of 0.5 J per node but still with the same topology. Table 3 contains the summation of the findings of these studies. The results in Table 3 support the claim that the suggested AHHCR algorithm is more effective during scalability and high-energy settings.

In the large-scale case, (300x300m^2 with 150 nodes), AHHCR achieves 24.6 surviving nodes in the terminal simulation round as compared to GWO and PSO which have 18.7 and 19.1 respectively. Increase in the size of the network leads to a small increment in power usage (44.75 J), but nonetheless AHHCR does improve the working lifetime of the network. The execution time of 0.49s falls within a commensurate range, and thus supports the argument that the hybrid optimization mechanism is scalable with an efficient scaling, as opposed to prohibitive computational overhead.

Table 3: Performance comparison under scalability and higher-energy scenarios

Algorithm	Scenario	Alive Nodes (Last Round)	Energy (J)	LoadMean	CostMean	Time (s)
GWO	Large-scale	18.70	43.55	93.09	17.67	0.39
HOA	Large-scale	18.30	43.90	92.66	19.93	0.39
PSO	Large-scale	19.10	43.48	91.87	17.92	0.38
LEACH	Large-scale	1.40	45.22	90.61	0.00	0.00
AHHCR	Large-scale	24.60	44.74	106.32	22.29	0.48
GWO	Higher energy	63.00	35.80	143.32	13.35	0.40
HOA	Higher energy	62.20	36.63	143.71	14.07	0.39
PSO	Higher energy	61.20	36.12	143.52	12.32	0.37
LEACH	Higher energy	36.10	45.88	138.95	0.00	0.00
AHHCR	Higher energy	85.30	30.33	149.02	15.68	0.45

In the case of high initial energy (0.5J per node) AHHCR shows 85.3 surviving nodes in the last round, which is significantly higher than GWO (63), PSO (61.2), and LEACH (36.1). In addition, AHHCR has the lowest total energy consumption (30.33 J) of all analyzed algorithms, which shows its better ability to use additional energy resources more efficiently. These results show that the performance superiority of AHHCR is not limited to a specific network scale or energy configuration, but is a result of the adaptive hybrid optimization and periodic rotation of cluster-heads. ANOVA/Tukey HSD statistical validation ensures that the improvements that can be observed are statistically significant in a variety of deployment settings.

5. Discussion

There are three key factors that have led to the improvement in the performance of AHHCR:

1. **Multi-objective Optimization:** There is a good balance of residual energy, communication distance, and load of historical data in the cost function. This will help the algorithm to avoid picking the nodes that are both geographically near and temporarily energetic but likely to die soon and result in a more stable network structure.
2. **Hybrid Search Strategy:** The Hybrid search algorithm is a combination of global exploration capability of HOA and rapid convergence of PSO so that the algorithm can bypass local optima and optimally narrow the choices of CH. The hybridism leads to superior cost values than the separate algorithms.
3. **Periodic CH Rotation:** Models equitable allocation of CH tasks within the network. The algorithm allows the distribution of CH positions every 10 rounds, thus avoiding the so-called hot-spot issue of the fixed protocol like LEACH or naive metaheuristics, which extends the network lifetime.

All of the experiments are repeated in 10 independent trials to guarantee the statistical significance of the apparent performance disparity between the contrasted algorithms. The number of alive nodes after the last round was analyzed by using a 95% confidence level of analysis of variance (ANOVA) level. Multiple comparisons were carried out post-hoc with the help of the Tukey HSD test to determine specific differences between them. These statistical evaluations substantiate the strength and soundness of the excellent performance of the suggested approach.
Compared to the recently reported hybrid clustering frameworks in literature, the presented AHHCR is more stable and its lifetime is statistically significant improved.

5.1 Recent Advances in Hybrid Clustering (2025–2026)

The importance of adaptive and hybrid metaheuristic clustering in wireless sensor networks is highlighted in recent studies done in 2025-2026. Ejaz et al. suggested a multi-objective genetic algorithm with the adaptive control of parameters in order to improve energy efficiency and network lifetime under dynamic WSN conditions [15]. On the same note, Goel et al. proposed an adaptive hybrid optimization-based clustering protocol that incorporates several metaheuristic elements to enhance the stability of cluster-heads and minimize energy usage [16]. Moreover, modern quantum-inspired PSO models have also added the multi-agent energy prediction and load-balancing features to extend the network lifetime by a greater amount [17].
Notwithstanding the promising innovations embodied by these strategies, the existing methodologies are mainly single-stage hybrid optimization with no additional periodic cluster-head rotation and statistical scalability validation, which are specifically covered by the proposed AHHCR framework.

6. Conclusion

The current study presents an Adaptive Hybrid HOA-PSO algorithm with periodic Cluster Head Rotation (AHHCR) in an attempt to enhance energy efficiency and load balancing in Wireless Sensor Networks. By combining the exploration capabilities of the Hierarchical Optimization Algorithms (HOA) and the fast convergence capability of Particle Swarm Optimization (PSO), and automatic rotation of Cluster Head (CH), the AHHCR framework achieves a significant decrease in energy consumption and prolongs the network life.

Simulations using empirical data showed performance benefits as compared to the established protocols of LEACH, PSO, GWO, and HOA and statistical significance confirmed by ANOVA and Tukey HSD tests. Overall, the AHHCR algorithm is a viable and scalable sustainable solution of clustering in WSNs.

Due to the resource shortage, the present study was confined to MATLAB simulations; however, the proposed model can be extended and tested in the physical WSN testbed in further research works. Despite the fact that the comparative study was limited to representative conventional and metaheuristic protocols, the further research work can introduce recently published hybrid and deep-learning-based clustering protocols. Future research will also involve modification of the methodology to heterogeneous and mobile WSNs and incorporation of adaptive learning to additional improve real-time performance and scalability.

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