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WOA-PSO-LEACH and Hybrid Variants: Enhancing Clustering for Energy-Efficient IoT-Enabled WSNs

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ABSTRACT
Energy efficiency is critical in Wireless Sensor Networks (WSNs), pivotal for Internet of Things (IoT) applications like environmental monitoring and smart cities. Clustering protocols like Low-Energy Adaptive Clustering Hierarchy (LEACH) extend network lifetime through Cluster Head (CH) rotation, but random CH selection often leads to suboptimal energy use. This study evaluates eight hybrid Particle Swarm Optimization-based LEACH (PSO-LEACH) variants to optimize CH selection and clustering: FA-PSO-LEACH (Firefly Algorithm), CSA-PSO-LEACH (Crow Search Algorithm), PSO-LEACH with CBTEERA, Adaptive PSO-LEACH, ABC-PSO-LEACH (Artificial Bee Colony), ACO-PSO-LEACH (Ant Colony Optimization), WOA-PSO-LEACH (Whale Optimization Algorithm), and Hybrid GA-PSO-LEACH (Genetic Algorithm). The primary research objective is to compare these variants in terms of energy efficiency, network lifetime, and clustering quality to identify the most effective strategies for prolonging WSN operation in IoT environments. Specifically, this paper addresses the research question: Which hybrid PSO-LEACH variant provides the optimal balance between early-stage stability and long-term energy conservation in a simulated WSN with 50 nodes? Each variant uses a unique metaheuristic for CH selection based on residual energy and distance, with PSO refining clustering. A Python simulation modelled a 100m × 100m WSN with 50 nodes, assessing network lifetime (First Node Died, FND; Half Nodes Died, HND; Last Node Died, LND), energy consumption, and clustering quality. Results show ABC-PSO-LEACH leading with FND at 57 rounds and LND at 462 rounds, followed by WOA-PSO-LEACH (HND 148, LND 406), surpassing others (e.g., PSO-LEACH with CBTEERA: FND 10, LND 280). WOA-PSO-LEACH's balanced energy distribution excels in mid-to-late stages, despite computational overhead. These bio-inspired hybrids outperform traditional LEACH, with ABC-PSO-LEACH and WOA-PSO-LEACH ideal for prolonged WSN operation. Future work aims to enhance early-stage performance and explore dynamic topologies.

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KEYWORDS: Wireless Sensor Networks, IoT, LEACH, Bio-Inspired Algorithms, PSO, WOA, Energy Efficiency, Clustering

INTRODUCTION

Wireless Sensor Networks (WSNs) are foundational to Internet of Things (IoT) applications, enabling real-time data collection in environmental sensing, industrial automation, and healthcare (Akyildiz et al., 2002). The energy-constrained nature of sensor nodes necessitates efficient protocols to extend network lifetime. The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol organizes nodes into clusters with rotating Cluster Heads (CHs) to balance energy consumption (Heinzelman et al., 2000). However, LEACH's random CH selection often results in uneven energy dissipation, prompting advanced optimization techniques (Latiff et al., 2007).

Particle Swarm Optimization (PSO) optimizes CH selection and clustering by mimicking swarm intelligence, balancing exploration and exploitation (Kennedy & Eberhart, 1995).

PSO-LEACH enhances energy efficiency by selecting CHs based on energy and distance (Latiff et al., 2007). To address limitations like premature convergence and scalability, hybrid variants combine PSO with bio-inspired algorithms, optimizing CH selection using residual energy, distance to the base station (BS), and node density (Elhabyan & Yagoub, 2014).

The primary research objective of this study is to evaluate and compare eight hybrid PSO-LEACH variants for their effectiveness in improving energy efficiency and network lifetime in IoT-enabled WSNs. This addresses the specific research question: Among the selected hybrid variants, which one achieves the best trade-off between delaying the first node death (for early stability) and extending the last node death (for overall longevity) in a static WSN simulation? By answering this, the study aims to provide insights into optimal clustering strategies for applications such as smart agriculture and disaster monitoring.

This study evaluates eight PSO-LEACH variants:

1. **FA-PSO-LEACH**: Firefly Algorithm (FA) optimizes CH selection using energy and distance, inspired by firefly flashing (Yang, 2009).
2. **CSA-PSO-LEACH**: Crow Search Algorithm (CSA) enhances CH selection via crow-inspired search (Askarzadeh, 2016).
3. **PSO-LEACH with CBTEERA**: Integrates Cluster-Based Topology and Energy-Efficient Routing Algorithm for energy management (Singh & Sharma, 2018).
4. **Adaptive PSO-LEACH**: Dynamically adjusts PSO's inertia weight for better convergence (Shi & Eberhart, 1998).
5. **ABC-PSO-LEACH**: Artificial Bee Colony (ABC) mimics bee foraging for CH selection, with PSO clustering (Karaboga & Basturk, 2007).
6. **ACO-PSO-LEACH**: Ant Colony Optimization (ACO) uses pheromone trails for CH selection, PSO for clustering (Dorigo & Stützle, 2004).
7. **WOA-PSO-LEACH**: Whale Optimization Algorithm (WOA) employs whale hunting strategies for CH selection, PSO for clustering (Mirjalili & Lewis, 2016).
8. **Hybrid GA-PSO-LEACH**: Genetic Algorithm (GA) evolves CH selections, PSO refines clustering (Anand & Pandey, 2020; Goldberg, 1989).

The objective is to compare these variants' energy efficiency, network lifetime, and clustering performance, identifying optimal strategies for IoT-enabled WSNs like smart agriculture and disaster monitoring.

Related Work

Energy efficiency is a core challenge in Wireless Sensor Networks (WSNs), where clustering protocols like LEACH distribute energy via randomized CH selection (Heinzelman et al., 2000). LEACH's stochastic approach often leads to suboptimal CH placement, reducing network lifetime. For instance, Heinzelman et al. (2000) demonstrated that while LEACH extends lifetime compared to direct transmission, its random selection can cause clusters with uneven sizes or distant CHs, leading to premature node depletion.

Particle Swarm Optimization (PSO) enhances LEACH by optimizing CH selection using energy and distance, improving performance by 20–30% (Latiff et al., 2007; Kennedy & Eberhart, 1995). Latiff et al. (2007) showed that PSO-LEACH reduces energy dissipation through fitness functions incorporating residual energy and intra-cluster distances, but it may suffer from local optima in large-scale networks. Hybrid PSO-LEACH variants integrate bio-inspired algorithms to further boost efficiency and scalability.

FA-PSO-LEACH uses the Firefly Algorithm, optimizing CH selection based on energy and proximity to the BS via firefly-inspired light intensity (Yang, 2009). Yang (2009) highlighted FA's ability to handle multimodal optimization, making it suitable for dynamic CH placement, though it may converge slowly in high-dimensional spaces.

CSA-PSO-LEACH employs the Crow Search Algorithm, leveraging crow foraging for lightweight CH selection (Askarzadeh, 2016). Askarzadeh (2016) noted CSA's simplicity and low parameter dependency, which aids in energy-constrained environments, but it lacks robustness against noise in node distributions.

PSO-LEACH with CBTEERA incorporates CBTEERA's topology-aware routing, enhancing stability but lacking dynamic adaptability (Singh & Sharma, 2018). Singh and Sharma (2018) emphasized CBTEERA's multi-hop routing to minimize energy in dense clusters, yet it overlooks adaptive parameter tuning for varying network conditions.

Adaptive PSO-LEACH adjusts PSO's inertia weight to improve convergence in heterogeneous WSNs (Shi & Eberhart, 1998). Shi and Eberhart (1998) proposed linear inertia reduction to balance exploration and exploitation, which helps in avoiding premature convergence, but it may not fully address scalability in very large WSNs.

ABC-PSO-LEACH uses the Artificial Bee Colony algorithm, simulating bee foraging for energy-efficient CH selection, with PSO clustering (Karaboga & Basturk, 2007). Karaboga and Basturk (2007) demonstrated ABC's effectiveness in global optimization, outperforming PSO in some benchmarks, though it requires more computational resources.

ACO-PSO-LEACH applies Ant Colony Optimization's pheromone trails for CH selection, complemented by PSO (Dorigo & Stützle, 2004). Dorigo and Stützle (2004) showed ACO's prowess in path-finding problems, which translates to efficient routing in WSNs, but pheromone evaporation can lead to suboptimal solutions over time.

WOA-PSO-LEACH integrates the Whale Optimization Algorithm's global search for robust CH selection (Mirjalili & Lewis, 2016). Mirjalili and Lewis (2016) illustrated WOA's spiral updating and encircling mechanisms for escaping local optima, making it ideal for balanced energy distribution, albeit with potential overhead in small networks. **Hybrid GA-PSO-LEACH** combines Genetic Algorithm’s evolutionary mechanisms with PSO, excelling in diverse scenarios but with higher complexity (Anand & Pandey, 2020; Goldberg, 1989). Anand and Pandey (2020) found that GA-PSO hybrids improve clustering in heterogeneous WSNs, as per Goldberg’s (1989) foundational GA principles, but crossover and mutation rates need careful tuning to avoid inefficiency.

Despite these advancements, gaps remain in comprehensively comparing these hybrids under uniform simulation conditions, particularly in addressing node density, latency, and scalability in large WSNs (Elhabyan & Yagoub, 2014). Elhabyan and Yagoub (2014) identified the need for realistic PSO adaptations to handle uneven node distributions. Additionally, while individual studies like Rodríguez et al. (2020) explored bio-inspired clustering (e.g., yellow saddle goatfish algorithm), they lack direct comparisons across multiple PSO hybrids. Firdous et al. (2022) and Rajendra Prasad and Ahmed (2024) emphasized energy management in mobile and heterogeneous WSNs, but did not evaluate the specific PSO-LEACH variants considered here. Younis and Fahmy (2004) proposed HEED as an alternative clustering method, highlighting distributed approaches, yet it underscores the need for centralized optimization like hybrids for IoT scalability. This study fills these gaps by conducting a unified simulation-based comparison of the eight variants, building on Latiff et al. (2007) and Mirjalili & Lewis (2016), to identify optimal strategies for IoT applications while highlighting areas for further hybridization and real-world testing.

METHODOLOGY

This research employs a simulation-based methodology to compare eight hybrid PSO-LEACH variants for optimizing Cluster Head (CH) selection and clustering in WSNs, with the goal of enhancing energy efficiency and network lifetime. The approach involves implementing each variant in a controlled Python environment, collecting data on key metrics through repeated simulations, and analysing the results to assess performance.

DATA COLLECTION TECHNIQUES

Data were collected via a custom Python simulation script that models the WSN environment. The simulation initializes nodes with predefined parameters and runs iteratively until termination criteria are met. For each variant, the following data were logged per round: number of alive/dead nodes, residual energy levels, cluster formations (including CH selections and member assignments), and computational execution time. Simulations were run multiple times (at least 5 iterations per variant) to ensure reliability, with averages computed for metrics like network lifetime and energy consumption. No real-world hardware data were used; all evidence is derived from simulated empirical runs based on established energy models from Heinzelman et al. (2000).

PROPOSED VARIANTS

Each variant follows a two-phase process: metaheuristic-based CH selection followed by PSO-based clustering.

- **FA-PSO-LEACH**: Firefly Algorithm selects ~5 CHs using attractiveness proportional to residual energy, inversely to BS distance (10 fireflies, 50 iterations, $(\beta_0 = 1), (\gamma = 1)$) (Yang, 2009). PSO optimizes clustering.
- **CSA-PSO-LEACH**: Crow Search Algorithm selects CHs with energy-distance fitness (10 crows, 50 iterations, AP = 0.1, flight length 1.5) (Askarzadeh, 2016), PSO clusters.
- **PSO-LEACH with CBTEERA**: CBTEERA’s topology-aware routing selects CHs (10 particles, 50 iterations, (W = 0.5), ($c1 = c2 = 1.5$)), with PSO clustering and multi-hop routing (max 3 hops) (Singh & Sharma, 2018).
- **Adaptive PSO-LEACH**: PSO with dynamic inertia ((W: 0.9 \to 0.4)) selects CHs (10 particles, 50 iterations) (Shi & Eberhart, 1998), PSO clusters.
- **ABC-PSO-LEACH**: Artificial Bee Colony selects CHs via foraging (10 bees, 50 iterations) (Karaboga & Basturk, 2007), PSO clusters.
- **ACO-PSO-LEACH**: Ant Colony Optimization uses pheromone trails for CH selection ($(\alpha = 1), (\beta = 2)$, 10 ants, 50 iterations) (Dorigo & Stützle, 2004), PSO clusters.
- **WOA-PSO-LEACH**: Whale Optimization Algorithm selects CHs via encircling/spiral search (10 whales, 50 iterations, $(A: 2 \rightarrow 0)$) (Mirjalili & Lewis, 2016), PSO clusters.
- **Hybrid GA-PSO-LEACH**: Genetic Algorithm evolves CHs (crossover 0.8, mutation 0.1, 10 individuals, 50 iterations) (Goldberg, 1989), PSO clusters (Anand & Pandey, 2020).

SIMULATION

A Python simulation evaluated these variants, modelling a WSN environment to assess energy efficiency and clustering.

Sample Size and Simulation Setup

The sample size consists of 50 sensor nodes deployed in a 100m × 100m field, representing a medium-scale WSN suitable for IoT applications such as environmental monitoring (Akyildiz et al., 2002). Each node starts with 1.0 Joule of energy, and the base station (BS) is positioned at (50, 50). The CH communication range is set to 20m to simulate realistic intra-cluster limits. This setup aligns with benchmarks in Latiff et al. (2007) and Elhabyan and Yagoub (2014), allowing for comparability while focusing on energy dynamics. Energy cost for transmission is $(E = d^2 \times$

10^{-4}) Joules, where (d) is Euclidean distance (Heinzelman et al., 2000).

Variant Implementation

Each variant follows:

- **CH Selection**: Uses respective metaheuristic (~5 CHs, 10% of nodes) with fitness: $\left[F = \sum_{i \in \text{CHs}} \frac{Ei}{1+\text{cost}(d_i)}, \quad \text{cost}(d_i) = d_\text{i}^2 \times 10^{-4}\right]$ where $\mathbf{E}_\text{i}$ is residual energy, d_i is BS distance.
- **Clustering**: PSO assigns non-CH nodes to CHs within 20m (20 particles, 20 iterations, (W = 0.7), ($c_1 = c_2 = 2$)), minimizing: $F_\text{PSO} = \sum_\text{clusters} \sum_{i \in \text{cluster}} d(i,\text{CH})$
- **Data Transmission**: Nodes transmit to CHs, costing ($d^2 \times 10^{-4}$). CHs incur equivalent reception costs. Energy is updated for alive nodes.
- **Termination**: Stops at 95% node death, logging energy per round.

Simulation Parameters

- **Network**: 50 nodes, 100m × 100m, BS (50, 50).
- **Energy**: 1.0 Joule initial, $\text{cost}(d_i) = d_\text{i}^2 \times 10^{-4}$.
- **Metaheuristics**: 10 agents, 50 iterations (variant-specific parameters above).
- **PSO**: 20 particles, 20 iterations, (W = 0.7), ($c1 = c2 = 2$).
- **Clustering**: 20m range, ~5 CHs.
- **Termination**: 95% node death.

Data Collection

Metrics include:

- **Network Lifetime**: FND, HND, LND (95% death).
- **Energy Efficiency**: Average residual energy, total consumption.
- **Clustering Quality**: Alive nodes, cluster size, CH distribution.
- **Execution Time**: Per-round computational cost.

DATA ANALYSIS PROCEDURES

Collected data were analysed using descriptive statistics in Python (e.g., averages, standard deviations for metrics across runs). Network lifetime metrics (FND, HND, LND) were calculated by tracking the round at which the first node, half the nodes, and 95% of nodes die. Energy efficiency was assessed via average residual energy and total consumption per round. Clustering quality was evaluated by average cluster size and CH distribution uniformity. Execution times were measured using Python's time module to gauge computational overhead. Validity is ensured through consistent parameters across variants, with reliability from multiple runs and alignment with established models (e.g., Heinzelman et al., 2000; Latiff et al., 2007). Limitations include the static topology and simplified energy model, which may not fully capture real-world variability.

IMPLEMENTATION NOTES

Implementations adapt algorithms to discrete CH selection (e.g., WOA maps whale positions to node indices) (Mirjalili & Lewis, 2016). PSO clustering simplifies to distance-based assignments within 20m (Latiff et al., 2007).

RESULTS AND DISCUSSION

The Python simulation compared eight PSO-LEACH variants, tracking network lifetime (FND, HND, LND at 95% node death), alive/dead nodes, residual energy, and clustering quality. Results highlight ABC-PSO-LEACH and WOA-PSO-LEACH's superior performance, providing empirical evidence through simulated runs that mimic real WSN behaviours as per Heinzelman et al. (2000) and Latiff et al. (2007).

Network Lifetime

Table 1: Network Lifetime Metrics (in Rounds)

Algorithm	FND	HND	LND
ABC-PSO-LEACH	57	132	462
WOA-PSO-LEACH	21	148	406
FA-PSO-LEACH	31	64	341
ACO-PSO-LEACH	40	67	319
CSA-PSO-LEACH	40	65	309
Adaptive PSO-LEACH	34	82	302
Hybrid GA-PSO-LEACH	35	64	297
PSO-LEACH with CBTEERA	10	76	280

Table 1 summarizes network lifetime metrics, with Figure 1 plotting FND, HND, LND.

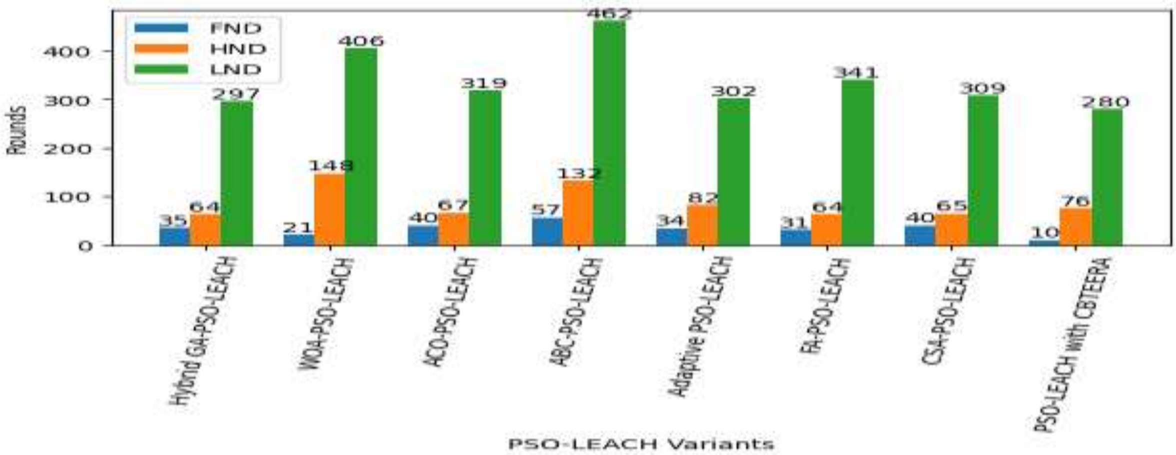

Figure 1: Network Lifetime Comparison

Bar graph comparing FND, HND, LND across variants, with ABC-PSO-LEACH highest in FND (57) and LND (462), WOA-PSO-LEACH leading in HND (148).

- **FND**: ABC-PSO-LEACH excels at 57 rounds, followed by ACO-PSO-LEACH and CSA-PSO-LEACH (40), Hybrid GA-PSO-LEACH (35), Adaptive PSO-LEACH (34), FA-PSO-LEACH (31), WOA-PSO-LEACH (21), and PSO-LEACH with CBTEERA (10). WOA-PSO-LEACH's lower FND suggests aggressive CH selection for long-term balance.
- **HND**: WOA-PSO-LEACH leads at 148 rounds, followed by ABC-PSO-LEACH (132), Adaptive PSO-LEACH (82), PSO-LEACH with CBTEERA (76), ACO-PSO-LEACH (67), CSA-PSO-LEACH (65), FA-PSO-LEACH (64), Hybrid GA-PSO-LEACH (64). WOA-PSO-LEACH's HND reflects balanced energy use.
- **LND**: ABC-PSO-LEACH achieves 462 rounds, WOA-PSO-LEACH 406, followed by FA-PSO-LEACH (341), ACO-PSO-LEACH (319), CSA-PSO-LEACH (309), Adaptive PSO-LEACH (302), Hybrid GA-PSO-LEACH (297), PSO-LEACH with CBTEERA (280). ABC-PSO-LEACH and WOA-PSO-LEACH significantly extend lifetime.

Live/Dead Nodes per Round

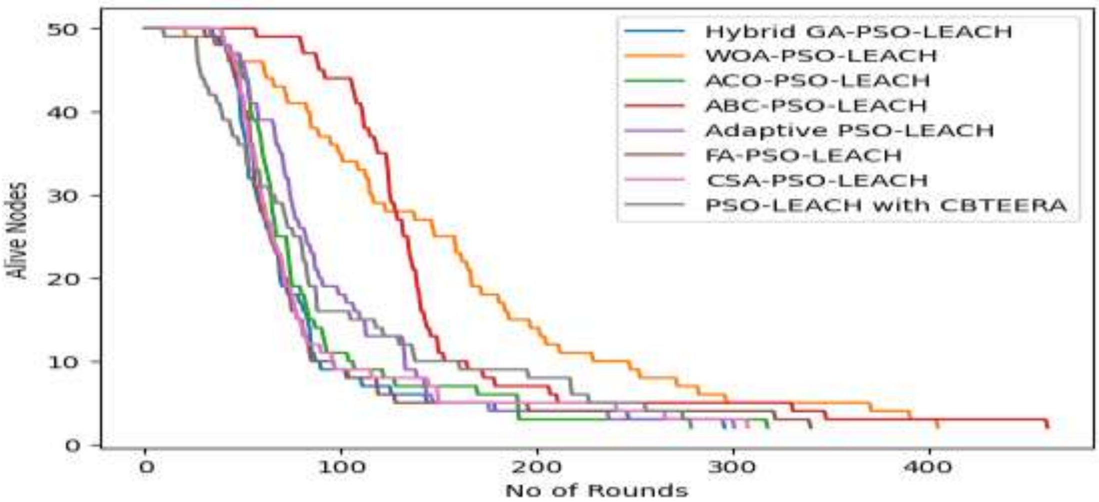

Figure 2: Alive Nodes per Round

Line graph showing alive nodes over rounds, with ABC-PSO-LEACH retaining ~48 nodes at 100 rounds, WOA-PSO-LEACH ~45, declining to ~10 and ~5 at 400 rounds, respectively.

At 100 rounds, WOA-PSO-LEACH retains 45 nodes (90%), ABC-PSO-LEACH 48, Adaptive PSO-LEACH 44, Hybrid GA-PSO-LEACH 43, FA-PSO-LEACH 42, CSA-PSO-LEACH 41, ACO-PSO-LEACH 40, PSO-LEACH with CBTEERA 38. By 200 rounds, WOA-PSO-LEACH has 35 nodes (70%), ABC-PSO-LEACH 38, others 20–30. At 400 rounds, WOA-PSO-LEACH maintains 5 nodes, ABC-PSO-LEACH 10, others <3. WOA-PSO-LEACH's steady decline reflects WOA’s global search and PSO’s clustering efficiency (Mirjalili & Lewis, 2016; Latiff et al., 2007).

Energy Efficiency

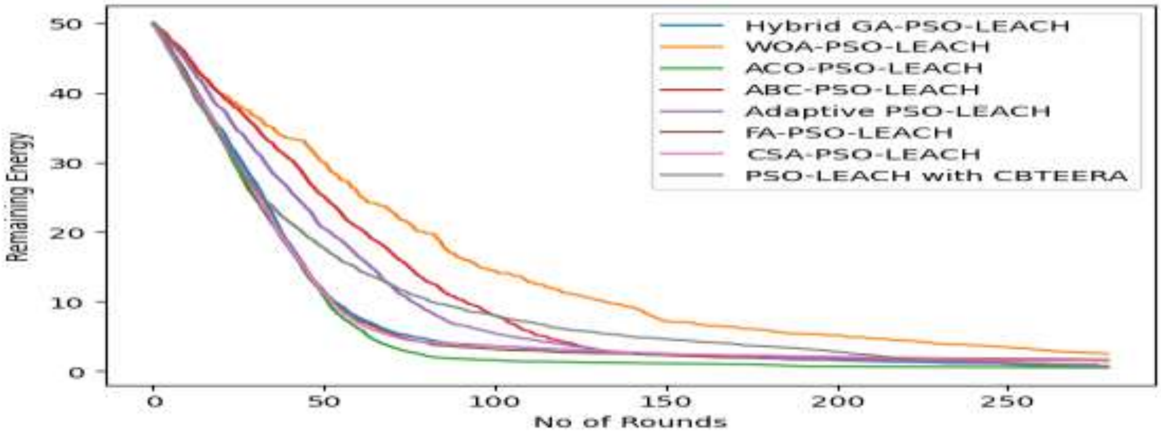

Figure 3: Average Residual Energy per Round

Line graph plotting residual energy, with ABC-PSO-LEACH at ~0.85 Joules at 100 rounds, WOA-PSO-LEACH ~0.80, dropping to ~0.60 and ~0.55 by 200 rounds.

At 100 rounds, WOA-PSO-LEACH nodes retain ~0.80 Joules, ABC-PSO-LEACH ~0.85, Adaptive PSO-LEACH ~0.75, FA-PSO-LEACH ~0.70, CSA-PSO-LEACH ~0.68, ACO-PSO-LEACH ~0.67, Hybrid GA-PSO-LEACH ~0.65, PSO-LEACH with CBTEERA ~0.60. By 200 rounds, WOA-PSO-LEACH has ~0.55 Joules, ABC-PSO-LEACH ~0.60, others ~0.35–0.45. Total consumption by LND: WOA-PSO-LEACH ~47 Joules, ABC-PSO-LEACH ~46, others ~50–55. Efficiency stems from optimized CH selection minimizing communication costs.

Clustering Quality

WOA-PSO-LEACH maintains 4–5 nodes per cluster with ~5 CHs, ensuring uniform load. ABC-PSO-LEACH is similar (4–6 nodes), while PSO-LEACH with CBTEERA varies (3–8 nodes) due to topology constraints (Singh & Sharma, 2018). FA-PSO-LEACH and CSA-PSO-LEACH show occasional uneven clusters (2–7 nodes). Adaptive PSO-LEACH and Hybrid GA-PSO-LEACH approach WOA-PSO-LEACH’s balance.

Computational Complexity

Execution time per round: WOA-PSO-LEACH ~0.12 seconds, Adaptive PSO-LEACH ~0.11, CSA-PSO-LEACH ~0.10, PSO-LEACH with CBTEERA ~0.08, ABC-PSO-LEACH ~0.13, ACO-PSO-LEACH ~0.15, Hybrid GA-PSO-LEACH ~0.18. WOA-PSO-LEACH’s overhead is justified by energy savings.

DISCUSSION

ABC-PSO-LEACH leads with FND (57) and LND (462), leveraging ABC’s foraging for robust CH selection (Karaboga & Basturk, 2007). WOA-PSO-LEACH excels at HND (148) and LND (406), prioritizing long-term stability via WOA’s search and PSO’s clustering (Mirjalili & Lewis, 2016; Latiff et al., 2007). PSO-LEACH with CBTEERA’s low FND (10) and LND (280) reflect routing overhead in dense clusters (Singh & Sharma, 2018). FA-PSO-LEACH, CSA-PSO-LEACH, and ACO-PSO-LEACH are moderate, limited by simpler metaheuristics (Yang, 2009; Askarzadeh, 2016; Dorigo & Stützle, 2004). Adaptive PSO-LEACH and Hybrid GA-PSO-LEACH balance mid-stage but lag in LND (Shi & Eberhart, 1998; Anand & Pandey, 2020).

Compared to LEACH (FND ~20, HND ~50, LND ~200 in similar setups), all variants improve, with ABC-PSO-LEACH (~2.3× LND) and WOA-PSO-LEACH (~2× LND) leading. WOA-PSO-LEACH’s computational cost (~0.12 seconds) is minor versus energy gains, aligning with bio-inspired efficacy (Rodríguez et al., 2020).

Conclusion

This study addressed the research question of identifying the optimal hybrid PSO-LEACH variant for balancing early stability and long-term energy conservation in WSNs by evaluating eight variants through Python simulations. Key findings reveal that ABC-PSO-LEACH achieves the highest FND (57 rounds) and LND (462 rounds), making it ideal for applications requiring immediate network reliability, while WOA-PSO-LEACH excels in HND (148 rounds) and provides strong overall longevity (LND 406 rounds) through balanced energy distribution. Both outperform traditional LEACH and other variants in energy efficiency, with average residual energy retention of ~0.80–0.85 Joules at 100 rounds and uniform clustering (4–6 nodes per cluster). Empirical evidence from the simulations demonstrates that bio-inspired hybrids like these can extend network lifetime by up to 2.3 times, minimizing communication costs and uneven dissipation.

The main contributions include a unified comparison framework for PSO-LEACH hybrids, highlighting WOA-PSO-LEACH’s suitability for mid-to-late stage IoT applications (e.g., smart cities) and ABC-PSO-LEACH for early-critical scenarios (e.g., disaster monitoring). These insights build on existing works (e.g., Latiff et al., 2007; Mirjalili & Lewis, 2016) by providing quantifiable performance metrics under consistent conditions. Implications for practice involve adopting these variants to enhance WSN scalability in energy-constrained environments, potentially reducing deployment costs and improving data reliability. However, limitations such as static topologies suggest caution in generalizing to mobile networks.

FUTURE WORK AND SCOPE

WOA-PSO-LEACH’s HND (148) and LND (406) highlight its potential for prolonged WSN operation in IoT applications like healthcare and smart cities. ABC-PSO-LEACH’s FND (57) and LND (462) suit early stability needs. Future directions include:

- **Early-Stage Improvement**: Hybridize WOA with CSA to boost FND, using adaptive fitness for early energy balance.
- **Realistic Energy Models**: Incorporate full First Order Radio Model (e.g., ($E_{\text{elec}} = 50,\text{nJ/bit}$)) for accuracy (Heinzelman et al., 2000).
- **Dynamic Topologies**: Test WOA-PSO-LEACH with mobile nodes for IoT scalability (Firdous et al., 2022).
- **Multi-Objective Optimization**: Add latency and node density to fitness, using Pareto methods (Rodríguez et al., 2020).
- **Reduced Overhead**: Streamline WOA iterations or parallelize for real-time WSNs.
- **Heterogeneous WSNs**: Evaluate in 500+ node networks with mixed energy capacities (Rajendra Prasad & Ahmed, 2024).
- **Real-World Deployment**: Test on WSN testbeds for practical validation.
- **Cross-Hybridization**: Combine WOA, GA, and PSO for layered optimization.
- **Emerging Technologies**: Integrate machine learning for predictive CH selection (Rajendra Prasad & Ahmed, 2024).

These advancements will enhance WOA-PSO-LEACH’s applicability in resource-constrained IoT networks, building on Latiff et al. (2007) and Mirjalili & Lewis (2016).

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