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Phase-Aware Performance Ehancement with Neural Gas Network Method of the Wireless Sensor Networks Routing*

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Abstract

Wireless Sensor Networks (WSNs) operate under severe energy constraints that fundamentally limit their operational lifetime and reliability. To mitigate this limitation, clustering has been widely adopted as an effective strategy to reduce communication overhead and improve overall energy efficiency; however, the benefits of clustering depend critically on the quality of the cluster-head (CH) selection process. Traditional CH selection mechanisms, such as LEACH-style probabilistic schemes, rely on static and non-adaptive decision rules that fail to respond to dynamic network conditions, often resulting in suboptimal CH placement and unbalanced energy consumption. Consequently, these approaches accelerate node depletion and degrade network stability [5] . The cluster-head selection problem itself is inherently combinatorial, highly non-linear, and NP-hard, particularly in heterogeneous WSNs where nodes differ in residual energy and communication cost, rendering classical deterministic or greedy solutions insufficient for achieving sustained energy-efficient operation [4]. In response, nature-inspired metaheuristic optimization algorithms have emerged as powerful tools for addressing the multi-objective optimization challenges of WSN routing and clustering [4], leveraging swarm intelli-

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gence, evolutionary adaptation, and physics principles to explore complex solution spaces. Algorithms such as Particle Swarm Optimization (PSO)[2], Biogeography-Based Optimization (BBO) , Simulated Annealing (SA) , Chimp Optimization Algorithm (ChOA) [3] and Cultural Algorithms (CA) , alongside learning-based approaches such as the Neural Gas Network (NGN) , have shown promising results for energy-aware CH selection. Despite this progress, existing studies often rely on heterogeneous simulation settings or aggregated metrics, obscuring how algorithm behavior evolves across different operational phases of the network[1]. This work addresses these limitations by conducting a unified, phase-aware comparative evaluation of six optimization-based clustering and routing strategies under an identical network model and fitness formulation, benchmarking them against a non-optimized baseline and analyzing their performance in terms of computational cost, convergence behavior, residual energy dynamics, node survivability, and overall network lifetime.

The evaluation is performed in a hierarchical WSN routing framework. A WSN is randomly deployed using a fixed seed for reproducibility, with uniform initial node energy and a centrally located sink. Node energy dissipation follows a distance-dependent radio model incorporating free-space and multipath propagation as well as data aggregation costs. Each algorithm aims to determine a binary cluster-head vector. the cluster-Head selection is formulated as a multi-objective optimization problem governed by a fitness function F:

$$F = w_1 E_{\text{norm}} + w_2 D_{\text{norm}} + w_3 P_{\text{life}} + w_4 P_{\text{balance}} + w_5 P_{\text{CH}} + w_6 P_{\text{dead}} \quad (1)$$

where E_{norm} is the normalized total energy consumption of the network per round, D_{norm} is the normalized average intra-cluster communication distance, P_{life} is the lifetime penalty based on the minimum residual energy among all nodes, P_{balance} is the energy-balance penalty, P_{CH} is the cluster-head count penalty that enforces a desired CH ratio of 10%, and P_{dead} is the penalty applied when any node reaches zero or negative residual energy. The weights w_1–w_6 are user-defined coefficients that regulate the contribution of each objective term to the overall fitness value.

Table 1. Comparative Performance Summary of Evaluated Algorithms

Algorithm	**Runtime**	**Convergence**		**Network Lifetime Events**			**Residual Energy**		
		Mean	**Std**	**FND**	**HND**	**LND**	$\mathbf{T_0}$	$\mathbf{T_{50}}$	**AUC**
NO-WSN	00:02	–	–	280	1507	4600	92%	12.6%	2.63×10^4
BBO	35:25	16.016	5.050	1521	2729	4524	90.5%	27.5%	3.81×10^4
ChOA	33:47	17.189	5.431	1486	2503	4711	94.2%	25.6%	3.65×10^4
CA	52:55	17.526	8.857	1168	2428	**4917**	**98.3%**	24.2%	3.60×10^4
NGN	11:16	**0.696**	**0.265**	432	2189	**Survived**	**Survived**	19.4%	3.47×10^4
SA	09:48	15.743	5.824	1457	**2880**	4554	91.1%	**28.5%**	$\mathbf{3.95 \times 10^4}$
PSO	26:41	21.885	17.704	955	2403	4897	97.9%	23.3%	3.53×10^4

Table 1 shows the comparative performance of the evaluated algorithms across computational cost, convergence, energy, and network-lifetime metrics, revealing pronounced trade-offs between efficiency, solution quality, and long-term survivability. Lightweight approaches such as SA and NGN achieve the lowest runtimes, making them attractive for scenarios with strict computational constraints; however, their optimization behaviors differ markedly. SA exhibits strong early-stage energy efficiency, delaying initial energy depletion and achieving the highest cumulative residual energy, yet it suffers from weaker late-stage sustainability. In contrast, PSO and CA extend network operation closer to the simulation horizon by postponing large-scale node failures, but at the cost of higher computational overhead and increased convergence variability. Notably, NGN demonstrates a distinct phase-dependent performance profile: despite faster early energy consumption and earlier initial node failures, it achieves superior convergence stability and effectively suppresses catastrophic late-stage network collapse, maintaining active nodes and residual energy throughout the entire simulation duration. These results confirm that optimization effectiveness in WSNs cannot be fully characterized by aggregated or end-point metrics alone, as algorithm performance varies significantly across different operational phases of the network lifetime.

This work provides a unified, phase-aware comparison of six optimization-based clustering and routing strategies for energy-efficient wireless sensor networks. The results show that although all best approaches outperform a baseline WSN, no single algorithm is optimal across all network phases, except an outstanding performance of NGN by the end of the life time of the WSN. These findings underscore the importance of phase-aware evaluation when assessing optimization strategies for WSNs. We suggest that an adaptive or a hybrid framework capable of dynamically selecting or combining optimization methods based on real-time network conditions may offer a more effective path toward sustained and reliable WSN operation in future IoT deployments.

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