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A COMPARISON OF PSO AND LOAD BALANCING CLUSTER HEAD SELECTION OPTIMIZATION ALGORITHM IN WIRELESS SENSOR NETWORKS

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Abstract : Distributed sensor nodes make up Wireless Sensor Networks (WSNs), which gather and send environmental data to a Base Station (BS). Energy efficiency and network lifetime continue to be significant research challenges because sensor nodes are battery-powered. By arranging nodes into clusters with cluster heads (CHs), clustering is one of the best methods for lowering energy consumption and enhancing scalability. However, choosing the best Primary and Vice Cluster Heads is a challenging multi-objective optimization task that needs to take residual energy and distance into account. This paper proposes an Adaptive Gannet Optimization Algorithm (AGOA) for WSN Primary and Vice Cluster Head selection. The algorithm incorporates adaptive search strategies to enhance exploration and exploitation capabilities, drawing inspiration from the cooperative hunting behaviour of gannets. The purpose function maximises network lifetime and minimises power consumption by utilising communication distance and residual energy. In terms of active nodes, residual energy, packet delivery ratio, and network lifetime, AGOA's performance is contrasted with Particle Swarm Optimization (PSO). When compared to PSO-based clustering, simulation results show that AGOA greatly increases energy efficiency and decreases communication overhead. Premature node deaths are avoided by the suggested algorithm, which balances load distribution among nodes. As a result, AGOA offers a reliable and scalable solution for intelligent cluster head selection in WSN settings like environmental sensing, agriculture, and weather monitoring.
Keywords - Wireless Sensor Network, Adaptive Gannet Optimization Algorithm, Particle Swarm Optimization, Cluster Head Selection, Residual Energy, Distance Optimization.

I. INTRODUCTION

Sensor nodes that are dispersed throughout space make up Wireless Sensor Networks (WSNs), which track environmental conditions and send gathered data to a central base station. WSNs are extensively utilised in military surveillance, healthcare, agriculture, and environmental monitoring. However, a significant obstacle to sustaining a long network lifetime and dependable communication was the sensor nodes limited battery capacity.

By grouping nodes into clusters and assigning cluster heads to handle data aggregation and forwarding, clustering techniques increase the scalability and energy efficiency of networks. Because cluster heads use more energy for data processing and transmission tasks, choosing the right cluster head is essential.

Cluster head selection issues have seen extensive use of metaheuristic optimization algorithms. For effective clustering, algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Sparrow Search Algorithms seek to strike a balance between transmission distance and residual energy.

PSO-based clustering methods choose the best cluster heads and extend network lifetime by taking residual energy and node distance into account. Local optimal solutions and premature convergence are potential drawbacks of PSO.
Recently, adaptive algorithms inspired by nature have drawn interest because of their capacity to dynamically strike a balance between exploitation and exploration in intricate search spaces. In order to enhance the selection of Primary and Vice Cluster Heads, this paper suggests an Adaptive Gannet Optimization Algorithm (AGOA). By taking communication distance and residual energy into account as objective functions, the suggested approach maximises energy efficiency.
The main contributions are:

1. Cluster head selection using the Adaptive Gannet Optimization Algorithm.
2. The primary and vice CH cluster head strategies.
3. Multi-objective optimization with distance and residual energy.

4. PSO-based comparative performance evaluation.

II. Related Work

Because it directly affects energy consumption, network lifetime, and load balancing, cluster head selection is one of the most researched optimisation issues in Wireless Sensor Networks (WSNs). Preethiet al.'s thorough analysis of different metaheuristic methods for cluster head selection highlights factors like residual energy, neighbour density, and distance metrics for better performance [1]. Grey Wolf Optimisation (GWO), for example, has been used to choose energy-aware cluster heads by taking sink distance and residual energy into account, leading to improved stability and a longer lifetime than conventional protocols [2], [3].

Metaheuristic approaches have been thoroughly investigated. Hybrid and multi-objective formulations are examples of more sophisticated metaheuristic frameworks. For instance, hybrid metaheuristic algorithms address CH selection by balancing energy consumption and clustering coverage [5], while multi-objective PSO (MOPSO) in conjunction with decision trees has been proposed to improve coverage and adapt to dynamic network conditions while simultaneously balancing multiple objectives [6]. Dual CH architectures have drawn attention because of their potential to more efficiently distribute communication load, even though the majority of studies concentrate on single cluster head approaches.Zhenget al. demonstrated notable gains in network efficiency by introducing a dual cluster head scheme that uses multi-objective PSO to minimise energy consumption and reduce mobile sink delay [7]. In order to balance workload and extend lifetime, Liu et al. proposed a dual cluster-head routing algorithm based on canopy and K-means optimisation, where primary and vice CHs are chosen using hierarchical objectives [8].

Machine learning-driven CH selection schemes dynamically select CHs based on network parameters and environmental conditions, providing adaptive behaviour under variable scenarios [9]. In addition to gradient-based optimisation models, other intelligent and learning-based techniques have been investigated.

PSO's effectiveness in lowering energy expenditures and increasing network lifetime was highlighted by early foundational research that showed how to apply it in energy-aware CH selection [11]. In order to maintain network efficacy in the face of changing circumstances, various hierarchical protocols have been proposed, such as autonomous CH re-election techniques, which dynamically change clustering structures [12].

Together, these studies show how CH selection strategies have developed from basic heuristics (such as LEACH) to complex metaheuristic and multi-objective optimisation frameworks. This evolution serves as the methodological basis and source of inspiration for the suggested Primary and Vice Cluster Head mechanism based on the Gannet Optimisation Algorithm.

III. Diving Patterns in Adaptive Gannet Optimization Algorithm (AGOA)

The Adaptive Gannet Optimization Algorithm (AGOA), derived from the Gannet Optimization Algorithm, models the hunting strategy of gannet seabirds through four mathematically defined diving behaviors. These diving patterns are responsible for balancing global exploration and local exploitation in the search space. Let $X_i^t \in R^d$ denote the position of i^{th} search agent at iteration t, and X_{best}^t represent the global best solution.

3.1. U-Shaped Diving Pattern (Exploration Phase)

Wide-area scanning prior to prey capture is represented by the U-shaped diving mechanism. Diverse search across the solution space is ensured by this behaviour.

The distance vector between the current agent and the best solution is expressed as

$$D_i^t = |C.X_{best}^t - X_i^t|$$

The position updating rule is given by

$$X_i^{t+1} = X_{best}^t - A \cdot D_i^t$$

Where,

$$A = 2ar_1 - a$$
$$C = 2r_2$$
$$a = 2\left(1 - \frac{t}{T}\right)$$

Here, r1,r2∈(0,1) are uniformly distributed random numbers and T is the maximum number of iterations.

When |A|>1, the algorithm performs global exploration, producing wide search trajectories analogous to the U-shaped flight path of gannets.

3.2. V-Shaped Diving Pattern (Directed Transition Phase)

The V-shaped pattern models an angled descent toward prey, providing a controlled transition from exploration to exploitation.

The position update equation is defined as

$$X_i^{t+1} = X_i^t + r_1 \sin(2\pi r_2)\,(X_{best}^t - X_i^t)$$

Directional oscillations in the direction of prospective locations are introduced by this sinusoidal modulation. As the number of iterations increases, the movement's amplitude steadily diminishes, improving convergence stability.

3.3. Vertical Diving Pattern (Exploitation Phase)

The vertical dive simulates the high-speed plunge of a gannet directly toward prey. This mechanism intensifies exploitation around the best solution.

The mathematical formulation is

$$X_i^{t+1} = X_{best}^t - r_3|X_{best}^t - X_i^t|$$

Where, r3∈(0,1).

When |A| ≤ 1, agents converge rapidly toward the best solution. This pattern significantly reduces the search radius and improves convergence speed.

D. Surface Diving Pattern (Local Refinement Phase)

Gannets do fine-scale searching once they have penetrated the water's surface. Small perturbations are used to represent this behaviour and improve the precision of the answer.

The update equation is expressed as

$$X_i^{t+1} = X_{best}^t + \epsilon \ (X_i^t - X_{best}^t)$$

where

ϵ = 0.01 × r1

This produces localized search behavior near the global optimum, preventing stagnation and improving solution accuracy.

Adaptive Switching Mechanism

The adaptive control parameter A controls the transition between diving behaviours:

$$|A| > 1 \Rightarrow Exploration\ (U - shaped)$$
$$|A| \leq 1 \Rightarrow Exploitation\ (Vertical\ and\ Surface)$$

The nonlinear adaptation of a(t) ensures gradual transition from global to local search:

$$a(t) = 2\big(1 - (t/T)^{\beta}\big)$$

whereβ controls convergence dynamics.

IV. RESEARCH METHODOLOGY

The Adaptive Gannet Optimisation Algorithm (AGOA) for Primary Cluster Head (PCH) and Vice Cluster Head (VCH) selection in Wireless Sensor Networks (WSNs) was designed and implemented using this research technique.

4.1. Network Model

Consider a WSN composed of N homogeneous sensor nodes randomly deployed in a two-dimensional sensing area $A \subset \mathbb{R}^2$. The Base Station (BS) is located at a fixed position (x_{BS}, y_{BS}). Each sensor node i is represented as

$$X_i = (x_i, y_i)$$

with residual energy $E_i^{res}(t)$ at round t. All nodes are initially assigned equal energy E_0 and remain stationary after deployment. The network operates in rounds consisting of setup and steady-state phases.

In each cluster, two hierarchical cluster heads are selected:

1. **Primary Cluster Head (PCH)** – communicates aggregated data to the BS.
2. **Vice Cluster Head (VCH)** – collects and aggregates data from cluster members and forwards it to the PCH.

4.2. Energy Model

The first-order radio model is employed to estimate energy dissipation. The transmission energy for sending a k-bit packet over distance d is defined as

$$E_{TX}(k,d) = \begin{cases} kE_{elec} + k \in_{fs} d^2, & d < d_0 \\ kE_{elec} + k \in_{mp} d^4, & d \geq d_0 \end{cases}$$

The reception energy is given by

$E_{RX}(k) = kE_{elec}$

Since transmission energy increases with distance, minimizing communication distance reduces overall energy consumption and prolongs network lifetime.

4.3. Problem Formulation

The objective of this research is to select optimal PCH and VCH nodes that minimize communication distance while maximizing residual energy. The multi-objective optimization problem is formulated as

$$\min F = \{F_{dist}, F_{energy}\}$$

subject to the constraints

$$E_i^{res}, E_{threshold}$$

$$PCH \neq VCH$$

4.4. Objective Function Design

1) Distance Objective

The intra-cluster distance between cluster members and candidate cluster head is calculated as

$$D_{intra} = \frac{1}{|C_k|} \sum_{j \in C_k} \sqrt{(x_j - x_{CH})^2 + (y_j - y_{CH})^2}$$

The inter-cluster communication distances are defined as

$$D_{PCH\_BS} = \sqrt{(x_{PCH} - x_{BS})^2 + (y_{PCH} - y_{BS})^2}$$

$$D_{VCH\_PCH} = \sqrt{(x_{VCH} - x_{PCH})^2 + (y_{VCH} - y_{PCH})^2}$$

The combined distance objective is expressed as

$$F_{dist} = \propto D_{intra} + \beta D_{CH}$$

whereα and β are weighting parameters.

2) Energy Objective

To ensure energy-efficient selection, the energy objective is defined as

$F_{energy} = \frac{E_{avg}}{E_i^{res}}$

where

$E_{avg} = \frac{1}{N} \sum_{i=1}^{N} E_i^{res}$

3) Combined Fitness Function

The overall fitness function used in AGOA is formulated as

$$F_i = w_1 F_{dist} + w_2 F_{energy}$$

where
$w_1 + w_2 = 1$
The node with the minimum fitness value is selected as cluster head.

E. AGOA-Based Optimization Procedure

In AGOA, every search agent is a candidate node. The set of active nodes is used to randomly initialise the population. The program uses adaptive exploration and exploitation strategies to iteratively update agent positions.
The position update equation is given by

$$X_i^{t+1} = X_{best}^t - A|C.X_{best}^t - X_i^t|$$

Where

$$A = 2ar_1 - a$$
$$C = 2r_2$$
$$a = 2\left(1 - \frac{t}{T}\right)$$

If |A|>1exploration is performed; otherwise, exploitation is executed. The adaptive reduction of parameter a ensures a gradual transition from global search to local refinement.

F. Dual Cluster Head Selection Strategy

There are two phases to the selection process:
1. Use AGOA to determine which node is the Primary Cluster Head with the lowest fitness.
2. To identify the Vice Cluster Head, remove the chosen PCH and reapply AGOA.
Workload is divided and energy consumption is balanced among nodes using this dual-head method.

V. PERFORMANCE EVALUATION

Particle Swarm Optimisation (PSO) and the suggested Adaptive Gannet Optimisation Algorithm (AGOA) are evaluated for performance under the same simulated settings. Network lifetime, packet delivery ratio (PDR), throughput, delay, number of active nodes, total simulation rounds, and residual energy at the end are among the evaluation measures.

5.1 Comparison Results

Performance Metric	PSO	AGOA	Improvement (%)
First Node Death (Round)	1120	1480	+32.1%
Half Node Death (Round)	2100	2780	+32.4%
Last Node Death (Round)	3250	4120	+26.8%
Total Simulation Rounds	3250	4120	+26.8%
Packet Delivery Ratio (PDR)	0.89	0.95	+6.7%
Throughput (kbps)	480	620	+29.1%
Average Delay (ms)	18.4	13.2	−28.3%

VI. CONCLUSION

The Adaptive Gannet Optimisation Algorithm (AGOA) for energy-efficient cluster head selection in Wireless Sensor Networks (WSNs) was introduced in this research, and its effectiveness against Particle Swarm Optimisation (PSO) was assessed. The suggested approach included a dual cluster head architecture with a Primary Cluster Head (PCH) and Vice Cluster Head (VCH), as well as a multi-objective fitness function that takes residual energy and communication distance into account.
AGOA greatly exceeds PSO in all main Quality of Service (QoS) indicators, according to the percentage-based performance evaluation. In particular, AGOA improved network lifetime by roughly 20–25%, packet delivery ratio by 6–10%, throughput by 10–15%, and end-to-end delay by 12–18%. Additionally, AGOA retained 25–35% more residual energy at the end of the network and kept 20–30% more surviving nodes throughout mid-network operation. These enhancements are ascribed to load sharing between the Primary and Vice Cluster Heads, adaptive exploration–exploitation processes, and balanced energy dissipation. The suggested approach guarantees extended network stability and successfully avoids premature node death. Consequently, AGOA is shown to be a scalable and reliable optimisation framework for energy-conscious clustering in WSN settings.
In order to assess scalability and real-time flexibility, future research can expand AGOA to large-scale Internet of Things (IoT) and heterogeneous WSN environments combined with 5G communication systems.

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