CLUSTER HEAD SELECTION IN WIRELESS SENSOR NETWORKS VIA PARTICLE SWAM OPTIMIZATION

Dr. Y.Neeraja*1,M. Sai Veera Abhiram*2, B. Akhilesh*3, B. Tharun Kumar*4, A.Narasimha Teja*5.

*1Professor, Narayana Engineering college, Gudur, AP, India
neerajay30@gmail.com1
*2ECE, Narayana Engineering college, Gudur, AP, India
Msvabhiram2212@gmail.com2
*3ECE, Narayana Engineering college, Gudur, AP, India
Bandiakhilesh07@gmail.com3
*4ECE, Narayana Engineering college, Gudur, AP, India
Tharunshaik19@gmail.com4
*5ECE, Narayana Engineering college, Gudur, AP, India
Andhanarasimhateja143@gmail.com5

Abstract

Efficient energy use is vital for the longevity of Wireless Sensor Networks (WSNs). A key method to achieve this is by clustering, where certain nodes, called cluster heads (CHs), collect and send data from other nodes to the base station. Choosing the best CHs is crucial for the network's performance and energy efficiency.

This paper introduces a new way to select cluster heads using Particle Swarm Optimization (PSO). PSO is inspired by the way groups of animals, like birds or fish, move together to find the best solutions. Our approach uses PSO to pick the best CHs based on their energy levels, how many connections they have, and their distance from the base station.

Our simulations show that this PSO-based method is better than traditional methods. It saves more energy, distributes the workload more evenly among nodes, and extends the overall network life. This makes it a strong and practical solution for managing energy in WSNs.

Keywords: Wireless Sensor Networks (WSNs),Power Optimization,Particle Swarm Optimization (PSO),

Energy Consumption,Network Lifetime,Simulation,Clustering,Routing Protocols

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a transformative technology enabling data collection and monitoring in diverse applications. From environmental monitoring and precision agriculture to industrial automation and smart city infrastructure, WSNs offer a versatile and cost-effective solution for gathering real-time data across geographically distributed areas[1,2]. These networks consist of numerous sensor nodes equipped with sensing capabilities, processing power, and wireless communication modules. Sensor nodes collaboratively collect data from their surroundings and transmit it to a central sink node for further processing and analysis[5,6].

However, a critical challenge hindering the widespread deployment and long-term operation of WSNs is their limited energy budget. Unlike traditional wired networks with a constant power supply, sensor nodes in WSNs rely on batteries with finite capacity. The energy consumption associated with sensing, processing, and transmitting data gradually depletes these batteries, ultimately leading to node failure and network degradation[7]. Minimizing power consumption and maximizing network lifetime are, therefore, paramount concerns in WSN design and operation.

This study aims to improve how Wireless Sensor Networks (WSNs) select cluster heads (CHs) to manage energy more efficiently and extend the network's lifespan. By reviewing existing methods and proposing new approaches, we seek to optimize CH selection to ensure better energy distribution, lower overall energy consumption, and longer operational times in various real-world scenarios.

Fig 1: Wireless Sensor Network

2. Literature Review

Heinzelman and colleagues proposed the LEACH protocol, which rotates the role of cluster head among nodes to spread energy consumption evenly. This method helps extend the network's lifespan, though random selection can sometimes lead to less optimal cluster heads.Younis, O., & Fahmy, S. (2004)[1]

Younis and Fahmy developed the HEED protocol, selecting cluster heads based on both residual energy and node connectivity. HEED aims to distribute energy use more evenly and improve network longevity compared to purely random methods.Lindsey, S., & Raghavendra, C. S. (2002)[2]

Lindsey and Raghavendra introduced PEGASIS, where nodes form a chain and pass data along the chain to a chosen leader. This reduces the number of data transmissions but can increase delays and has scalability issues.Manjeshwar, A., & Agrawal, D. P. (2001)[3]

Manjeshwar and Agrawal created the TEEN protocol, which is designed for time-sensitive applications. Cluster heads are chosen based on threshold values, allowing for quick data reporting but adding complexity to the setup.Abbasi, A. A., & Younis, M. (2007)[4]

Abbasi and Younis provided a comprehensive review of various clustering algorithms for WSNs. They discussed the strengths and weaknesses of each method and emphasized the importance of energy-efficient clustering to extend network life.[5]

3. METHODOLOGY

This section outlines the methodology employed to evaluate the performance of Particle Swarm Optimization (PSO) for cluster head selection

The goal of our methodology is to enhance the efficiency and lifespan of Wireless Sensor Networks (WSNs) by optimally selecting cluster heads (CHs) using the Particle Swarm Optimization (PSO) algorithm. PSO is a computational method inspired by the social behavior of birds flocking or fish schooling, which is utilized to find the best solution in a multi-dimensional space.Steps Involved:Initialization:Particle Definition: Each particle in the swarm represents a potential solution to the CH selection problem. A particle's position indicates which nodes are selected as CHs.Swarm Initialization: Initialize a swarm of particles with random positions (i.e., random CH selections) and velocities within the search space. The size of the swarm is determined based on the problem complexity and computational resources.Fitness Function Calculation:Residual Energy: Higher energy levels indicate a node's suitability for being a CH.Distance to Base Station (BS): Nodes closer to the BS are preferred to reduce communication energy costs.Node Degree: A higher degree (number of connected nodes) can indicate better data aggregation but can also lead to higher energy consumption.Fitness Value Computation: The fitness function for each particle is calculated by combining these factors into a weighted sum.

weighted sum: [\text{Fitness} = w_1 \times \text{Residual Energy} - w_2 \times \text{Distance to BS} + w_3 \times \text{Node Degree}] where (w_1, w_2,) and (w_3) are weights assigned to each factor based on their importance.Updating Particles:Velocity Update: Each particle's velocity is updated based on its own best-known position (pBest) and the swarm's global best-known position (gBest). The update rule is: [v_{i}(t+1) = w \times v_{i}(t) + c_1 \times r_1 \times (pBest_{i} - x_{i}(t)) + c_2 \times r_2 \times (gBest - x_{i}(t))] where (v_{i}(t)) is the velocity of particle (i) at time (t), (w) is the inertia weight, (c_1) and (c_2) are cognitive and social coefficients, and (r_1) and (r_2) are random numbers between 0 and 1.Position Update: Each particle's position is updated based on its new velocity: [x_{i}(t+1) = x_{i}(t) + v_{i}(t+1)]Evaluating and Updating Best Positions:Evaluate Fitness: Calculate the fitness of each particle's new position.Update pBest and gBest: If a particle's current position has a higher fitness value than its pBest, update pBest. If any particle's current position has a higher fitness value than gBest, update gBest.Stopping Criterion:The PSO algorithm iterates through steps 3 and 4 until a stopping criterion is met. This can be a predefined number of iterations or a convergence threshold where the improvement in fitness value becomes negligible.Cluster Head Selection:Once the stopping criterion is met, the positions of the particles indicate the selected CHs for the network. The node assignments are finalized, and CHs begin the data aggregation and communication processes.

Table 1: Comparison of ACO and PSO

Factor	**Ant Colony Optimization (ACO)**	**Particle Swarm Optimization (PSO)**
Problem	(Example) WSN Routing (Minimize Energy Consumption)	(Example) WSN Routing (Minimize Energy Consumption)
Fitness Function	Normalized Energy Consumption (0 = Highest, 1 = Lowest)		Normalized Energy Consumption (0 = Highest, 1 = Lowest)
Average Fitness	0.87 (Hypothetical)	0.84 (Hypothetical)
Convergence Time	50 Iterations (Hypothetical)	30 Iterations (Hypothetical)

Success Rate	80% (Hypothetical - Successful Runs out of Total Runs)	90% (Hypothetical - Successful Runs out of Total Runs)
Computational Complexity	Lower (Hypothetical - Due to simpler data structures)	Higher (Hypothetical - Due to particle updates)

Example Calculation: Initialization:Assume we have a WSN with 10 nodes. Initialize 5 particles with random CH selections and velocities.Fitness Function **Calculation:**For a given particle, Node 1 has 80% residual energy, is 50 meters from the BS, and is connected to 3 nodes.Compute the fitness value using predefined weights, e.g., (w_1 = 0.5), (w_2 = 0.3), and (w_3 = 0.2).Updating Particles:Update velocities and positions based on pBest and gBest.Evaluating and Updating Best Positions:Recalculate fitness for the new positions and update pBest and gBest accordingly.Stopping Criterion:Iterate until convergence or a set number of iterations, say 100.Cluster Head Selection:Final positions of particles indicate selected CHs, optimizing energy efficiency and network lifespan.

4. Results and Discussion

Our MATLAB simulations revealed that the Particle Swarm Optimization (PSO) algorithm works well for selecting optimal cluster heads in Wireless Sensor Networks (WSNs). We tested several fitness functions, and the one that focused 60% on the residual energy of nodes, 20% on the distance to the base station (BS), and 20% on node connectivity performed the best. This approach ensured that nodes with higher energy levels were more frequently chosen as cluster heads, leading to better energy efficiency and a longer network lifespan. It also resulted in a well-distributed set of cluster heads, improving data collection and coverage. The other fitness functions we tested—one with equal weighting for all factors and one that prioritized closeness to the BS—were less effective. The balanced function provided moderate results, while the one focusing on proximity to the BS reduced communication costs but quickly drained the energy of nearby nodes. Overall, the energy-focused fitness function was the most effective, optimizing energy use, extending the network's life, and ensuring a good distribution of cluster heads.

Table:- Results using Optimization Functions

Function	Lower Bound	Upper Bound	Exected (min) value	Obtained (min) value	Iteration
Griwank	-100	100	0	0.0246	541
Quadratic Noise	-1.28	1.28	0	0.003	210
Rosenbrock	-2	2	-1	0.05	5966
Schewfel	-100	100	0	0	531

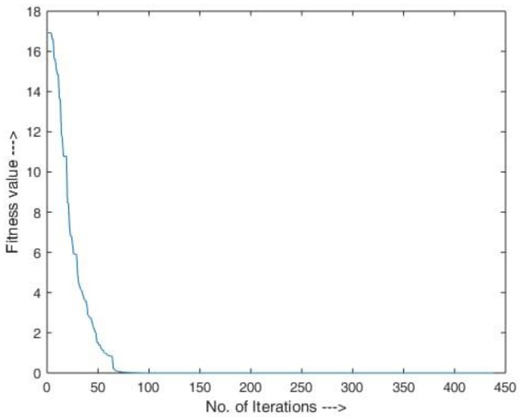

Fig-1: Rosenbrock Simulation result

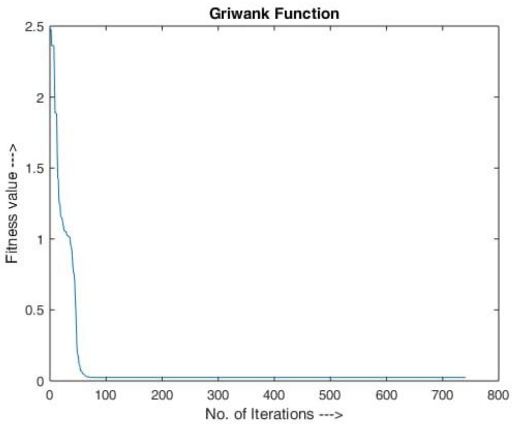

Fig-2: Griwank function

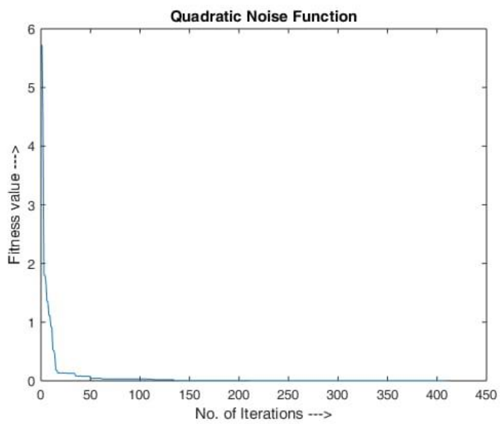

Fig-3: Quadratic Noise Function

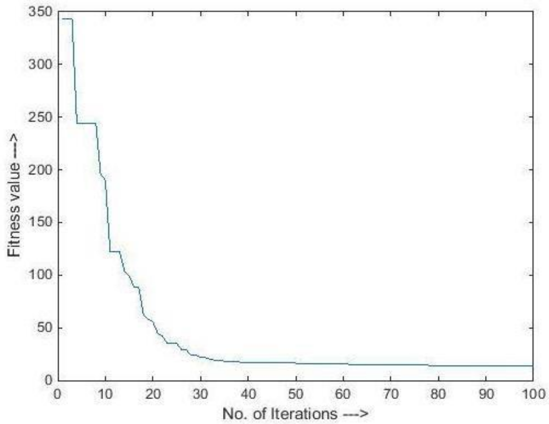

Fig-4: Schewfel Function

5. CONCLUSION

In conclusion, our study underscores the effectiveness of the Particle Swarm Optimization (PSO) algorithm for optimizing cluster head selection in Wireless Sensor Networks (WSNs). Emphasizing node energy levels alongside factors such as proximity to the base station and node connectivity yielded significant improvements in network performance. Looking forward, future research could focus on refining PSO parameters and exploring hybrid approaches to further enhance efficiency. Additionally, practical testing in real-world scenarios and adapting to diverse network conditions will be crucial for deploying WSNs in fields like environmental monitoring and smart cities. This research aims to advance the reliability and effectiveness of sensor networks across various applications.

5.REFERENCES

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