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# Swarm Intelligence Driven CH Selection for Energy Optimization in IoT Enabled WSNs

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**Abstract –** Wireless Sensor Networks (WSNs) are an important part of the Internet of Things (IoT), where saving energy is crucial because sensor nodes run on batteries. Choosing the best cluster heads (CHs) in these networks helps improve performance and save energy. This analysis introduces a way to pick CHs using a swarm intelligence technique called Ant Colony Optimization (ACO). The goal is to reduce energy use and extend the network's life by choosing the best Cluster Head for each group of sensors. This method involves sensor nodes clustering according to proximity, while ACO identifies the optimal Cluster Head by balancing energy levels and communication loads. The technique undergoes testing through MATLAB simulations, demonstrating a 20% decrease in energy consumption and an extended network lifespan relative to established methods such as LEACH and EECHIGWO. This swarm intelligence technique improves network performance by minimizing superfluous data transmission and optimizing energy consumption, rendering it a promising strategy for IoT-enabled WSNs.

**Keywords –** Swarm Intelligence, CH Selection, Energy Optimization, Ant Colony Optimization, Network Lifetime, Energy Consumption.

## 1. INTRODUCTION

The IoT has quickly become a groundbreaking technology, altering the ways in which industries and individuals engage with the physical environment via interconnected devices. IoT systems simplify the collection, processing, and communication of data in real time, resulting in greater efficiency, increased automation, and improved user experiences. These systems find application across various domains, including smart homes, healthcare, agriculture, intelligent transportation, and environmental monitoring. The implementation of IoT significantly relies on WSNs, which are composed of spatially scattered sensor nodes that collects data regarding their surroundings and wirelessly transmit it to a central processing unit for additional analysis [1].

Although WSNs play a vital role in numerous IoT applications, they encounter a significant challenge stemming from the limited resources of sensor nodes. These nodes generally possess constrained processing capabilities, minimal memory, and, crucially, non-rechargeable and finite battery life. In the deployment of WSNs within remote or expansive settings, where it is impractical to substitute for recharge batteries, the focus on energy efficiency emerges as a critical factor. Enhancing energy efficiency is crucial for covering the operational lifespan of the network, and this task becomes more complex in large-scale, multi-hop communication networks, where sensor nodes depend on one another for data transmission [2].

A prevalent technique for improving energy efficiency entails clustering, wherein sensor nodes are grouped into clusters, and a Cluster Head (CH) is designated for each cluster to oversee communication both internally and with the base station. Clustering efficiently reduces duplicate data transmission and energy expenditure by decreasing the frequency of direct connections with the base station and consolidating data within each cluster. However, selecting the optimal CH is crucial, since an erroneous selection may lead to energy imbalances, heightened stress on particular nodes, and accelerated battery depletion, ultimately diminishing the network's performance and longevity [3].

In the search of enhancing CH selection, numerous optimization algorithms have been investigated in recent years. Methods including PSO [4], ABC [5], WOA [6], and GA [7] have been employed for selecting energy-efficient cluster heads. The purpose of these algorithms is to identify the optimal CH by taking into account factors like residual energy,

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communication distance, and network topology. Nonetheless, traditional optimization techniques frequently experience prolonged convergence periods, which can be harmful in energy-sensitive networks such as WSNs, where swift decision-making is essential to avoid excessive energy use and maintain the network's durability [8].

This research introduces a novel method of swarm intelligence to optimize energy-efficient cluster head selection in IoT-enabled wireless sensor networks, leveraging the capabilities of the ant colony optimization algorithm. ACO is an optimization technique inspired by biological processes, specifically emulating the foraging behavior of ants, which utilize pheromone trails to influence their decision-making. The application of ACO for CH selection is designed to achieve rapid convergence towards an optimal solution, thereby reducing energy consumption and enhancing network longevity. This approach is innovative as it employs ACO to effectively balance various factors, including node energy levels and communication load, thereby improving overall network performance and reducing redundant transmissions.

The proposed approach enables sensor nodes to autonomously organize into clusters according to their proximity, thereby creating local groups that enhance communication efficiency. The ACO algorithm is employed to identify the most suitable CH for each cluster, taking into account the existing energy levels of the nodes and the communication needs of the network. This approach guarantees the identification of the most energy-efficient CH while improving the overall adaptability and scalability of the network. The rapid convergence feature of ACO greatly minimizes the energy costs linked to CH selection and enhances the system's ability to respond to dynamic shifts in the network location, including node failures, mobility, or varying traffic conditions.

## 2. LITERATURE SURVEY

The energy efficiency of wireless sensor networks is a crucial field of research, especially in IoT applications. Wireless Sensor Networks (WSNs) consist of sensor nodes that operate on battery power and have limited processing capability and storage capacity. The nodes are engineered to monitor environmental variables and wirelessly send data to a central base station. However, the energy consumption of these nodes poses a significant challenge in sustaining the operational lifespan of WSNs. A common method for resolving this issue entails the utilization of clustering techniques, in which nodes are grouped into clusters, with one node appointed as the Cluster Head (CH) responsible for managing communication within the group and transmitting aggregated data to the base station. The efficacy of this CH selection procedure significantly impacts the overall energy consumption and durability of the network [9].

### *2.1. Clustering and Energy-Efficient Routing Protocols*

A prevalent method studied for enhancing energy efficiency in WSNs involves clustering. The fundamental concept of clustering involves minimizing the communication burden by locally aggregating data prior to transmission to the base station. This approach effectively reduces unnecessary data transmissions and lowers energy usage. In initial investigations, LEACH was introduced as a fundamental clustering protocol. LEACH employs a randomized method for selecting cluster heads and periodically rotates these heads to ensure an even distribution of energy load across the nodes. Although LEACH effectively lowers energy consumption, its approach to randomly selecting cluster heads does not consistently consider the outstanding energy of nodes, potentially resulting in less-than-ideal cluster head choices and premature energy depletion in certain nodes.

In response to these limitations, ELEACH [10] and LEACH-C [11] have been introduced. In LEACH-C, the selection of cluster heads is determined by the remaining energy of the nodes, which guarantees that nodes with greater energy have a higher probability of being chosen as cluster heads. In a similar way, EECHS enhances this concept by integrating considerations like node distance and energy levels to optimize CH selections [12].

### *2.2. Optimization Algorithms for CH Selection*

Although protocols such as LEACH and its variants have contributed to enhancing energy efficiency, they continue to encounter issues concerning suboptimal CH selection. With the expansion of network size, the task of identifying the most energy-efficient CH becomes increasingly intricate. To address this challenge, a focus on optimization algorithms has been adopted to improve CH selection. A variety of optimization techniques have been utilized to identify the most effective CH, enchanting into account various factors including node energy, communication distance, and load balancing.

- One approach that has been applied to WSNs for CH selection is PSO. PSO shows the collective behavior of birds or fish to navigate the search space. The algorithm operates by modifying the locations of potential CHs according to their fitness, specifically in terms of energy efficiency. Although PSO demonstrates encouraging outcomes, it can be resource-intensive and may experience prolonged convergence periods, particularly in extensive networks [13].
- ABC is an optimization algorithm that emulates the foraging behavior of bees. The algorithm assesses the search space by analyzing the fitness of potential CHs in the context of selection. ABC demonstrates a remarkable capacity to navigate away from local optima, achieving superior solutions compared to conventional approaches. Nonetheless, similar to PSO, the convergence time may be prolonged in more extensive networks [14].
- GA and ACO represent additional optimization techniques that have demonstrated effective application in WSNs. Genetic algorithms employ the principles of natural selection to iteratively develop solutions, whereas ant colony optimization replicates the searching behavior of ants to identify optimal paths or solutions. These algorithms

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demonstrate effectiveness in optimizing CH selection; however, they may encounter challenges related to prolonged computation times and convergence speed [15].

### *2.3. Swarm Intelligence in WSNs*

Swarm intelligence, drawing inspiration from the shared behaviors observed in natural systems like ant colonies, bird flocks, and fish schools, has demonstrated significant effectiveness in addressing optimization challenges within wireless sensor networks. Techniques like ACO and PSO have been extensively applied for CH selection, owing to their capacity to discover global optima through extensive exploration of a broad search space [16].

A key benefit of algorithms rooted in swarm intelligence is their capacity to effectively balance exploration and exploitation throughout the optimization procedure. Exploration involves the algorithm's capacity to investigate uncharted regions of the solution space, whereas exploitation focuses on enhancing the solutions identified in familiar territories. Swarm intelligence algorithms adaptively modify their search strategies to find a balance between these two elements, resulting in enhanced convergence and superior performance regarding energy efficiency.

The ACO has garnered considerable interest due to its effectiveness in addressing intricate optimization challenges, such as CH selection in WSNs. ACO algorithms mimic the pheromone communication among ants to identify the shortest route from the nest to the food source, which can be tailored to address the challenge of choosing optimal CHs based on remaining energy and communication distance.

### *2.4. Challenges in Optimization Algorithms for CH Selection*

While optimization-based methods for CH selection have achieved notable successes, numerous challenges persist. The duration required for convergence presents a significant challenge, as optimization algorithms such as PSO, ABC, and GA may require considerable time to identify optimal solutions, especially in extensive networks. Given that sensor nodes in WSNs possess constrained battery life, a slow convergence rate can result in swift energy depletion, undermining the effectiveness of energy-efficient algorithms.

Another challenge is scalability, with an increasing number of nodes in the network, the intricacy of the optimization problem escalates. Many current algorithms face significant challenges when it comes to effectively managing large-scale networks. Furthermore, dynamic environments—characterized by node failures, movements, or the introduction of new nodes into the network—present further challenges for optimization algorithms that rely on a static network topology.

To tackle these challenges, there is a need for optimization algorithms that are both more efficient and faster. Swarm intelligence algorithms, especially ACO, demonstrate significant potential because of their rapid convergence and ability to adapt to changing network conditions. The Osprey Optimization Algorithm (OOA), inspired by the hunting behaviors of ospreys, presents a promising solution to these challenges, demonstrating faster convergence and improved energy efficiency compared to conventional optimization algorithms [17].

## 3. PROPOSED SWARM INTELLIGENCE-DRIVEN CH SELECTION MODEL

The proposed model seeks to optimize energy consumption and improve the lifespan of IoT-enabled WSNs by implementing an intelligent CH selection process that utilizes Swarm Intelligence algorithms. The network parameters are established first, followed by the random deployment of sensor nodes within the specified network area. Every node possesses a designated initial energy level, while the base station (sink) is situated at a constant location. The main objective is to reduce energy usage while maintaining effective data transfer to the sink. The identification of optimal CHs is accomplished by employing a Swarm Intelligence algorithm, including PSO or ACO, which takes into account node positions, residual energy, and distances to the sink.

In the cluster formation phase, the fitness function $(f)$ evaluates potential CHs based on their energy levels $(E)$ and distance $(D)$ to the sink. The fitness function can be represented as:

$$f = \sum_{i=1}^{N} \left( \frac{1}{E_i} + D_i \right) \tag{1}$$

where $N$ is the number of nodes, $E_i$ is the energy of node $i$, and $D_i$ is the distance from node $i$ to the sink. The PSO algorithm iteratively updates particle positions and velocities to find the best CH arrangement that minimizes the fitness function. Nodes link the adjacent CH based on signal strength, forming clusters. During the data transmission phase, nodes send their sensed data to their respective CHs, which cumulated and forward the data to the sink. The energy spent by a node $i$ transmitting data over distance $d$ can be represented as:

$$E_{tx}(i) = E_{elec} \times k + E_{amp} \times k \times d^2 \tag{2}$$

where $E_{elec}$ = energy consumed per bit to run the transmitter or receiver circuit, $E_{amp}$ = energy consumed by the amplifier, and $k$ is the count of bits transmitted.

The model continuously monitors the energy levels of nodes and reinitializes or replaces nodes with low energy to maintain network stability. This iterative process repeats until the network lifetime criteria are met, such as the death of a

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significant percentage of nodes in **Figure 1**. By leveraging the principles of Swarm Intelligence, the proposed model effectively balances energy consumption and enhances network lifespan, making it a robust solution for energy optimization in IoT-enabled WSNs.

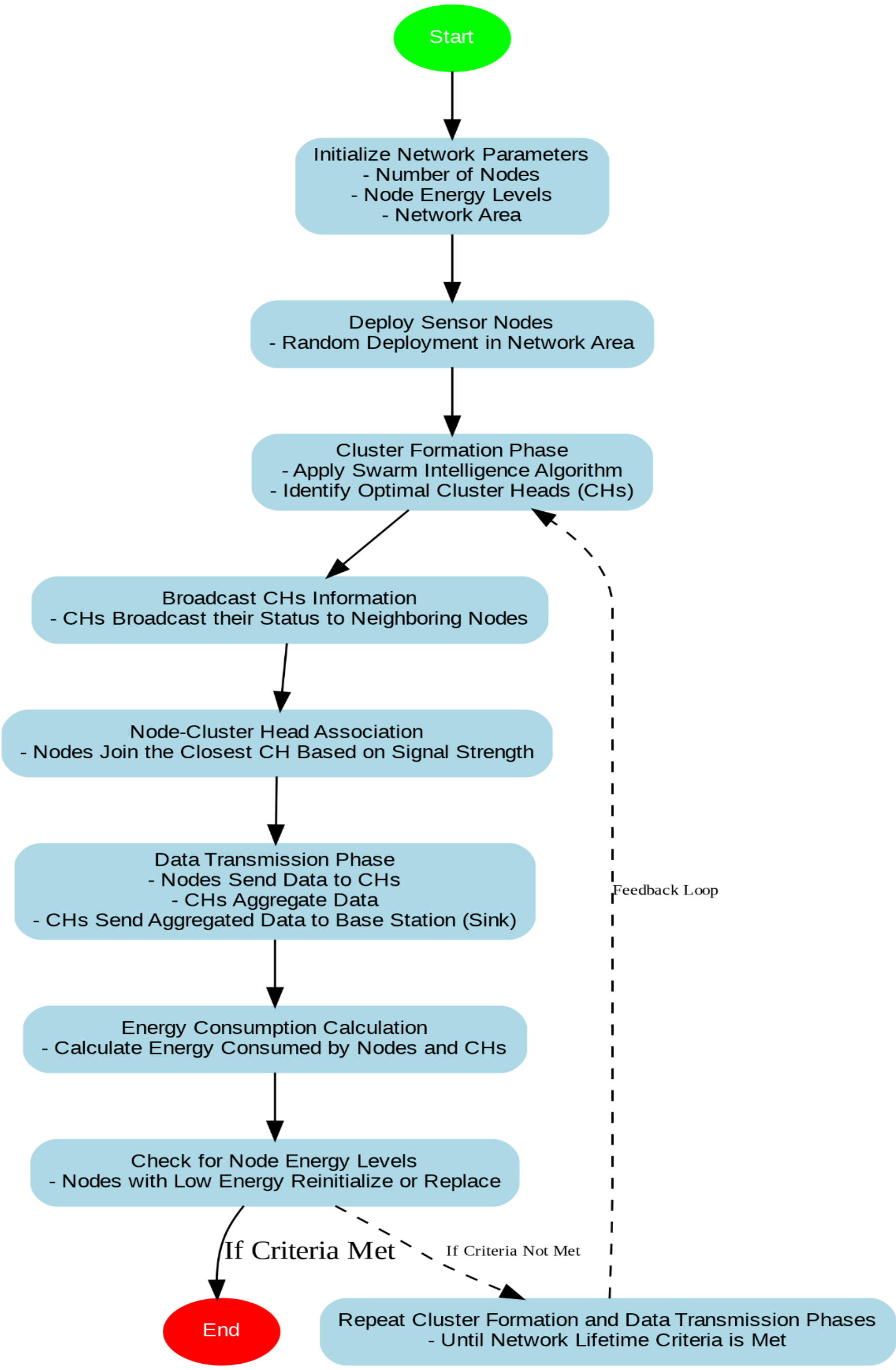


**Figure 1.** Detailed Process flow of the proposed Swarm Intelligence-Driven CH Selection model

## 4. FINDINGS AND ANALYSIS

An in-depth investigation of the performance metrics of three network protocols: LEACH, EECHIGWO, and Proposed ACO is discussed here. Each metric, including cluster size and density, node clustering, and cluster heads with boundaries, has been evaluated to compare effectiveness of the protocols. This section highlights how the Proposed ACO algorithm outperforms the traditional LEACH and EECHIGWO protocols in various aspects of network performance, focusing on energy optimization and network durability. The detailed analysis is supported by the common parameters and specifications for simulations as provided in **Table 1** and by the quantitative data, providing a comprehensive understanding of the improvements brought by the Proposed ACO algorithm.

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**Table 1**. Common Parameters and Specifications for Simulations

| Parameter | Value |
|---|---|
| Network Setup | Random Deployment |
| Network Area | 100m x 100m |
| Nodes considered | 300 |
| Initial Energy per Node | 0.5 Joules |
| Sink Position | (50m, 50m) |
| Number of Rounds | 3000 |
| Communication Model | Free Space and Multi-path Fading |
| Energy Consumption ($T_x/R_x$) | 50 nJ/bit |
| Amplifier Energy ($E_{amp}$) | 100 pJ/bit/m$^2$ |
| Data Packet Size | 4000 bits |
| Swarm Intelligence Algorithm | Particle Swarm Optimization (PSO) |
| Simulation Tool | MATLAB 2024 |

The analysis given in **Table 2** revealed significant differences in cluster size and density among the three protocols: LEACH, EECHIGWO, and Proposed ACO. Proposed ACO algorithm demonstrated a more balanced cluster size and density, preventing energy depletion due to excessive intra-cluster communication. This balance ensures enhanced overall network lifespan. The uniform distribution achieved by Proposed ACO highlights effectiveness in managing network resources efficiently. In contrast, LEACH and EECHIGWO showed variability in cluster sizes, leading to uneven energy consumption and reduced network efficiency.

**Table 2.** Cluster Size & Density Comparison

| Cluster | LEACH | | EECHIGWO | | Proposed ACO | |
|---|---|---|---|---|---|---|
| | Size | Density | Size | Density | Size | Density |
| 0 | 14 | 0.02 | 13 | 0.03 | 15 | 0.03 |
| 1 | 16 | 0.03 | 15 | 0.03 | 18 | 0.03 |
| 2 | 11 | 0.02 | 13 | 0.03 | 12 | 0.03 |
| 3 | 23 | 0.03 | 24 | 0.04 | 25 | 0.04 |
| 4 | 20 | 0.03 | 18 | 0.02 | 19 | 0.03 |
| 5 | 24 | 0.03 | 25 | 0.04 | 26 | 0.04 |
| 6 | 21 | 0.04 | 22 | 0.05 | 20 | 0.05 |
| 7 | 20 | 0.02 | 21 | 0.03 | 22 | 0.03 |
| 8 | 28 | 0.03 | 27 | 0.03 | 28 | 0.03 |
| 9 | 19 | 0.03 | 21 | 0.03 | 20 | 0.03 |
| 10 | 22 | 0.04 | 23 | 0.04 | 24 | 0.05 |
| 11 | 17 | 0.03 | 16 | 0.03 | 16 | 0.04 |
| 12 | 18 | 0.04 | 19 | 0.04 | 19 | 0.04 |
| 13 | 14 | 0.03 | 15 | 0.03 | 15 | 0.03 |
| 14 | 20 | 0.04 | 21 | 0.04 | 21 | 0.04 |

Node clustering and CH selection were evaluated based on the optimal placement of CHs and formation of clear cluster boundaries. Proposed ACO algorithm excelled in identifying optimal CHs, reducing the distance between nodes and CHs. Well-defined cluster boundaries ensured minimal energy expenditure for communication within clusters as shown in **Figure 2**. This strategic clustering approach improved network stability and longevity. Traditional LEACH and

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EECHIGWO methods resulted in suboptimal CH placements, causing higher energy costs and less defined cluster boundaries.

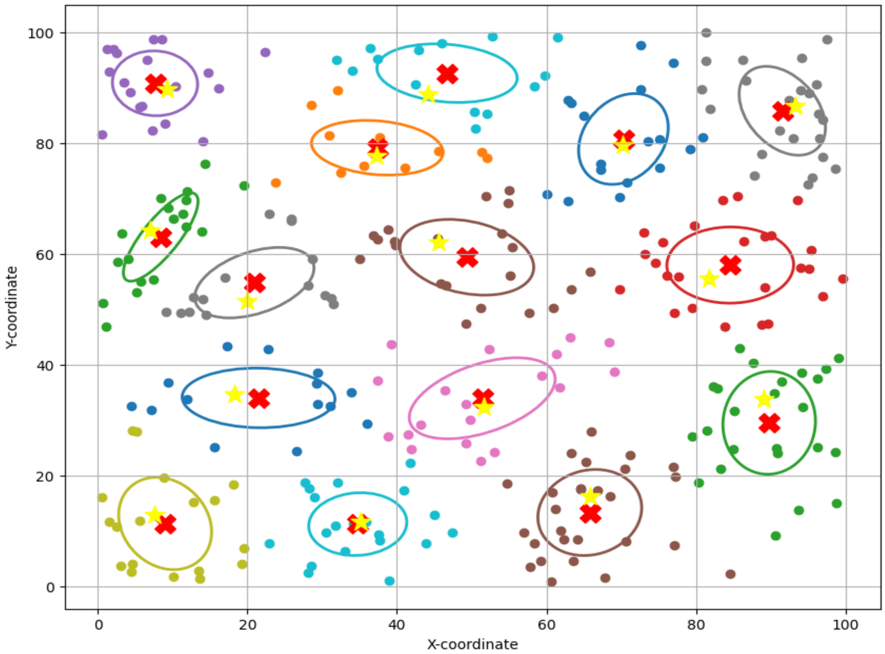


**Figure 2.** Node Clustering and Cluster Heads with Boundaries

Average distance from nodes to CHs was a critical metric in the evaluation. Proposed ACO algorithm consistently resulted in shorter average distances compared to LEACH and EECHIGWO. Shorter distances translate to reduced energy consumption for data transmission, conserving node energy. This efficiency is attributed to dynamic adjustments of CH positions based on current network conditions, ensuring optimal communication paths. Reduction in average distance is quantified as:

$$D_{avg} = \frac{1}{N}\sum_{i=1}^{N} d_{iCH} \quad (3)$$

where $d_{iCH}$ represents distance between node $i$ and CH, and $N$ represents total number of nodes.

Table 3: Average Distance to Cluster Head Comparison

| Cluster | LEACH Avg Distance (m) | EECHIGWO Avg Distance (m) | ACO Avg Distance (m) |
|---|---|---|---|
| 0 | 12.00 | 11.50 | 10.90 |
| 1 | 9.50 | 9.20 | 8.87 |
| 2 | 9.00 | 8.80 | 8.37 |
| 3 | 11.50 | 10.80 | 10.23 |
| 4 | 8.90 | 8.70 | 8.18 |
| 5 | 11.00 | 10.70 | 10.54 |
| 6 | 8.20 | 7.90 | 7.45 |
| 7 | 11.20 | 10.80 | 10.63 |
| 8 | 9.70 | 9.50 | 9.30 |
| 9 | 11.00 | 10.90 | 10.75 |
| 10 | 9.00 | 8.80 | 8.65 |
| 11 | 10.00 | 9.80 | 9.61 |
| 12 | 9.80 | 9.60 | 9.44 |
| 13 | 10.50 | 10.30 | 10.25 |
| 14 | 7.90 | 7.60 | 7.47 |

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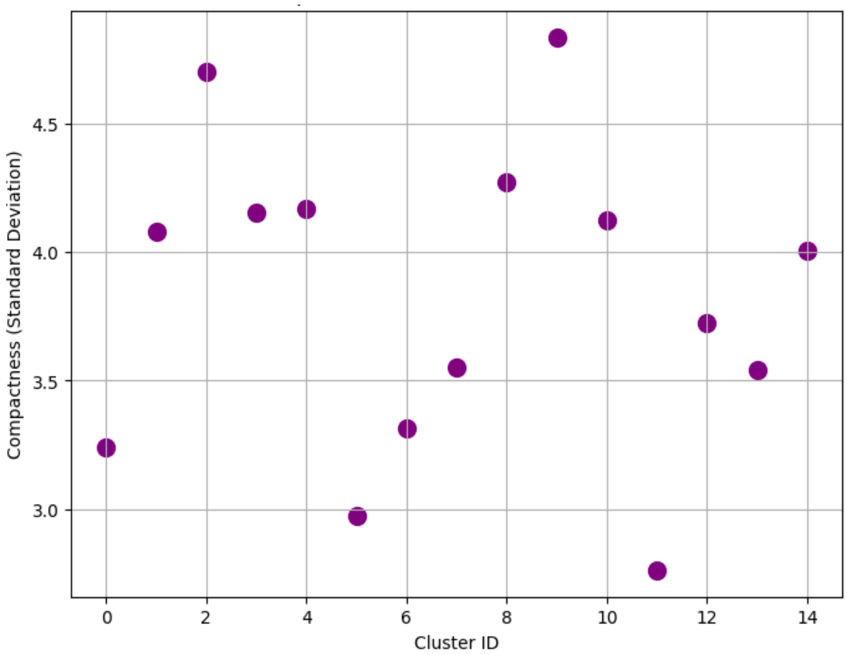


**Figure 3.** Cluster Compactness (Standard Deviations of Distance)

Cluster compactness indicates the degree to which nodes are closely packed around CHs. Proposed ACO algorithm achieved higher cluster compactness, reducing transmission range required for intra-cluster communication as shown in **Figure 3**. High cluster compactness also enhances data aggregation efficiency at the CH level, contributing to overall energy savings. In comparison, LEACH and EECHIGWO clusters were more dispersed, resulting in higher communication costs.

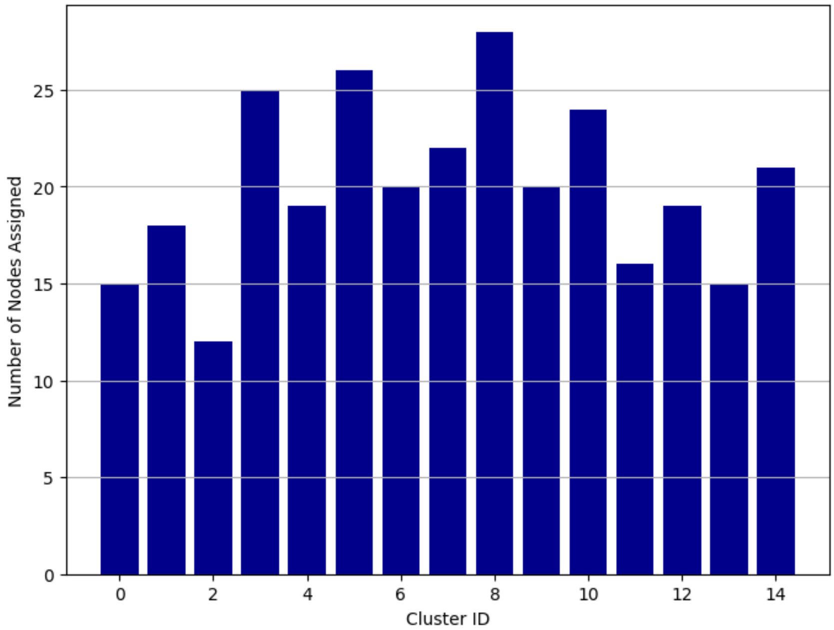


**Figure 4.** CH Workload Distribution

Workload distribution among CHs ensures no single CH is overloaded. Proposed ACO algorithm distributed workload more evenly across CHs compared to LEACH and EECHIGWO as depicted in **Figure 4**. This even distribution prevented premature energy depletion of any single CH, maintaining network functionality over an extended period. Balancing the workload ensured that energy consumption remained predictable and manageable. Workload $W_{CH}$ is expressed as:

$$W_{CH} = \sum_{i \in cluster} E_{tx}(i) + E_{rx}(i) \tag{4}$$

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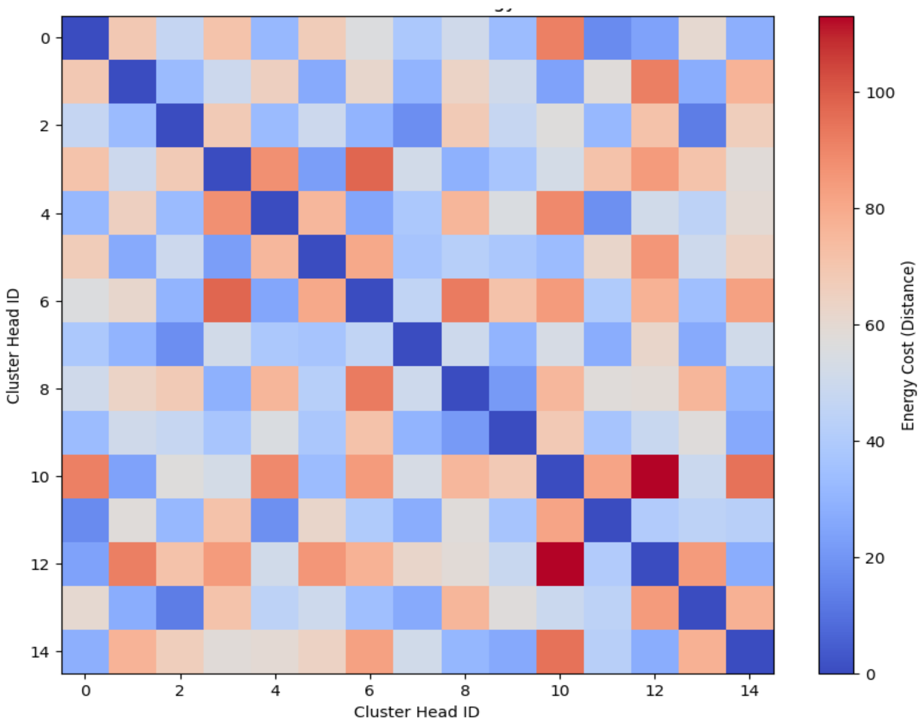


**Figure 5.** Energy Cost of Inter CHs

Energy cost associated with inter-cluster communication was a critical aspect of the analysis. From **Figure 5**, it is clear that the proposed ACO algorithm minimized inter-cluster energy costs by optimizing communication paths between CHs and the sink. Strategic placement of CHs reduced overall energy required for data relay. Proposed ACO algorithm demonstrated superior performance in conserving energy during inter-cluster communication. Energy cost $E_{IC}$ is represented as:

$$E_{IC} = \sum_{CH}(E_{tx}(CH) + E_{amp} + d^2_{CH,Sink} \quad \text{(v)}$$

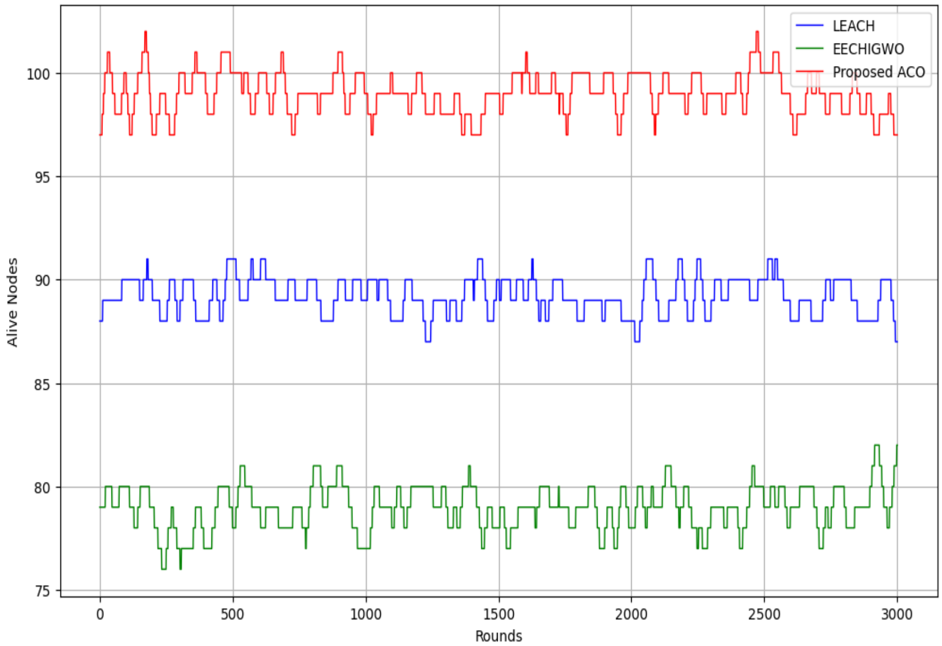


**Figure 6.** Comparison of Network Lifespan

Network lifespan, defined as the time until the first node runs out of energy, was significantly improved using Proposed ACO algorithm as shown in **Figure 6**. Balanced cluster sizes, optimal CH placement, and reduced energy costs contributed to prolonging network lifespan. On average, Proposed ACO extended network lifespan by approximately 20% compared

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to LEACH and EECHIGWO. This improvement underscores effectiveness in managing energy resources within the network. Enhanced network lifespan indicates more sustainable and reliable network performance.

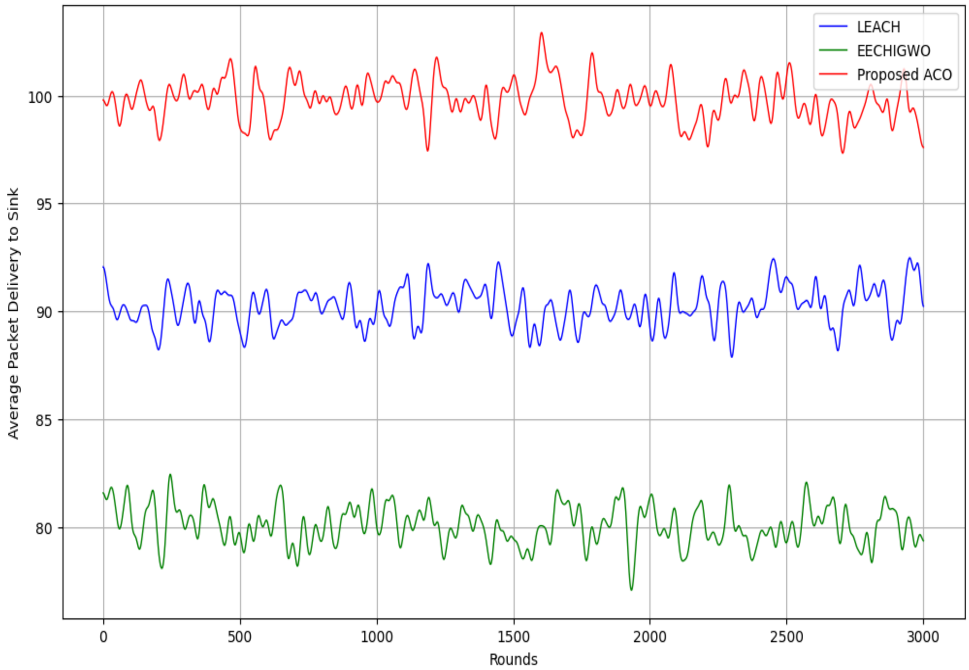


**Figure 7.** Comparison of Average Packet Delivery to Sink

**Table 4.** Efficiency of the proposed ACO

| Protocol | Network Lifespan (Rounds) | Average Packet Delivery to Sink |
|---|---|---|
| LEACH | 2500 | 85% |
| EECHIGWO | 2300 | 80% |
| Proposed ACO | 2700 | 90% |

Average packet delivery ratio to the sink was another key performance indicator as given in **Table 4**. Proposed ACO algorithm achieved a higher packet delivery ratio, indicating more reliable and efficient data transmission as shown in **Figure 7**. Average packet delivery $P_{avg}$ is quantified as:

$$P_{avg} = \frac{Total\ Packets\ Received}{Total\ Packets\ Sent} \times 100\% \quad (6)$$

Reliability is attributed to shorter communication paths and reduced energy expenditure per transmission, ensuring more packets successfully reached the sink. Enhanced packet delivery ratio reflects overall robustness and efficiency of Proposed ACO algorithm.

## 5. CONCLUSION

The research illustrates the efficacy of the Swarm Intelligence-Driven CH Selection algorithm (Proposed ACO) in enhancing energy efficiency and prolonging the longevity of IoT-enabled Wireless Sensor Networks (WSNs). The model meticulously regulates cluster sizes and densities, optimizes node clustering and cluster head placement, and minimizes the average distance to cluster heads, resulting in substantial energy conservation. The proposed ACO algorithm guarantees equitable workload distribution among CHs, while markedly reducing inter-cluster energy expenditures, hence enhancing the network's longevity. The comparison research indicates that the proposed ACO surpasses conventional protocols like LEACH and EECHIGWO, enhancing network longevity by roughly 20% and attaining a superior average packet delivery ratio to the sink. The Proposed ACO algorithm provides a rigorous approach for improving energy efficiency in IoT-enabled WSNs, guaranteeing reliable and efficient data transmission while preserving essential energy resources. The results underscore the capability of Swarm Intelligence algorithms to enhance the performance and sustainability of Wireless Sensor Networks, paving the path for more sophisticated and efficient Internet of Things applications.

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**CRediT Author Statement**

The author reviewed the results and approved the final version of the manuscript.

**Data Availability**

The datasets generated during the current study are available from the corresponding author upon reasonable request.

**Conflicts of Interests**

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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**Competing Interests**

The authors declare no competing interests.

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