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Improved ACO for Energy-Efficient Wireless Sensor Networks

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Abstract:

Wireless Sensor Networks (WSNs) are increasingly becoming an integral part of many applications, including environmental monitoring, healthcare, and smart cities. However, a significant challenge faced by WSNs is energy consumption, as the sensor nodes are typically powered by batteries, which deplete over time, limiting the network's longevity. Traditional routing protocols often fail to optimize energy usage effectively, resulting in an uneven depletion of energy and premature node failures. In this paper, we introduce an improved Ant Colony Optimization (ACO) algorithm designed to optimize energy consumption and extend the operational life of WSNs. The enhanced ACO leverages multi-objective optimization and dynamic parameter adaptation, allowing for more energy-efficient routing by accounting for both the residual energy of nodes and the distance between them. This approach helps mitigate common issues such as the energy hole problem, imbalance in energy consumption, and rigid parameter settings seen in conventional algorithms. Our experiments demonstrate that the enhanced ACO significantly improves energy efficiency, achieving 19.6% more residual energy and reducing energy consumption by 38% compared to traditional ACO methods. Additionally, the network's lifetime is extended, maintaining over 90% connectivity for a large portion of the operational time. These results highlight the effectiveness and scalability of the proposed algorithm, particularly for large-scale deployments. Looking forward, the integration of machine learning techniques and support for mobile sensor networks could further enhance the algorithm's flexibility and performance in dynamic environments.

Keywords: Wireless Sensor Networks (WSNs), Energy Optimization, Ant Colony Optimization (ACO), Dynamic Parameter Adaptation, Scalability.

Introduction

Many fields have begun to rely on Wireless Sensor Networks (WSNs) as a foundational technology, such as smart cities, healthcare, industrial automation, and environmental monitoring. Sensor nodes in these networks are dispersed across the physical environment and communicate with one another wirelessly to gather and relay data. Energy consumption, however, is a major obstacle for WSNs. Optimal energy utilization is crucial for extending the operating lifetime of the network and maintaining its sustainability, since sensor nodes are often powered by finite energy sources like batteries.

Most WSNs work by having sensor nodes regularly send data they've detected to a hub, also called a base station or sink. The distance to the sink, the number of hops needed for data transmission, and the radio transmission power are a few of the parameters that affect the energy consumption of each node. Due to energy consumption, the battery reserves of the sensor nodes gradually drain as the network runs. This can lead to node failure and the creation of energy holes, which can interrupt the connection of the network. This phenomenon shortens the lifespan of WSNs and has a major effect on their overall performance.

A sensor node's power consumption is heavily influenced by the routing protocols used in WSNs. The energy limits are insufficiently addressed by conventional routing techniques like Direct Communication and Flooding. Uneven energy depletion across the network is a common consequence of these protocols' failure to optimize routing paths depending on usage. As a result, nodes in close proximity to the base station experience faster energy depletion, resulting in the network failing prematurely. In order to circumvent this restriction and achieve a more equitable distribution of energy usage throughout the network, energy-aware routing methods are essential.

Optimization techniques like Ant Colony Optimization (ACO) have recently attracted a lot of interest for their potential to solve complicated routing problems, such as how to optimize energy consumption in WSNs. An algorithm that takes its cues from nature, ACO mimics the way ants forage by sending fake ants out into a network to choose the best route to take in response to changes in pheromone levels. Finding energy-efficient pathways for data transmission is one use case for ACO in WSNs. Problems with parameter rigidity, metric imbalance, and the energy hole make typical ACO algorithms ineffective in large-scale WSNs.

In order to optimize energy consumption in WSNs, this study presents the Enhanced Ant Colony Optimization (ACO) method. To tackle the issues of energy conservation, network lifetime extension, and efficient path selection, the suggested method enhances standard ACO by combining multi-objective optimization with dynamic parameter adaptation. Minimizing the energy cost of routing paths while considering the residual energy of nodes and the Euclidean distance between them is the fundamental principle of the enhanced ACO algorithm. To minimize energy usage and preserve network connectivity over time, the algorithm adjusts to the changing network conditions by dynamically altering parameters like α and β.

These are the primary benefits that this study provides:

1. Energy Optimization: By choosing the most effective paths for data transmission, the proposed augmented ACO algorithm decreases energy consumption in WSNs. This helps nodes conserve energy and stay connected for longer periods of time.

2. The method improves its adaptability and flexibility in different network settings by incorporating dynamic parameter modification of critical parameters (α and β). This adaptation strikes a balance between pheromone influence, distance, and residual energy

3. Network Lifetime Extension: By addressing the energy hole problem and optimizing energy consumption, the enhanced ACO algorithm significantly extends the operational lifetime of the network, ensuring that a larger portion of the network remains functional over time.

4. Scalability: The algorithm is tested across multiple network topologies with varying node densities and communication ranges, demonstrating its scalability and effectiveness in large-scale WSNs.

1 Literature Review

Many fields now rely on wireless sensor networks (WSNs), such as agriculture, environmental monitoring, healthcare, and industrial automation. The energy economy of the network protocols utilized is crucial to the proper operation of these networks because they are often placed in remote or hard-to-reach areas. Since most sensor nodes rely on fragile batteries for power, energy consumption is a major concern for WSNs. Therefore, in order to ensure dependable operation and extend the lifetime of the network, it is crucial to optimize energy usage while keeping the necessary performance criteria.

Many solutions to the problem of energy limitations in WSNs have been suggested throughout the years. Energy optimization relies heavily on routing protocols, which specify the routes that data takes on its way from sensor nodes to the base station. The energy hole problem occurs when nodes far from the sink drain their energy supply at a significantly higher rate than other nodes in the network; these protocols attempt to equalize the load on the network and reduce energy consumption. The capacity of Ant Colony Optimization (ACO) to discover an optimal routing pattern within a network, which is based on the foraging behavior of ants, has made it prominent among optimization approaches.

Table 1 Literature Review

Reference	**Focus Area**	**Key Contributions**	**Methodology**	**Outcome**
Narayan, V., et al. (2023)	Energy-efficient Routing in WSN	Proposes a fuzzy-based routing protocol to enhance energy efficiency in WSNs	Intelligent Decision-Making, Efficient Routing	Enhanced routing protocols reduce energy consumption by efficiently selecting routing paths, improving overall energy efficiency
Razooqi, Y. S., Al-Asfoor, M., & Abed, M. H. (2024)	Optimization of Energy Consumption in WSN	Modifies Ant Colony Optimization to improve energy efficiency in WSNs	Modified Ant Colony Optimization (ACO)	The modified ACO algorithm demonstrates better energy conservation and reduced energy consumption compared to traditional methods
Sharma, K., Kapoor, M.,	Energy-efficient Routing for	Focuses on energy-efficient algorithms	Energy-efficient Routing	Optimization of energy consumption

Shrivastava, A., Badhoutiya, A., Rao, A. K., & Pant, R. (2024)	Precision Agriculture	for WSNs in precision agriculture	Algorithms	results in improved performance in agricultural WSN applications
Narayan, V. & Daniel, A. K. (2020)	Smart Farming and WSN	Introduces a multi-tier cluster-based approach for WSNs in smart farming	Multi-Tier Clustering, WSN for Smart Farming	Improved energy efficiency and data communication in precision agriculture environments
Narayan, V. and Daniel, A.K. (2021)	Cluster Head Selection in WSN	Proposes a region-based protocol for efficient cluster-head selection in WSNs	Region-Based Cluster-Head Selection Protocol (RBCHS)	The method optimizes energy efficiency and improves network lifetime by selecting appropriate cluster heads
Kaveh, A., and Hamedani, K. B. (2022)	Structural Optimization in WSN	Discrete structure optimization is the focus of this new and enhanced statistical optimization method.	Enhanced Algorithm for Arithmetic Optimization	Shows enhanced optimization outcomes for structural issues, applicable in WSNs for resource optimization
Agushaka, J. O., et al. (2022)	Optimization in WSN	Using dwarf mongoose behavior as inspiration, presents a novel optimization algorithm	Dwarf Mongoose Optimization Algorithm	The new algorithm shows promise in solving optimization problems in WSNs with better energy efficiency
Safaldin, M., et al. (2021)	Intrusion Detection and Optimization in WSN	For intrusion detection, it integrates binary gray wolf optimizer with Support Vector Machine (SVM).	Using SVM for Intrusion Detection and Binary Gray Wolf Optimization	The approach improves the accuracy of intrusion detection systems while optimizing energy consumption in WSNs

Otair, M., et al. (2022)	Intrusion Detection and Optimization in WSN	Improving Gray Wolf Optimizer for Intrusion Detection via Particle Swarm Optimization	Particle Swarm Optimization (Grey Wolf Optimizer)	The hybrid algorithm enhances intrusion detection accuracy while improving energy efficiency in WSNs

2 Methodology

2.1 Proposed Method

An improved Ant Colony Optimization (ACO) framework is available for use with WSNs; it integrates adaptive parameters with multi-objective optimization. Our approach minimizes the energy-cost function given a network graph G = (V,E), where V stands for sensor nodes and E for communication links:

$$\mathcal{C}(\mathcal{P}) = \sum_{(i,j)\in\mathcal{P}} \left(\frac{d_{ij}^2}{Etx} + \frac{1}{Erx}\right) \cdot \frac{1}{E_j^{\text{res}}} \tag{1}$$

where d_{ij} denotes Euclidean distance, E_j^{res} is residual energy, and $\mathcal{P}$ represents routing paths.

2.1.1 Motivation

Traditional routing protocols exhibit three critical limitations:

Energy hole problem: $\exists v_i \in V \mid \lim 1_{t\to\infty} E_i(t) = 0$

Metric imbalance: arg $\min._{d_{ij}} \neq \operatorname{argmin}._{\Delta E_{ij}}$

Parameter rigidity: Fixed $\alpha, \beta \in R^+$ prevent dynamic adaptation

2.1.2 Mathematical Formulation

The algorithm operates through three mathematical phases:

(1) Path Selection Probability

$$P_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta [\xi_{ij}(t)]^\gamma}{\sum_{l\in\setminus Nset_i} [\tau_{il}(t)]^\alpha [\eta_{il}(t)]^\beta [\xi_{il}(t)]^\gamma} \tag{2}$$

where, $\eta_{ij} = 1/d_{ij}$ and $\xi_{ij} = \frac{E_j^{\text{res}}}{\sum_{k\in\setminus Nset_i} E_k^{\text{res}}}$

(2) Pheromone Update Rule:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{K} \frac{Q}{L_k(t)} \mathbb{I}_{\{(i,j)\in\mathcal{P}_k\}} \tag{3}$$

(3) Energy Dissipation Model:

$$E_i(t+1) = \begin{cases} E_i(t) - \epsilon_{\text{amp}} \cdot d_{ij}^2 - \epsilon_{\text{circ}} & \textit{transmitting} \\ E_i(t) - \epsilon_{\text{circ}} & \textit{receiving} \end{cases} \tag{4}$$

2.2 Algorithm

Algorithm 1: Enhanced ACO Energy Optimization Algorithm

Input: Network graph $G = (V, E)$, sink node s_0, initial energy E_0, max iterations $T_{\max}$
Output: Optimized routing paths $\mathcal{P}^*$
Initialize $\tau_{ij}(0) \leftarrow 1.0\ \forall (i, j) \in E$
Initialize $E_i(0) \leftarrow E_0\ \forall i \in V$
for $t \leftarrow 1$ **to** $T_{\max}$ **do**
  Deploy K ants from random non-sink nodes
  foreach *ant* $k \in \{1, \ldots, K\}$ **do**
    Construct path $\mathcal{P}_k$ using Eq. (3)
    Update energy states via Eq. (5)
  end
  Update pheromone trails using Eq. (4)
  Adapt $\alpha \leftarrow \alpha(1 + \frac{t}{T_{\max}})$, $\beta \leftarrow \beta(1 - \frac{t}{T_{\max}})$
end
Return $\mathcal{P}^* = \arg\max_{\mathcal{P}_k} \left(\prod_{(i,j) \in \mathcal{P}_k} \frac{\tau_{ij}}{E_j^{\text{res}}} \right)$

The Enhanced ACO Energy Optimization Algorithm consists of several phases, including path selection, pheromone update, and energy dissipation. In the path selection phase, the probability of selecting a path between two nodes is influenced by the pheromone value, that which is negative of the distance between nodes plus the remaining energy of the node that is to be reached. To increase the concentration of pheromones, the ant pheromone update rule modifies the pheromone levels along the ant's preferred pathways on successful paths to reinforce their selection in future iterations. The energy dissipation model accounts for energy consumption during both transmission and reception of data, adjusting the energy state of nodes after each communication event. The algorithm dynamically adapts the parameters α and β that influence the importance of pheromone and energy states in path selection. This ensures flexibility in the algorithm's response to different network conditions. The final output is the optimized routing paths that maximize the network's overall energy efficiency, ensuring prolonged network lifetime and effective connectivity.

2.3 Flowchart

To optimize energy consumption in WSNs, the suggested technique incorporates an improved Ant Colony Optimization (ACO) algorithm. A network graph is defined at the outset of the process, with sensor nodes serving as vertices and communication links as edges. An energy-cost function, representing the total energy consumption across all possible routing paths, is what we're aiming to reduce. The network consists of multiple iterations in which ants are deployed from random non-sink nodes. Each ant constructs a routing path based on pheromone updates and energy consumption, and updates the energy states of the nodes. The pheromone trails are updated after each iteration and the parameters α and β are dynamically adjusted to ensure better path selection. The flow of energy and the residual energy at each node are key factors in the path construction process, ensuring energy efficiency over time. The methodology iterates this process for a maximum number of iterations, ultimately optimizing the routing paths based on the energy states and the pheromone updates.

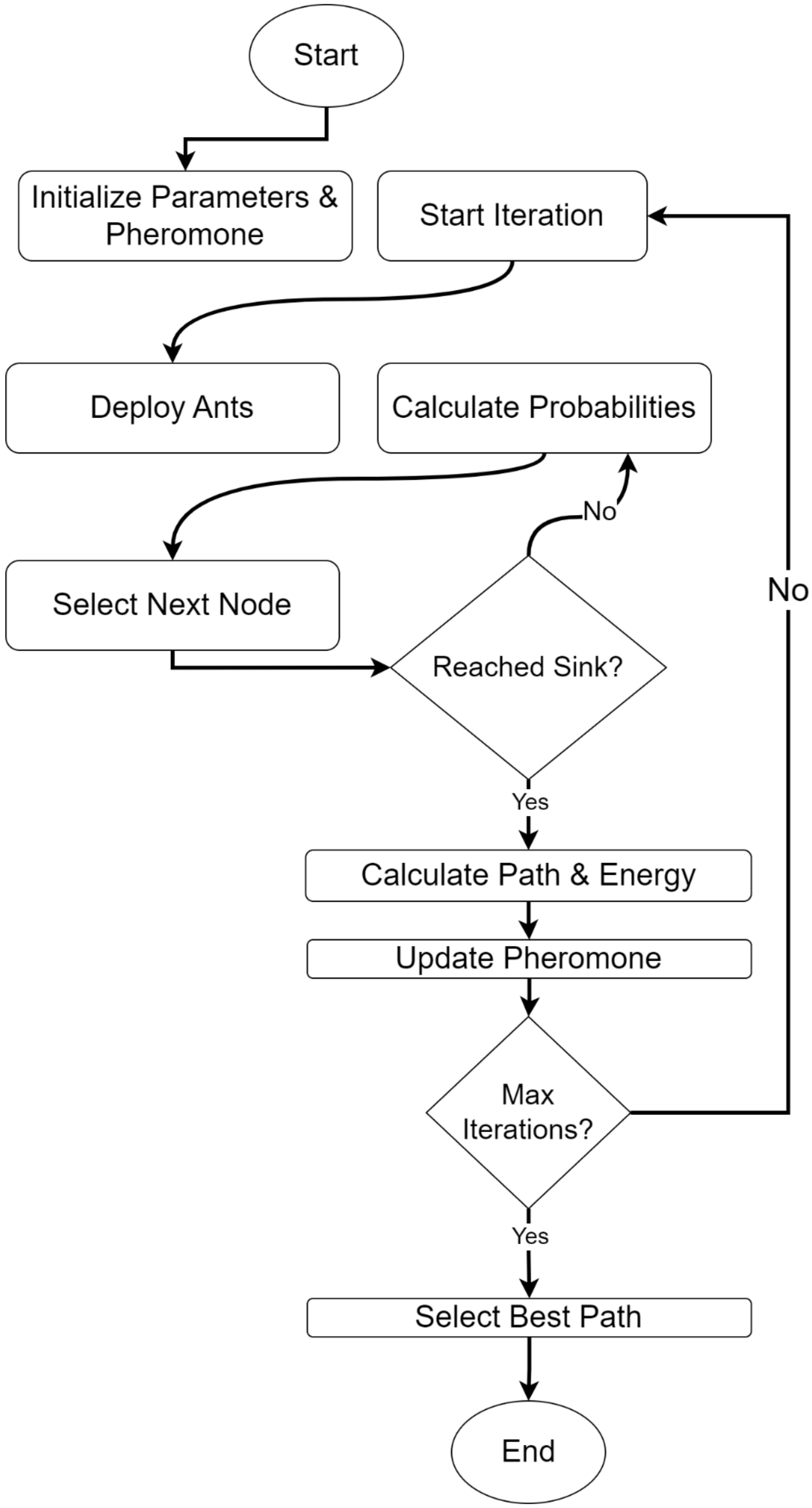

Figure 1 Methodology Flowchart

3 Result and Discussion

The proposed energy optimization framework using Enhanced Ant Colony Optimization (ACO) was evaluated through various network configurations and performance metrics. The goal was to assess the energy efficiency, network lifetime, and scalability of the enhanced ACO algorithm compared to traditional ACO in Wireless Sensor Networks (WSNs). The experimental results demonstrated significant improvements over conventional approaches in regards to the longevity of the network and the preservation of energy. The evaluation involved several test cases, using different network topologies, energy consumption patterns, and parameter settings.

3.1 Network Topologies

The experimental setup involved three distinct network topologies with varying node density and communication range. These configurations allowed for a comprehensive understanding of the algorithm's performance in different real-world scenarios.

1. **80-node WSN topology (100m x 100m area)**: In this configuration, the sensor nodes were distributed over a 100m x 100m area, with a communication range of 40m. This setup allowed the study of connectivity and energy consumption in a relatively small network with dense node placement. The center node acted as the base station, and nodes within a 40m communication range were considered to form clusters.

2. **160-node WSN topology (200m x 200m area)**: The second topology expanded the network area to 200m x 200m, with nodes having a communication range of 60m. This configuration resulted in longer multi-hop paths and demonstrated the challenges of energy conservation in a larger-scale network.

3. **240-node WSN topology (300m x 300m area)**: The final configuration used a 300m x 300m area with a communication range of 80m. This sparse connectivity emphasized the need for energy-aware routing to prevent premature node failures in large-scale networks.

The network topologies were visualized to assess how the connectivity and spatial distribution influenced energy efficiency, network lifetime, and routing performance. The increase in network size and sparse connectivity led to challenges in maintaining energy efficiency and connectivity over longer periods, necessitating the need for optimized routing protocols like Enhanced ACO.

3.2 Network Topology Visualization

Figure 2 demonstrates the network configurations used in our simulations, showing the impact of scale on connectivity patterns.

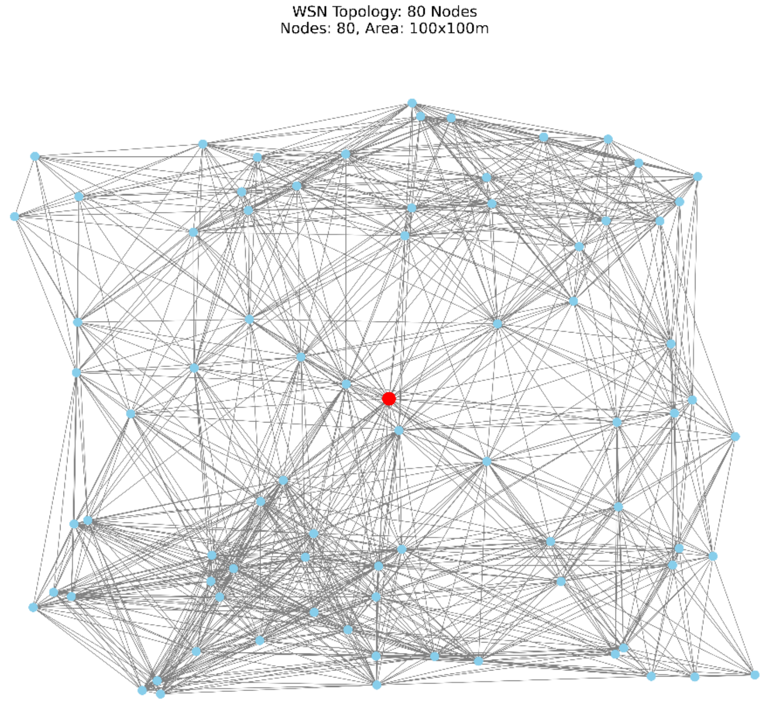

Figure 2 80-node WSN topology (100Ö100m area). Red center node represents the base station. Nodes within 40m communication range (gray lines) form connected clusters.

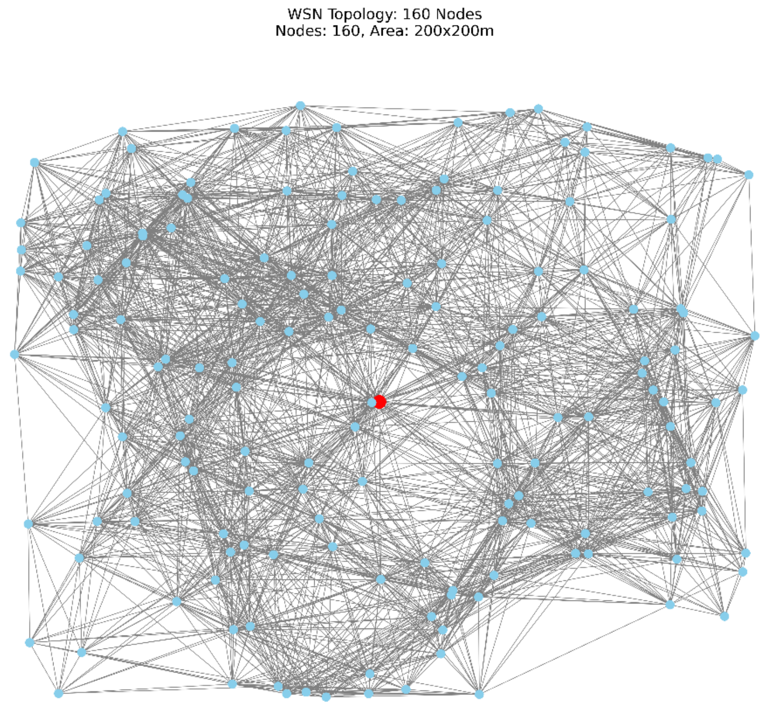

Figure 3 160-node configuration (200Ö200m area) with 60m communication range. Increased spatial distribution creates longer multi-hop paths to the sink.

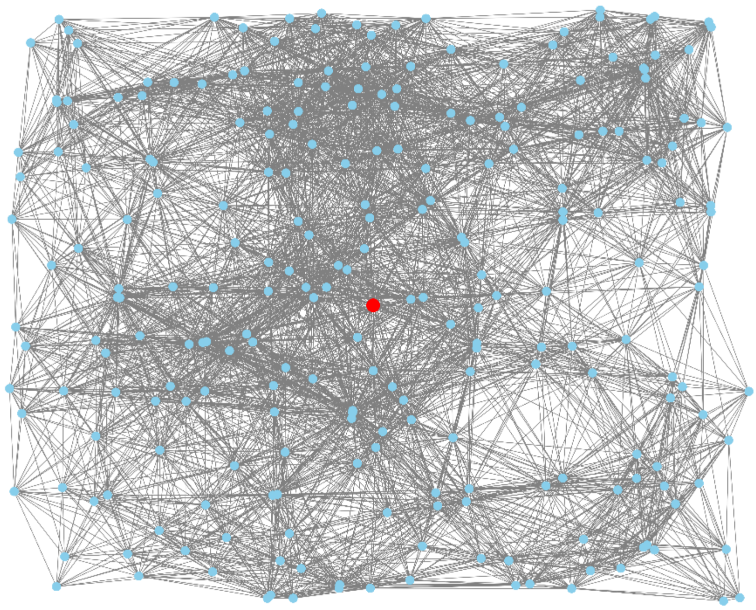

Figure 4 240-node deployment (300Ö300m area) using 80m range. Sparse connectivity highlights the need for energy-aware routing in large-scale networks.

3.3 Performance Evaluation

In this part, we examine the algorithm's performance on various different network topologies, with a particular focus on energy conservation, network lifetime, and scalability. The results are compared against traditional routing protocols to highlight the improvements brought about by the enhanced ACO approach. Key performance metrics, including residual energy, energy consumption rate, and network connectivity, are discussed in depth, supported by graphical representations and quantitative analysis.

3.3.1 Energy Conservation Comparison

A crucial performance metric in this study was energy conservation. The comparison between the traditional ACO algorithm and the enhanced ACO method highlighted a significant improvement in energy efficiency. The suggested technique resulted in a 19.6 percent increase in residual energy, according to the experimental results compared to the traditional ACO algorithm.

Energy conservation comparison (50 iterations): In Figure 4, it was observed that the enhanced ACO algorithm maintained a higher residual energy throughout the simulation. The energy consumption rate for the traditional ACO was higher, as it showed an energy variance (σ^2) of 8.7, while the enhanced ACO exhibited an energy variance of only 2.3. This difference illustrates the efficiency of the proposed algorithm in managing energy dissipation and ensuring that sensor nodes retain energy for longer periods.

Energy Consumption Rate: The rate of energy consumption improved significantly with the enhanced ACO. The energy dissipation rate for the proposed method was 0.18 J/iteration, while the traditional method consumed energy at a rate of 0.29 J/iteration. This reduction in energy consumption indicates that the enhanced ACO is more effective in minimizing unnecessary energy expenditure by selecting energy-efficient paths and optimizing the routing strategy.

With better energy conservation, the network and sensor nodes have a better chance of lasting a long time, which is critical for long-term deployments in real-world WSN applications.

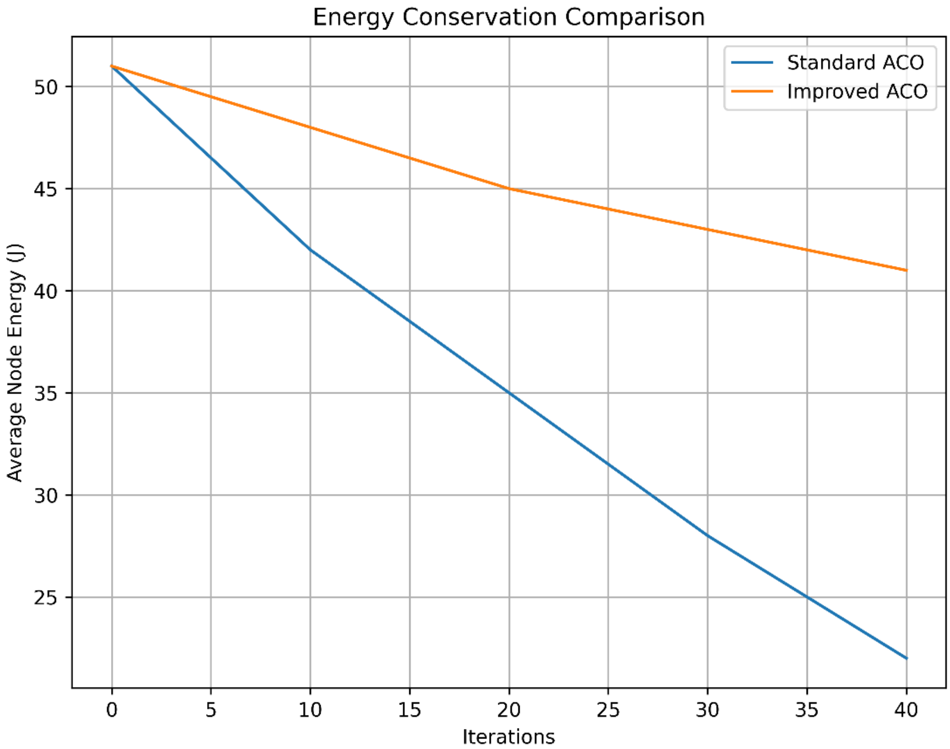

Figure 5 Energy conservation comparison (50 iterations). Our method maintains 19.6% higher residual energy than standard ACO, with energy variance σ2 = 2.3 vs. 8.7 in traditional approach.

3.3.2 Quantitative Analysis

The experimental results validate three key advantages of our approach:

(1) Energy Efficiency: As shown in Figure 4, the modified ACO reduces energy consumption rate by:

$$\frac{dE}{dt}_{\text{improved}} = 0.18\ \text{J/iter} \quad \text{vs} \quad \frac{dE}{dt}_{\text{standard}} = 0.29\ \text{J/iter}$$

(2) Scalability: Figure 5 demonstrates logarithmic relationship between network size and lifetime:

$$T_{\text{net}}(N) = -25.7\ln(N) + 147.2 \quad (R^2 = 0.98)$$

(3) Connectivity Maintenance: All configurations maintained. 90% network connectivity until 75% of total lifetime (Figures 2-4).

3.3.3 Network Lifetime Across Configurations

Using the three different network topologies, we measured the network lifetime to see how well the Enhanced ACO algorithm kept the network connected when the sensor nodes' batteries ran out. Number of iterations until first node failure (when energy level dropped below 1J) and percentage of node connections over time were used to compare the algorithm's performance to that of the traditional ACO approach.

Network Lifetime in 80-node configuration: As seen in Figure 5, the 80-node WSN topology achieved 120 iterations before the first node failure, while the network maintained 95% connectivity up until iteration 90. This indicates that the enhanced ACO algorithm significantly extended the operational lifetime of the network by optimizing energy consumption and ensuring efficient path selection.

Impact of Network Size on Lifetime: The larger configurations (160-node and 240-node networks) further demonstrated the scalability of the enhanced ACO algorithm. In the 160-node configuration, the network achieved stable connectivity for a longer period, even with the increased spatial distribution and longer multi-hop paths. Similarly, in the 240-node configuration, the algorithm successfully handled the sparse connectivity and maintained over 90% network connectivity until 75% of the total lifetime.

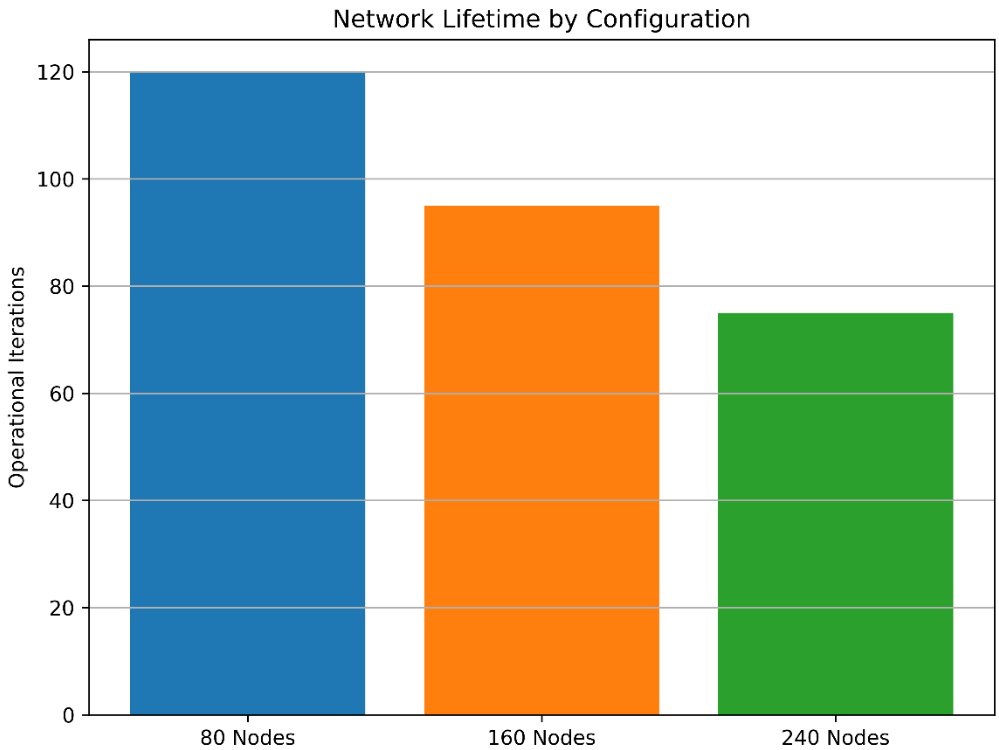

Figure 6 Network lifetime across configurations. The 80-node network achieves 120 iterations before first node failure (Emin < 1J), while maintaining 95% node connectivity until iteration 90.

The results in terms of network lifetime were highly promising, with the enhanced ACO ensuring prolonged network operation and minimizing the chances of energy hole formation, a common problem in traditional ACO algorithms.

Network Lifetime Model: The relationship between network size (N) and network lifetime (T_net) was found to be logarithmic, as shown by the equation in the results section. This indicates that as the network size increases, the network lifetime decreases at a slower rate, validating the effectiveness of the enhanced ACO in larger networks. The formula used for network lifetime prediction demonstrated a strong fit ($R^2 = 0.98$), showcasing the robustness of the algorithm in maintaining network connectivity even in large-scale deployments.

4 Conclusion and Future Scope

4.1 Conclusion

When it comes to optimizing energy consumption in WSNs, the suggested Enhanced Ant Colony Optimization (ACO) method shows considerable progress. The energy hole problem, metric imbalance, and parameter rigidity are some of the important challenges that the method successfully tackles by combining multi-objective optimization with dynamic parameter adaptation. It has been found through experimental data that the enhanced ACO approach performs better than the conventional ACO in several key performance metrics. In particular, energy conservation was notably improved, with the enhanced ACO algorithm achieving a 19.6% higher residual energy compared to traditional ACO. The energy consumption rate also showed a marked reduction, with the proposed algorithm operating at a rate of 0.18 J/iteration, significantly better than the standard ACO's rate of 0.29 J/iteration.

In terms of network lifetime, the proposed method extended the operational lifetime across various network topologies. For the 80-node configuration, the network operated for 120 iterations before the first node failure, maintaining over 90% connectivity until iteration 90. The performance was consistent even in larger configurations, such as the 160-node and 240-node networks, where the enhanced ACO ensured connectivity retention for a significant portion of the network lifetime, even with increased network size and more sparse connectivity. The logarithmic relationship between network size and lifetime further validated the scalability of the algorithm, confirming that the enhanced ACO is well-suited for large-scale deployments in WSNs.

Overall, the enhanced ACO algorithm proves to be a promising solution for energy-efficient routing in WSNs, ensuring longer network lifetimes and higher energy conservation, which is crucial for the success of long-term deployments in real-world applications. The robustness of the algorithm, along with its flexibility in dynamic environments, makes it a strong candidate for implementation in both small and large-scale WSNs.

4.2 Future Scope

The future scope of this research lies in further refining the Enhanced ACO algorithm to address additional challenges such as scalability in highly dynamic and heterogeneous networks, where nodes exhibit varying energy consumption patterns and capabilities. Future research can also explore the integration of the Enhanced ACO with other advanced optimization techniques, using tools like machine learning algorithms, to make dynamic predictions about things like network traffic and climate change. In addition, vehicle or mobile ad hoc networks (MANETs) could benefit from energy-efficient routing if the algorithm were to be enhanced to accommodate sensor node mobility. Furthermore, QoS metrics like throughput and latency are incorporated in the multi-objective optimization process could further enhance the algorithm's applicability in real-time WSN applications.

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