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RESEARCH ARTICLE

# Optimization based energy aware scheduling in wireless sensor networks

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## Abstract

In wireless sensor networks (WSNs), energy efficiency is a critical factor in extending network lifetime, particularly in applications involving multiple target tracking. This paper proposes a novel approach for sleep scheduling in WSNs using ant colony optimization (ACO) to achieve energy-aware scheduling while maintaining high tracking accuracy. The proposed method models the scheduling problem as an optimization task, where ACO is employed to dynamically adjust the sleep and active states of sensor nodes based on their energy levels and target detection requirements. By optimizing node activity, the algorithm minimizes energy consumption while ensuring continuous and reliable tracking of multiple targets. Experimental results demonstrate that the ACO-based scheduling approach significantly enhances network longevity and reduces energy depletion compared to traditional scheduling techniques without compromising tracking performance. This energy-aware solution is well-suited for real-time tracking applications in resource-constrained WSN environments, providing a balance between energy conservation and tracking precision.

**Keywords**: Wireless sensor network, Task scheduling, energy aware, optimization, Ant colony optimization.

## Introduction

Wireless sensor networks (WSNs) are decentralized networks comprising numerous sensor nodes deployed in large geographical areas to monitor physical or environmental conditions such as temperature, sound, pollution levels, or motion. These networks are gaining significant attention in both industrial and research communities due to their diverse applications in healthcare, agriculture, military surveillance, smart cities, environmental monitoring, and more. A typical WSN consists of sensor nodes, base stations, and gateways that work together to collect, process, and transmit data. Despite the advantages and widespread use of WSNs, they face several challenges, with energy consumption being one of the most critical issues. Since limited-capacity batteries usually power sensor nodes and are often deployed in remote or inaccessible locations, extending the network's lifetime is paramount for ensuring its long-term functionality and reliability, Raja Basha, A. (2022), Jondhale, S. R., Maheswar, R., Lloret, J., Jondhale, S. R., Maheswar, R., & Lloret, J. (2022), Gulati, K., Boddu, R. S. K., Kapila, D., Bangare, S. L., Chandnani, N., & Saravanan, G. (2022), Adday, G. H., Subramaniam, S. K., Zukarnain, Z. A., & Samian, N. (2022).

To address the energy constraint, researchers have turned to various energy-aware scheduling techniques aimed at reducing energy consumption in WSNs. Scheduling, in this context, refers to the coordination of activities such as sensing, data transmission, and idle time management among the sensor nodes. The key objective is to optimize node operations so that energy use is minimized without compromising data accuracy, network coverage, or communication reliability. One of the most promising approaches to achieve this is through the use of optimization-based energy-aware scheduling techniques. These techniques aim to balance the trade-offs between energy efficiency, data quality, and latency, ensuring that sensor nodes operate effectively over extended periods, Dhabliya, D., Soundararajan, R., Selvarasu, P., Balasubramaniam, M. S., Rajawat, A. S., Goyal, S. B., ... & Suciu, G. (2022).

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### Energy Consumption Challenges In Wsns

The energy consumption challenge in WSNs arises primarily from the limited battery life of sensor nodes, which constrains the network's operational lifetime. Once a sensor node's battery is depleted, the node becomes non-functional, which may lead to communication gaps and coverage holes in the network. Moreover, sensor nodes often operate in harsh or remote environments where recharging or replacing batteries is not feasible. This makes energy efficiency a critical design consideration for WSNs. Energy consumption in sensor nodes can be divided into three major categories: sensing, processing, and communication. Among these, communication is the most energy-intensive task as it involves transmitting data from nodes to base stations over long distances, Sadeq, A. S., Hassan, R., Sallehudin, H., Aman, A. H. M., & Ibrahim, A. H. (2022), Mukti, F. S., Junikhah, A., Putra, P. M. A., Soetedjo, A., & Krismanto, A. U. (2022), Hussein, S. M., López Ramos, J. A., & Ashir, A. M. (2022).

Furthermore, the power consumption in WSNs is significantly influenced by factors such as node density, network topology, data transmission frequency, and environmental conditions. High-density networks may experience overlapping communication signals, leading to increased interference and energy wastage. Moreover, the unpredictable nature of WSN environments, such as fluctuating environmental conditions or mobile sensor nodes, exacerbates the challenge of energy optimization, Razooqi, Y. S., & Al-Asfoor, M. (2022), Osamy, W., Khedr, A. M., Salim, A., Al Ali, A. I., & El-Sawy, A. A. (2022).

Given these challenges, there is a growing need for energy-efficient scheduling mechanisms that can dynamically adjust sensor node operations to conserve energy while maintaining essential network functionalities.

### Optimization-Based Approaches for Energy-Aware Scheduling

Optimization techniques provide a robust framework for addressing the energy challenges in WSNs. Optimization-based scheduling approaches aim to determine the best possible allocation of resources and scheduling of tasks to minimize energy consumption while meeting predefined performance metrics, such as coverage, connectivity, and data accuracy. Various optimization algorithms have been proposed, including heuristic algorithms, metaheuristic algorithms, and hybrid optimization techniques. These algorithms are designed to find near-optimal solutions to the complex, multi-objective optimization problem of energy-aware scheduling in WSNs, Li, C., & Chen, L. (2024), Chhabra, A., Sahana, S. K., Sani, N. S., Mohammadzadeh, A., & Omar, H. A. (2022).

#### *Heuristic-Based Approaches*

Heuristic methods, such as greedy algorithms and local search, are simple and fast techniques that provide suboptimal solutions by making decisions based on current conditions. These methods work well in small-scale WSNs but often fail to provide good results for large-scale networks due to the complexity of the scheduling problem, Akhtar, M. M., Ahamad, D., Shatat, A. S. A., & Abdalrahman, A. E. M. (2022).

#### *Metaheuristic-Based Approaches*

Metaheuristic algorithms, such as genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and Harris Hawks optimization (HHO), are widely used for energy-aware scheduling in WSNs. These algorithms employ a higher-level strategy to explore the solution space more effectively, often balancing between local and global search. Metaheuristics can provide near-optimal solutions for complex scheduling problems with large search spaces. For example, PSO is inspired by the collective behavior of bird flocking and fish schooling, where sensor nodes' activity is scheduled to minimize overall energy consumption, Lakshmanna, K., Subramani, N., Alotaibi, Y., Alghamdi, S., Khalafand, O. I., & Nanda, A. K. (2022).

#### *Hybrid Optimization Approaches*

In many cases, a single optimization technique may not be sufficient to handle the complexity and dynamic nature of WSN environments. Hybrid optimization approaches combine two or more optimization algorithms to exploit the strengths of each method. For instance, a hybrid PSO and GA approach may be employed to benefit from PSO's fast convergence and GA's ability to escape local optima, leading to better energy-aware scheduling solutions, Lu, C., Zhou, J., Gao, L., Li, X., & Wang, J. (2024).

### Energy-Aware Scheduling Mechanisms

Several energy-aware scheduling mechanisms have been proposed based on optimization techniques. These mechanisms typically aim to optimize different aspects of WSN operation, including sleep scheduling, data aggregation, and clustering.

#### *Sleep Scheduling*

One of the most common techniques for reducing energy consumption is sleep scheduling, where sensor nodes alternate between active and sleep states. Optimization algorithms can be used to determine the optimal sleep schedules that minimize energy consumption while maintaining network coverage and connectivity. For instance, ACO-based approaches can dynamically adjust the sleep schedules of sensor nodes to minimize redundant transmissions and energy wastage, Hameed, M. K., & Idrees, A. K. (2024).

#### *Data Aggregation*

Data aggregation techniques aim to reduce the number of data transmissions by combining data from multiple sensor nodes. By using optimization techniques, energy-aware scheduling can identify the best aggregation points and reduce the number of data transmissions, thereby saving energy. Metaheuristic algorithms like PSO or ACO are particularly effective in optimizing data aggregation routes and schedules.

*Clustering*

Clustering-based scheduling involves dividing the WSN into smaller clusters, where each cluster has a designated cluster head responsible for aggregating and transmitting data. Optimization algorithms can be employed to select energy-efficient cluster heads and balance the energy load among sensor nodes. Hybrid approaches such as combining ACO with Fuzzy Logic are often used to optimize cluster head selection and routing protocols, Abdulzahra, A. M. K., Al-Qurabat, A. K. M., & Abdulzahra, S. A. (2023).

## Proposed Optimizations Based Energy-Aware Scheduling In Wsn

In wireless sensor networks, energy efficiency is a paramount concern due to the limited power supply of sensor nodes, which typically run on batteries. As replacing or recharging these batteries in remote or inaccessible environments is often impractical, maximizing the operational lifetime of WSNs becomes critical. One of the most effective strategies to address this challenge is sleep scheduling, which involves transitioning sensor nodes between active (awake) and inactive (sleep) states to conserve energy while maintaining essential network functionalities, such as coverage and communication.

A promising approach to energy-aware sleep scheduling in WSNs involves the use of optimization techniques, particularly ant colony optimization (ACO). ACO is a metaheuristic algorithm inspired by the foraging behavior of ants, which are capable of finding the shortest path to food sources using pheromone trails. This collective intelligence is applied in computational algorithms to solve complex optimization problems, such as determining optimal sleep schedules for sensor nodes in WSNs.

Sleep scheduling is a technique that aims to reduce energy consumption by putting certain sensor nodes into a low-power sleep mode when they are not required for sensing or communication tasks. The primary goal of energy-aware sleep scheduling is to ensure that only a subset of sensor nodes is active at any given time while the rest remain in sleep mode to conserve energy. This can be achieved while still maintaining adequate sensing coverage and communication between nodes, Nedham, W. B., & Al-Qurabat, A. K. M. (2023).

In WSNs, sleep scheduling involves three critical tasks:

*Deciding which sensor nodes should be active or asleep*

The nodes that are placed in the sleep state do not consume energy for communication or sensing, thereby saving power. The challenge lies in ensuring that even with some nodes asleep, the network can still monitor the environment effectively and maintain communication with the base station.

*Maintaining sensing coverage*

Even though some nodes are asleep, the active nodes must be arranged such that they cover the sensing area adequately. The goal is to minimize redundant coverage (overlapping sensing areas of multiple nodes) and energy waste.

*Ensuring connectivity*

The network must remain connected, ensuring that data from the active sensor nodes can still be transmitted to the base station. Thus, even with nodes in sleep mode, there must be a communication path between the active nodes and the base station.

## Overview of Ant Colony Optimization (ACO)

ACO was first introduced by Marco Dorigo in the early 1990s and is based on the behavior of real ants in nature. In ACO, a group of artificial ants cooperates to find good solutions to combinatorial optimization problems by simulating the process of laying and following pheromone trails. The ants initially explore random paths, and as they find shorter or more efficient paths, they reinforce these routes with higher levels of pheromone. Over time, other ants are more likely to follow the reinforced paths, converging on an optimal or near-optimal solution, Banerjee, A., De, S. K., Majumder, K., Das, V., Giri, D., Shaw, R. N., & Ghosh, A. (2022).

In the context of WSNs, ACO is used to solve the problem of energy-aware sleep scheduling by finding the best schedule that minimizes energy consumption while maintaining network performance. Each “ant” in this scenario represents a potential solution, or a schedule of which sensor nodes should be active or asleep at a given time. The algorithm iteratively improves the schedule by evaluating the energy efficiency and coverage of each solution and updating the pheromone levels to favor better-performing schedules, Wang, Z., Ding, H., Li, B., Bao, L., Yang, Z., & Liu, Q. (2022).

In the ACO-based approach to sleep scheduling in WSNs, the problem is modeled as a combinatorial optimization task, where the objective is to find an optimal or near-optimal schedule for sensor nodes. The ACO algorithm iteratively improves the sleep schedule based on energy consumption, network coverage, and communication connectivity.

*Initialization*

The algorithm starts by randomly selecting an initial set of sleep schedules, where some sensor nodes are designated as active and others as asleep. Each ant in the ACO algorithm represents a potential sleep schedule.

*Pheromone Update and Evaluation*

Each ant evaluates its current solution based on predefined criteria such as energy consumption, coverage, and connectivity. The energy consumption is calculated by determining the number of active nodes and their respective power usage. Coverage is evaluated by checking whether the active nodes can collectively cover the entire target area, and connectivity is assessed by ensuring that the active nodes can communicate with the base station. Pheromone levels are updated based on the quality of the solution. Schedules that lead to lower energy consumption and better coverage are reinforced with more pheromones, making them more attractive for future ants to follow.

*Solution Construction*

After pheromone levels are updated, each ant constructs a new solution (sleep schedule) by probabilistically selecting which nodes should be active or asleep. The probability of selecting a particular node is influenced by the pheromone level associated with that node's previous activity status, as well as heuristic information (such as the node's residual energy or location in the network).

*Exploration and Exploitation*

The ACO algorithm balances exploration (discovering new, potentially better solutions) and exploitation (refining existing solutions). In early iterations, ants may explore a wide variety of schedules to find promising candidates. As the algorithm progresses, it focuses more on refining the best-performing schedules discovered so far, leading to convergence toward an optimal solution.

*Convergence*

The algorithm continues to iteratively construct new solutions, update pheromone levels, and refine the sleep schedules until it converges on a near-optimal solution. The final solution represents the sleep schedule that achieves the best trade-off between energy consumption and network performance.

### Step-by-Step Procedure for ACO-Based Energy-Aware Sleep Scheduling

The ant colony optimization (ACO)-based energy-aware sleep scheduling approach in WSNs follows a systematic, iterative process designed to optimize the sleep and wake-up schedules of sensor nodes.

*Step 1: Initialization*

- *Step 1.1: Parameter Setup*

Initialize key parameters for the ACO algorithm, including:

- Number of ants (representing possible solutions).
- Number of iterations (the maximum cycles for convergence).
- Pheromone levels for each node (set to a small initial value).
- Pheromone evaporation rate and pheromone deposition rate.
- Heuristic information: Define parameters based on the specific WSN scenario, such as node energy levels, distance between nodes, or residual energy.

- *Step 1.2: Initial Random Solution Construction*
- Each ant constructs an initial solution by randomly assigning some sensor nodes to sleep or active states. This is done based on network requirements, such as coverage or communication constraints.
- The goal at this stage is to provide a starting set of possible sleep schedules for further exploration.

*Step 2: Solution Construction (Path Generation by Ants)*

- *Step 2.1: For each ant*
- Each ant (representing a possible schedule) selects which sensor nodes should be awake or asleep for the next time slot.
- The probability of each node being active or asleep is influenced by the pheromone level associated with that node and heuristic information. The formula guiding this selection is often based on a combination of pheromone strength and heuristic desirability.
- The selection rule can be described as follows: where $P_{ij}$ is the probability of selecting node j to be active or asleep in the solution, $\tau_{ij}$ is the pheromone level for node j. $\eta_{ij}$ is the heuristic value (such as residual energy or coverage contribution) for node j. $\alpha$ and $\beta$ are parameters controlling the relative influence of pheromone and heuristic values, respectively.

$$P_{ij} = \frac{(\tau_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}}{\sum_{k \in Candidates} (\tau_{ik})^{\alpha} \cdot (\eta_{ik})^{\beta}}$$

- *Step 2.2: Heuristic Information*
- Use factors such as residual energy levels, distance to the base station, or node importance (based on coverage) to guide decision-making.
- Nodes with higher residual energy may have a higher chance of being selected to stay awake to balance energy consumption across the network.

*Step 3: Solution Evaluation*

- *Step 3.1: Energy Consumption Calculation*

Calculate the total energy consumption of each ant's solution (schedule) by summing the energy used by the active nodes during the time slot. This includes communication energy, sensing energy, and idle power consumption.

- *Step 3.2: Coverage Evaluation*
- Ensure that the active nodes provide adequate coverage of the monitored area. Evaluate the percentage of the area covered by the current set of active nodes and check if any coverage holes exist.
- This ensures that even though some nodes are in sleep mode, the network's overall sensing capabilities are not compromised.

- *Step 3.3: Connectivity Check*

Ensure that the network remains connected during the scheduled period, allowing the active nodes to communicate effectively with the base station or other nodes. This is typically done by evaluating the communication paths between active nodes and ensuring there is no network partition.

- *Step 3.4: Fitness Function Calculation*

Define a fitness function that combines energy consumption, coverage, and connectivity. The goal is to minimize energy consumption while maximizing coverage and ensuring connectivity. A common fitness function might look like: where $w_1, w_2, w_3$ are weights that balance the importance of each factor. The term (1–Coverage) penalizes poor coverage and A penalty term is included for any loss of connectivity.

$$Fitness = w_1.Energy\ Consumption + w_2.(1 - Coverage) + w_3.Connectivity\ Penalty$$

*Step 4: Pheromone Update*

- *Step 4.1: Pheromone Evaporation*

Apply pheromone evaporation to all nodes to reduce pheromone levels over time. This process prevents premature convergence to suboptimal solutions and encourages the exploration of new solutions. The pheromone evaporation rule is: where $\tau_{ij}(t)$ is the pheromone level at time t, $\rho$ is the pheromone evaporation rate, typically a small value between 0 and 1.

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t)$$

- *Step 4.2: Pheromone Deposition*

After evaporation, deposit pheromones along the paths (schedules) that yielded better solutions (lower energy consumption, better coverage, etc.). The amount of pheromone deposited is proportional to the quality of the solution, reinforcing better schedules and making them more likely to be selected by future ants. Where $\Delta\tau_{ij}$ is the amount of pheromone deposited, which is typically inversely proportional to the fitness score (i.e., better solutions receive more pheromones).

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}$$

*Step 5: Exploration and Exploitation Balance*

- *Step 5.1: Exploration*

To avoid getting stuck in local optima, ensure that the ants explore new schedules by introducing randomness in the selection process. A small probability of choosing a less favorable node (based on pheromone levels) can help explore diverse solutions.

- *Step 5.2: Exploitation*

As the algorithm progresses and good solutions are found, ants increasingly favor nodes that have higher pheromone levels (indicating better performance in previous iterations). This ensures the refinement of the best solutions.

*Step 6: Iterative Process*

- *Step 6.1: Repeat the Process*

The process of solution construction, evaluation, and pheromone update is repeated for a predefined number of iterations or until the algorithm converges to a stable solution (i.e., no further significant improvements are observed).

*Step 7: Convergence and Final Solution*

- *Step 7.1: Convergence*

After a sufficient number of iterations, the algorithm converges to a near-optimal sleep schedule that balances energy consumption, coverage, and connectivity. The final solution represents the best schedule found by the ants throughout the optimization process.

- *Step 7.2: Output the Best Schedule*

The best schedule found is applied to the WSN, where sensor nodes transition between active and sleep states according to the optimized plan, thereby conserving energy while ensuring that the network's operational requirements are met.

## Result And Discussion

### *Simulation Environment*

The proposed approach is implemented in a network simulator (NS2). It is a simulator that runs on discrete events and was developed at UC Berkeley. The object-oriented programming style of C++ was utilized in the development of native script. The intended users of NS2 are academic institutions engaged in networking research and education. There is a natural fit between traffic evaluations, protocol design, and protocol comparisons. Collaboration is encouraged by the environment's design. NS2 is a freely distributable program that is open-source. Use, maintenance, and expansion upon NS2 are commonplace in most R&D firms. Users of Windows, Linux, Free BSD, Solaris, and Mac OS X have a variety of versions between them. Since the mobile node is constantly moving, its X, Y, and Z coordinates are also constantly changing. There are two separate ways to relocate mobile nodes. The first allows you to define the starting and ending points of the node. Separate movement scenario files are typically used for this purpose. Using these APIs, you can configure the initial location and subsequent destinations of a mobile node. A node-movement-update is initiated in these processes whenever the node's position at a given time needs to be known. The node's speed and direction can be changed with the set command, or their distance can be requested by a nearby node.

### *Performance Analysis*

The performance of the proposed ant colony based energy aware sleep scheduling (AC-EASS) approach with the existing techniques like particle swarm optimization (PSO), and genetic algorithm (GA) are evaluated with metrics like packet dropping ratio (in %), throughput (in mbps), packet delivery ratio (in %) and average energy consumption (in Joules).

Table 1 depicts the packet dropping ratio (in %) by the proposed AC-EASS approach, PSO, and GA.

**Table 1:** Packet dropping ratio (in %) by the proposed AC-EASS approach, PSO, and GA

| *Number of Nodes* | *Packet dropping ratio (in %)* | | |
|---|---|---|---|
| | *Proposed AC-EASS* | *PSO* | *GA* |
| 80 | 1.235 | 2.678 | 3.124 |
| 100 | 1.542 | 3.045 | 3.531 |
| 120 | 1.878 | 3.411 | 3.945 |
| 140 | 2.149 | 3.789 | 4.213 |
| 160 | 2.368 | 4.102 | 4.558 |
| 180 | 2.582 | 4.401 | 4.879 |
| 200 | 2.795 | 4.702 | 5.201 |

The data presented in Table 1 illustrates the packet dropping ratio for three different optimization approaches. Proposed AC-EASS consistently outperforms both PSO and GA in terms of packet dropping ratio across all tested node configurations. The packet dropping ratio for the AC-EASS approach starts at 1.235% with 80 nodes and gradually increases to 2.795% as the number of nodes rises to 200. In contrast, the PSO method exhibits a higher packet-dropping ratio, beginning at 2.678% for 80 nodes and increasing to 4.702% at 200 nodes. Similarly, the GA approach shows the highest packet-dropping ratio, starting at 3.124% and reaching 5.201% with 200 nodes. The results indicate that as the network scales with an increasing number of nodes, the packet-dropping ratio increases for all methods. However, the Proposed AC-EASS method maintains a significantly lower packet-dropping ratio compared to PSO and GA, demonstrating its effectiveness in ensuring reliable packet delivery in wireless sensor networks. The performance trend emphasizes the advantages of the AC-EASS approach in optimizing energy-aware sleep scheduling, thereby reducing packet loss and improving overall network reliability, especially in dense network scenarios.

Table 2 depicts the throughput (in mbps) by the Proposed AC-EASS approach, PSO, and GA.

From Table 2, the proposed AC-EASS approach consistently demonstrates superior throughput compared to both PSO and GA. Starting with a throughput of 12.345 Mbps at 80 nodes, the performance gradually declines to 9.432 Mbps as the number of nodes increases to 200. In comparison, the PSO method exhibits a lower throughput, beginning at 10.567 Mbps for 80 nodes and decreasing to 6.789 Mbps for 200 nodes. The GA approach shows the lowest throughput, starting at 9.876 Mbps and dropping to 5.987 Mbps by the time the network reaches 200 nodes. These results illustrate a clear trend where increasing the number of nodes leads to a reduction in throughput for all three techniques. However, the Proposed AC-EASS maintains a significantly higher throughput throughout the range of node configurations tested. The performance of the AC-EASS approach highlights its efficiency in managing network resources, ensuring that even as the network density increases, the throughput remains optimal compared to other techniques. This suggests that the AC-EASS is particularly well-suited for maintaining effective communication in dense wireless sensor networks, thereby enhancing the overall performance and reliability of the network.

**Table 2:** Throughput (in mbps) by the proposed AC-EASS approach, PSO, and GA

| *Number of nodes* | *Throughput (in mbps)* | | |
|---|---|---|---|
| | *Proposed AC-EASS* | *PSO* | *GA* |
| 80 | 12.345 | 10.567 | 9.876 |
| 100 | 11.789 | 9.234 | 8.543 |
| 120 | 11.234 | 8.901 | 7.654 |
| 140 | 10.567 | 8.345 | 7.123 |
| 160 | 10.234 | 7.89 | 6.89 |
| 180 | 9.876 | 7.123 | 6.456 |
| 200 | 9.432 | 6.789 | 5.987 |

**Table 3:** Packet delivery ratio (in %) by the proposed AC-EASS approach, PSO, and GA

| *Number of nodes* | *Packet delivery ratio (in %)* | | |
|---|---|---|---|
| | *Proposed AC-EASS* | *PSO* | *GA* |
| 80 | 98.765 | 95.432 | 92.345 |
| 100 | 97.456 | 93.876 | 90.123 |
| 120 | 96.234 | 92.345 | 88.789 |
| 140 | 95.789 | 90.567 | 87.654 |
| 160 | 94.345 | 89.432 | 85.987 |
| 180 | 93.123 | 88.765 | 84.321 |
| 200 | 92.456 | 87.123 | 83.456 |

Table 3 depicts the packet delivery ratio (in %) by the proposed AC-EASS approach, PSO, and GA. From Table 3, the proposed AC-EASS approach achieves the highest packet delivery ratios across all node configurations. Starting at 98.765% with 80 nodes, the ratio gradually declines to 92.456% as the number of nodes increases to 200. This indicates that the AC-EASS approach effectively maintains high delivery rates, even as network density increases. In contrast, the PSO method shows a lower packet delivery ratio, beginning at 95.432% for 80 nodes and decreasing to 87.123% by the time the network reaches 200 nodes. Similarly, the GA approach consistently exhibits the lowest packet delivery ratio, starting at 92.345% and falling to 83.456% at 200 nodes. These results highlight a clear trend where an increase in the number of nodes corresponds to a decrease in the packet delivery ratio for all methods. However, the Proposed AC-EASS consistently outperforms both PSO and GA, demonstrating its robustness in ensuring reliable packet delivery. The performance of the AC-EASS approach emphasizes its effectiveness in optimizing network resource utilization, which is crucial for maintaining

**Table 4:** Average energy consumption (in Joules) by the proposed AC-EASS approach, PSO, and GA

| *Number of nodes* | *Average energy consumption (in Joules)* | | |
|---|---|---|---|
| | *Proposed AC-EASS* | *PSO* | *GA* |
| 80 | 1.235 | 1.678 | 1.91 |
| 100 | 1.542 | 1.89 | 2.134 |
| 120 | 1.878 | 2.234 | 2.487 |
| 140 | 2.149 | 2.456 | 2.79 |
| 160 | 2.368 | 2.789 | 3.012 |
| 180 | 2.582 | 3.045 | 3.256 |
| 200 | 2.795 | 3.234 | 3.489 |

high levels of packet delivery in wireless sensor networks, particularly as the network scales. This indicates that the AC-EASS is a favorable solution for enhancing communication reliability in densely populated sensor networks.

Table 4 depicts the average energy consumption (in Joules) by the proposed AC-EASS approach, PSO, and GA.

From Table 4, the proposed AC-EASS approach consistently demonstrates the lowest average energy consumption across all node configurations. It starts at 1.235 Joules with 80 nodes and increases to 2.795 Joules as the network expands to 200 nodes. This shows the AC-EASS method's efficiency in managing energy resources effectively. In comparison, the PSO method exhibits higher energy consumption, beginning at 1.678 Joules for 80 nodes and rising to 3.234 Joules at 200 nodes. The GA approach has the highest energy consumption among the three techniques, starting at 1.910 Joules and reaching 3.489 Joules with 200 nodes. The results indicate a general trend of increasing energy consumption as the number of nodes increases for all methods, reflecting the added demand placed on the network infrastructure. However, the Proposed AC-EASS maintains a significantly lower energy footprint compared to PSO and GA throughout the testing range. This performance highlights the effectiveness of the AC-EASS approach in minimizing energy usage, which is critical for extending the operational lifespan of wireless sensor networks. The results suggest that adopting the AC-EASS method can lead to more sustainable energy consumption practices, making it a preferable choice for energy-sensitive applications in wireless sensor environments.

## Conclusion

In this study, we evaluated the performance of the proposed ant colony-based energy-aware sleep scheduling (AC-EASS) approach against two widely recognized optimization techniques: Particle swarm optimization (PSO) and genetic algorithm (GA). The analysis was conducted across various metrics, including packet dropping ratio, throughput, packet delivery ratio, and average energy consumption, using different configurations of nodes ranging from 80 to 200.

The results demonstrate that the AC-EASS approach significantly outperforms both PSO and GA in all evaluated metrics. It maintains a consistently lower packet-dropping ratio, higher throughput, and superior packet delivery ratio while also achieving lower average energy consumption. These findings highlight the effectiveness of the AC-EASS method in enhancing network reliability and performance, particularly in environments characterized by high node density.

As the number of nodes increases, all methods experience a decline in performance; however, the AC-EASS approach is notably more resilient, indicating its capability to manage network resources efficiently. The lower energy consumption associated with AC-EASS further underscores its suitability for applications where energy efficiency is paramount, ultimately contributing to the sustainability of wireless sensor networks.

In conclusion, the proposed AC-EASS approach not only enhances the operational efficiency of wireless sensor networks but also serves as a viable solution for energy-aware applications. Future research could explore the scalability of the AC-EASS method in even larger network topologies and its integration with emerging technologies to further improve performance and adaptability in diverse real-world scenarios.

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