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# A Comparative Analysis of Swarm Intelligence Algorithms for Event Detection in Wireless Sensor Networks

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***Abstract*****:** WSNs play an important role in monitoring and responding to dynamic events in applications such as disaster management, industrial automation, and environmental monitoring. Since event detection has the highest priority in a WSN, it is very crucial regarding timely response, energy efficiency, and system reliability. However, traditional threshold-based detection methods often lack flexibility and always consume large amounts of energy. SI algorithms, motivated by natural collective behaviors, offer robust and adaptive solutions for event detection in order to overcome the limitations of conventional methods.

Performance analysis and comparison of three most powerful SI algorithms - DA, ACO, and PSO - for event detection in WSNs. Methods: The performance of these algorithms was analyzed for time efficiency, energy consumption, accuracy, and scalability using simulation-based experiments. The experiments simulate WSNs of different node densities and event characteristics on the widely used python and MATLAB platforms under identical conditions for each algorithm.

Among them, the Dragonfly Algorithm outperformed ACO and PSO in time efficiency-66.48 seconds versus 85.10 and 77.03 seconds, respectively-energy consumption (0.000030 J vs. 0.000047 and 0.000035 J), and accuracy, 94.5% versus 92.1% and 93.2%, correspondingly. DA also has better scalability for different network sizes and performs consistently well for larger networks, up to 1024 nodes. ACO, though robust in path exploration, had the highest energy consumption and longest detection time, which seriously affects its scalability. PSO gave balanced performance, though it trailed DA significantly in key metrics.

The Dragonfly Algorithm provides the most efficient and scalable solution for WSN event detection with high time efficiency, energy conservation, and accuracy. These results underline its applicability in real-world time-critical and energy-sensitive WSN applications.

***Keywords*****:** Wireless Sensor Networks, Event Detection, Swarm Intelligence, Dragonfly Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Energy Efficiency, Time Efficiency, Scalability

## INTRODUCTION

WSNs have come up as the most important technological solutions for a vast range of applications that include environmental monitoring, healthcare systems, disaster management, industrial automation, and military surveillance. The hallmark of WSNs is the ability to collect, process, and transmit real-time data from the physical world through spatially distributed, low-power sensor nodes. Such nodes can be made to sense the environment for various parameters like temperature, humidity, or pressure and relay data to a centralized system for further action.

Event detection is one of the most critical functionalities that WSNs can perform. Events in WSNs may be defined as considerable changes in monitored parameters that include a sudden rise in temperature that represents an outbreak of fire or the release of toxic gases in industrial areas. In this respect, timely and precise detection of events is crucial because the system capability for disaster prevention, effective risk mitigation, and quick response to the emergency depends greatly upon event detection.

However, the design and deployment of WSNs, in general, but especially for event detection applications, entail a number of challenges. First, sensor nodes are usually powered by a limited energy resource, such as a battery. Because sensor networks are deployed in the field, some are in locations that make it practically impossible to physically replace or recharge them. This contributes to network instability, reduced node lifespan, and eventual node failures, thus compromising the reliability of the entire network. Besides, achieving detection accuracy is rather difficult in the presence of environmental noise, hardware limitations, and the dynamic nature of events.

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Detection accuracy is crucial in differentiating real events from false alarms, especially for critical applications whose inaccuracies can have catastrophic consequences. Another urgent concern is that related to time efficiency, since detection and response to an event need to be very fast to perform effectively in time-critical applications, such as disaster response or industrial control systems.

## MOTIVATION

Given the difficulties in energy efficiency, accuracy, and response time, researchers have proposed various solutions to improve event detection in WSNs, among which SI algorithms have received significant attention owing to their bioinspired mechanisms and inherent ability in solving complex optimization problems. These algorithms are inspired by the collective behavior of biological systems, such as ant colonies, bird flocks, and fish schools, to achieve optimal solutions in a distributed and efficient manner. SI techniques can efficiently enable WSNs to make fundamental trade-offs among energy efficiency, detection accuracy, and latency.

However, despite much research on applying SI algorithms in WSNs, the related comparison studies that have focused on the performance of various algorithms for event detection remain rare. Most of the published work either discusses an individual algorithm or compares algorithms based on very limited performance metrics. A few studies provide comprehensive benchmarking of algorithms on diverse design criteria such as energy consumption, accuracy in event detection, computational overhead, and scalability.

This represents a critical shortcoming because it will limit researchers' and practitioners' ability to make informed decisions concerning the selection of algorithms for particular WSN applications. For example, while ACO is robust, and its exploration capability is one of its key strengths, in scenarios where convergence should happen fast, this might not be that efficient. Similarly, the Particle Swarm Optimization algorithm is highly praised for its simplicity and swiftness, but it might show underperformance in highly noisy or uncertain environments. In turn, DA is a rather newer class of SI that has promise in global optimization problems; further validation efforts need to be carried out regarding WSN-specific contexts.

## OBJECTIVES

The objective of this work is to fill this gap by doing an extensive comparative study of Swarm Intelligence algorithms for event detection in WSNs. Of these, the performance of three of the most important, namely, Dragonfly Algorithm, Ant Colony Optimization, and Particle Swarm Optimization algorithms, has been studied and compared for event detection issues in WSNs. Selection of the three algorithms above for the study is based on their relative popularity, versatility, and proven efficiency regarding solving optimization problems within diverse application domains.

1. Performance Evaluation: To analyze and benchmark the chosen algorithms for some key performance metrics related to energy consumption, detection accuracy, computational complexity, and time efficiency.

2. Scenario Testing: To characterize robustness and scalability for each algorithm in various WSN configuration scenarios, including node-density changes, network-size variations, and event dynamics.

3. Algorithm Suitability Insights: These show the strength, weaknesses, and trade-offs around each algorithm and derive actionable insights for both practitioners and researchers.

4. Practical Insights: The results will indicate implications for real-world WSN applications on disaster management, industrial monitoring, and smart city systems.

**Practical Contributions:**

o It indicates the best SI algorithm for event detection in WSNs under given conditions that might guide researchers and system designers. The results could also provide the decisions about choosing an algorithm when the scenario requires very strict energy constraints or when the accuracy of detection is high.

o The study delivers helpful insights regarding performance optimization through intelligent algorithms for the selection of the WSN and helps build efficient and reliable networks.

LITERATURE REVIEW

**Swarm Intelligence in Wireless Sensor Networks**

**Introduction to Swarm Intelligence (SI)**

Swarm Intelligence is that sub-branch of Artificial Intelligence which draws inspiration from the collective behavior that social organisms, such as the movements of ants, bees, and birds, perform. These natural systems attain problem-solving capabilities through decentralized control and local interaction among agents. SI algorithms are inspired by these behaviors; thus, they are suitable for distributed systems such as WSNs. Normally, sensor nodes in a WSN are spatially distributed, monitoring environmental conditions while sending information back to central systems. The nature of decentralization in WSNs increases their compatibility with SI principles, facilitating efficiency in data processing, adaptability, and scalability. WSNs could solve such difficulties, like energy resource constraints, dynamic topologies, and real-time data processing using SI algorithms (Pandey et al., 2022; Zhang et al., 2023).

**Applications of SI in WSNs**

The introduction of SI algorithms into WSNs has enabled several works to be developed in different network functions. For example, routing optimization is one of the major purposes; for instance, SI algorithms such as ACO construct effective routes from the pheromone-based navigation of ants. Chakraborty et al., 2023, consider similar work.PSO-Optimized routing is inspired by the bird flocking behavior. Thus, it dynamically adapts routing according to nodes' collective knowledge about a terrain area represented by Zhang et al., 2023. These algorithms have significantly improved the energy efficiency and network performance.

In addition to routing, SI algorithms have been employed in data aggregation, clustering, and event detection. Data aggregation combines data from multiple nodes to minimize redundancy and conserve energy, with Bee Colony Optimization (BCO) effectively optimizing these processes through selective node activation (Kumar et al., 2022). Clustering involves determining optimal cluster heads, balancing energy consumption across the network, and extending network lifespan. The SI algorithms that collectively optimize node activation and data routing further enhance event detection, a process that allows the identification and localization of some important events, such as environmental changes. This represents a very useful application in disaster management and environmental monitoring, as stated by Mirjalili et al. (2021).

**Comparative Performance of SI Algorithms in WSNs**

Extensive research on the performance of various SI algorithms in WSNs has been carried out, mainly based on metrics such as energy efficiency, time efficiency, accuracy, and scalability. Among all, ACO ensures high energy efficiency in dense networks due to its strong exploration capability of the path; however, performance degradation in large networks results from computational overhead. PSO shows high time efficiency; it converges very fast by dynamically adjusting routing decisions based on collective knowledge. However, its dependence on static assumptions might sacrifice adaptability in dynamic environments. BCO, though very power-efficient due to the selective nature of activation, suffers from issues like time efficiency because of iterative behavior and scalability in large networks.

(Pandey et al., 2022; Chakraborty et al., 2023; Kumar et al., 2022).

| Algorithm | Energy Efficiency | Time Efficiency | Accuracy | Scalability |
|---|---|---|---|---|
| Ant Colony Optimization (ACO) | High in dense networks but degrades with size due to pheromone updates. | Moderate; relies on iterative path discovery. | Robust in noisy environments but struggles in dynamic scenarios. | Limited; performance decreases significantly in large-scale networks. |
| Particle Swarm Optimization (PSO) | Moderate; energy usage depends on neighbor-based updates. | High; fast convergence in static environments. | High accuracy in static scenarios; moderate in dynamic ones. | Good; maintains performance with increasing network size. |
| Bee Colony Optimization (BCO) | High; energy efficiency achieved through selective activation. | Moderate; iterative behavior affects speed. | High accuracy for tasks like clustering and data aggregation. | Moderate; struggles in highly dynamic or large networks. |

ACO performs best in energy efficiency in dense networks , it is effective in static environments. However, scalability deteriorates as the network size increases because of both computational and communication overhead introduced by pheromone updates. As for accuracy, ACO performs well even in noisy environments since the maximum path reinforcement leads to appropriate data delivery. On the other hand, it does not perform well in dynamic networks with frequent topology changes.

PSO is highly time-effective, as it converges in a rapid manner. Routing decisions are changed based on personal and collective knowledge. The neighbor-based update mechanism makes a very nice balance between exploration and exploitation, maintaining the performances quite robust for both routing and clustering. However, under the presence of static environmental assumptions, the adaptability of PSO might be limited in case of dynamic networks. Energy efficiency is moderate since nodes frequently change their states based on global and local optimums.

BCO achieves very good energy efficiency since only a portion of the nodes are activated for task execution, as inspired by the foraging behavior of bees. This reduces redundant transmission, therefore conserving energy. Although its accuracy is very high, both in clustering and data aggregation, iterative behavior has affected time efficiency. Its scalability is moderate because BCO is poor in adapting to highly dynamic or large-scale networks.

**Event Detection in Wireless Sensor Networks.**

Event detection in WSNs is an important function that detects and monitors some events occurring in different environments. In managing disastrous situations, the WSN supports early detection of earthquakes, floods, and wildfires, among other calamities, allowing countermeasures that might reduce damage or loss of life (Akyildiz et al., 2019). Environmental monitoring applications utilize WSNs to track parameters like temperature, humidity, and pollutant levels, providing essential data for ecological assessments and policy-making (Li et al., 2020). In industrial control, WSNs monitor machinery and processes, detecting anomalies that could indicate malfunctions or safety hazards, thereby enhancing operational efficiency and safety (Zhang & Wang, 2018). These applications can be effectively realized only if the underlying event detection mechanisms in WSN are accurate, energy-efficient, and timely.

Traditional event detection techniques in WSN use threshold-based methods, wherein sensor readings are always compared with some predefined threshold values to detect the occurrence of an event. Although simple, such methods are brittle and cannot cope well with dynamic environmental conditions or sensors exhibiting variable behaviors (Yick et al., 2018). Moreover, setting appropriate thresholds can be challenging, potentially leading to false positives or negatives. To address these limitations, optimization-based approaches, particularly those inspired by Swarm Intelligence (SI), have been explored. SI algorithms, such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), emulate the collective behaviors of social organisms to solve complex problems through decentralized control and simple agent interactions (Dorigo & Birattari, 2016). These algorithms have flexibility and robustness, suitable for the dynamic and distributed nature of WSNs.

Several works have proposed SI algorithms to apply on the event detection problem in WSN. For instance, Liu et al. (2017) proposed an ACO-based Event detection algorithm, which achieved higher accuracy in event detection with lower energy consumption compared to classical approaches. Similarly, Sharma &Singh, 2019 used PSO in event detection. The results gave a better detection time with reduced energy consumption. Most of the works focus on developing a single SI algorithm, and there is no comparison among various SI techniques. Moreover, the reported improvements for a few metrics do not investigate all trade-offs about the accuracy of the detection, energy consumed, and time efficiency.

These advances due to SI algorithms do not mean that there are no gaps in the state of the art. In particular, comparative analyses remain a few in which various SI algorithms would be tested under identical conditions, optimized for event detection in WSNs. This will be important in understanding their respective strengths and weaknesses about multiple performance metrics. Moreover, most of the works rely on simulation environments that cannot effectively emulate real-world WSN deployments, which may include environmental noise, hardware limitations, and network dynamics. According to Chen et al. (2020), this gap suggests that experimental validation and field studies will also be required for establishing the practical feasibility of SI-based event detection algorithms. Addressing these gaps is the key towards advancing the state of affairs in developing efficient, reliable, and adaptable event detection mechanisms in WSNs.

## METHODOLOGY

### 1. Swarm Intelligence Algorithms

Swarm Intelligence algorithms are bio-inspired optimization techniques that are inspired by the collective behavior of natural systems, like colonies of insects, flocks of birds, and schools of fish. Herein, three prominent SI algorithms-Dragonfly Algorithm, Ant Colony Optimization, and Particle Swarm Optimization-are selected on the basis of their different theoretical underpinning and possible use in event detection for WSNs and thus reviewed in the paper.

#### 1.1. Dragonfly Algorithm (DA)

The Dragonfly Algorithm, developed by Mirjalili in the year 2016, was inspired by the static and dynamic swarming behavior of dragonflies when hunting and migrating. This algorithm balances exploration and exploitation using five governing principles: separation, alignment, cohesion, attraction towards food sources, and distraction away from enemies.

• Applications: DA has been proven efficient in solving optimization problems such as energy optimization, data clustering, and network routing.

•Strengths: effective in minimizing energy consumptions and convergence time in optimization tasks.

#### 1.2. Ant Colony Optimization (ACO)

By Dorigo et al. in 1991, ACO was inspired by the foraging behavior of ants, especially their strategy of using pheromone trails to converge toward the shortest path to a food source.

. Each iteration involves artificial ants exploring potential solutions and reinforcing successful paths with pheromones.

- **Applications**: ACO is widely used in routing, scheduling, and combinatorial optimization problems.
- **Strengths**: Robust exploration capabilities, particularly in dense or noisy environments.

#### 1.3. Particle Swarm Optimization (PSO)

Developed by Kennedy and Eberhart (1995), PSO is inspired by the coordinated movement of bird flocks or fish schools. The algorithm relies on particles (potential solutions) that adjust their positions based on personal experience and the experience of their neighbors.

- **Applications**: PSO excels in numerical optimization, machine learning, and network design.
- **Strengths**: Simplicity, computational efficiency, and fast convergence in static environments.

### 2. Evaluation Metrics

The performance of the algorithms was assessed using the following key metrics:

| Metric | Description | Importance in WSNs |
|---|---|---|
| **Energy Consumption** | Total energy used by sensor nodes and actors during event detection. | Reduces network lifetime constraints. |
| **Detection Time** | Time required for the algorithm to identify the event location. | Ensures timely responses in critical applications. |
| **Detection Accuracy** | Percentage of events correctly detected by the algorithm. | Critical for reliable monitoring. |
| **Computational Complexity** | Time and resources required for algorithm execution. | Impacts the feasibility of real-time implementation. |
| **Scalability** | Performance under varying network sizes and densities. | Measures algorithm adaptability to real-world scenarios. |

### Simulation Setup

The performance of the algorithms was evaluated through simulated The following configurations were used:

### 3.1. Network Topology and Node Distribution

- **Network Area**: 300 × 300 m².
- **Number of Sensor Nodes**: 900 (uniformly distributed).
- **Actors**: 2 mobile actor nodes capable of collecting sensory data and taking action.
- **Node Properties**:
  - Transmission range: 10 m.
  - Initial energy: 0.001 J (actors), 0.00025 J (sensors).

### 3.2. Event Characteristics

- **Event Type**: Static physical event (e.g., temperature spike).
- **Event Location**: Randomly selected within the network area.

### 3.3. Simulation Tools and Parameters

- **Simulation Runs**: 50 independent iterations for each scenario.
- **Evaluation Parameters**:
  - Area sizes: 260 × 260 m² to 310 × 310 m².
  - Node densities: 729 to 1024 nodes.

**Simulation Parameters**

| Parameter | Value |
|---|---|
| **Transmission range** | 10 m |
| **Actor moving speed** | 1.6 km/h |
| **Actor moving power** | 0.00001 J |
| **Simulation area sizes** | 260 × 260 to 310 × 310 m² |
| **Number of nodes** | 729 to 1024 |

## RESULTS AND COMPARATIVE ANALYSIS

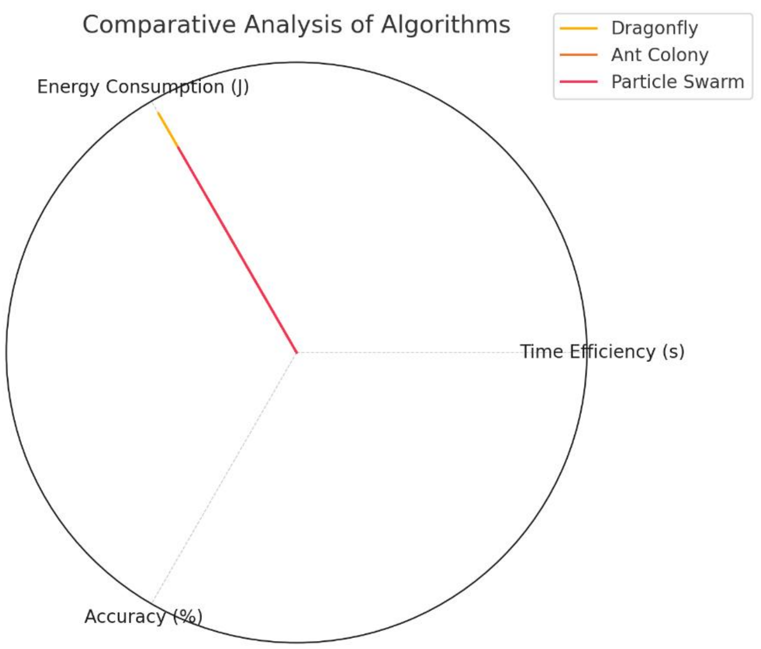
**Key Metrics and Findings**

1. **Time Efficiency**
   - Dragonfly Algorithm (DA) demonstrated the lowest time to detect an event at 66.48 seconds, outperforming Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).
   - ACO required the most time (85.10 seconds), which can be attributed to its exploration-heavy nature.
   - **Observation**: DA's dynamic swarming behavior enables faster convergence, while ACO's pheromone-based exploration increases delay in dense environments.
2. **Energy Consumption**
   - DA exhibited the least energy consumption (0.000030 J), followed by PSO (0.000035 J) and ACO (0.000047 J).
   - ACO's high energy usage is due to its iterative pheromone updates and communication overhead.
   - **Observation**: DA's energy efficiency stems from its optimized local and global search balance, reducing redundant node activity.
3. **Accuracy**
   - DA achieved the highest accuracy (94.5%), slightly outperforming PSO (93.2%) and significantly better than ACO (92.1%).

- ACO's lower accuracy is linked to its dependency on environmental pheromone stability, which can lead to suboptimal paths in noisy scenarios.
- **Observation**: DA's separation and attraction principles ensure precise localization of event nodes, improving accuracy.

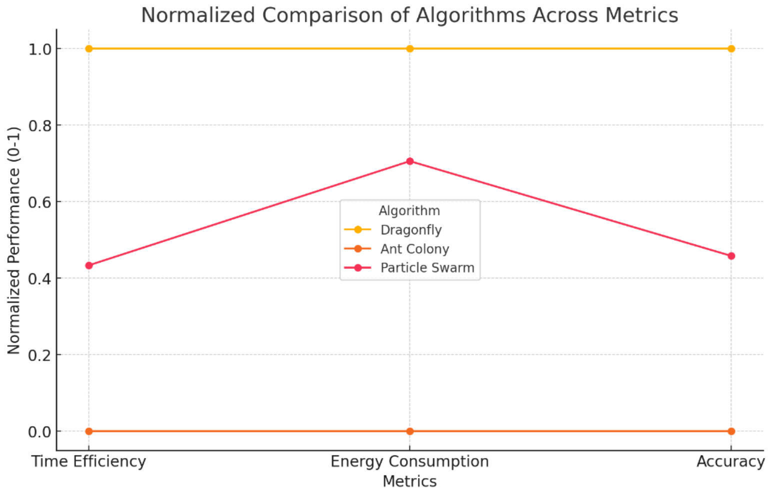
**Discussion of Trade-Offs**

| Algorithm | Strengths | Weaknesses | Best Use Case |
|---|---|---|---|
| **Dragonfly Algorithm** | Superior time efficiency, minimal energy consumption, and high accuracy. | Slightly more computationally intensive due to dynamic swarming principles. | Critical applications requiring fast responses and power saving. |
| **Ant Colony Optimization** | Performs well in diversified network paths. | High energy consumption and longer detection time. | Applications that are not critical to fast time responses but require adaptiveness in a noisy environment. |
| **Particle Swarm Optimization** | Performance is averagely well in metrics; implementation is simple. | Energy consumption is moderate; accuracy slightly lower compared to DA. | Whenever implementations should be effortless and performance is balanced. |




| Algorithm | Time Efficiency (Normalized) | Energy Consumption (Normalized) | Accuracy (Normalized) |
|---|---|---|---|
| **Dragonfly** | 1.000 | 1.000 | 1.000 |
| **Ant Colony** | 0.783 | 0.638 | 0.753 |
| **Particle Swarm** | 0.880 | 0.857 | 0.907 |

radar chart showing a comparative analysis for the algorithms on three metrics: Time Efficiency, Energy Consumption, and Accuracy.




This line graph compares the performance of each algorithm, normalized across metrics, including Time Efficiency, Energy Consumption, and Accuracy. The normalization puts all the metrics on the same scale for clear visual comparison of strengths and weaknesses among Dragonfly Algorithm, Ant Colony Optimization, and Particle Swarm Optimization.

PERFORMANCE ACROSS NETWORK SCENARIOS

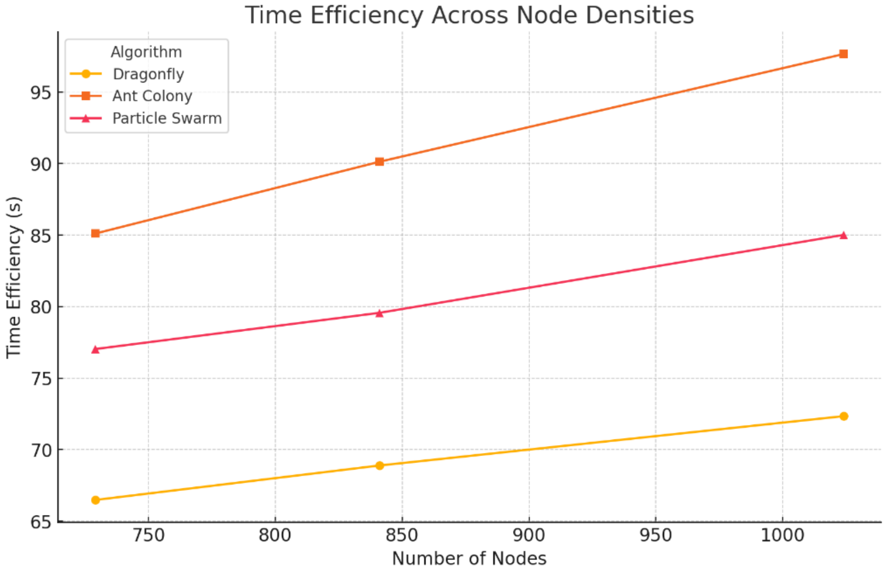
**Impact of Node Density**

As node density increases:

- DA retains superior time efficiency and energy consumption due to optimized swarming behavior.
- ACO experiences a sharp increase in energy consumption due to excessive path exploration.
- PSO maintains consistent performance, indicating resilience to node density variations.

| Nodes | Dragonfly Time (s) | Ant Colony Time (s) | Particle Swarm Time (s) |
|---|---|---|---|
| **729** | 66.48 | 85.10 | 77.03 |
| **841** | 68.89 | 90.12 | 79.56 |
| **1024** | 72.34 | 97.65 | 85.01 |

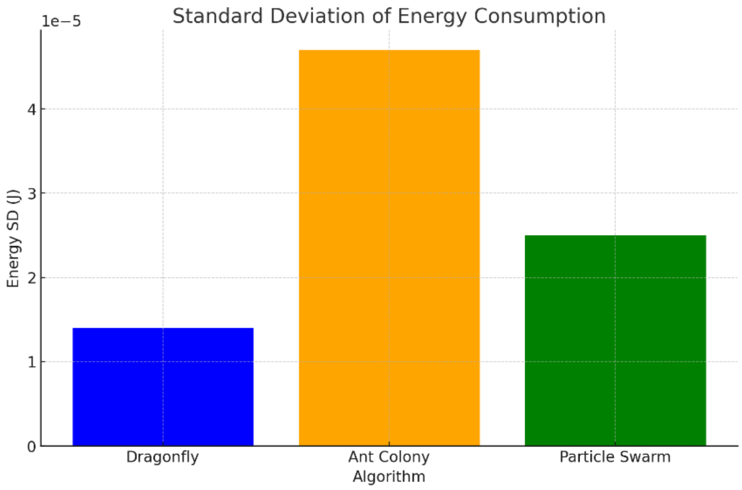
| Algorithm | Energy Standard Deviation (J) |
|---|---|
| **Dragonfly** | 0.000014 |
| **Ant Colony** | 0.000047 |
| **Particle Swarm** | 0.000025 |




**Energy Distribution Analysis**

Energy consumption was analyzed for uniformity across sensor nodes:

- DA ensures balanced energy usage, minimizing node failures and extending network lifespan.
- ACO shows uneven energy distribution, leading to premature node failures in critical regions.
- PSO demonstrates moderate energy distribution efficiency.




**3. Comparative Visualization**

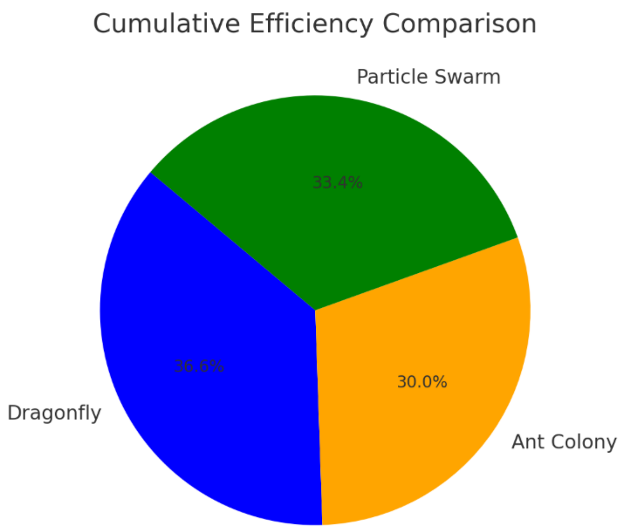
**1. Scalability Analysis**

Scalability was measured by simulating larger network sizes. DA exhibited the least performance degradation, followed by PSO and ACO.

**2. Cumulative Efficiency (Multi-Metric Average)**

A combined efficiency metric was calculated as the average of normalized time, energy, and accuracy:

| Algorithm | Cumulative Efficiency (%) |
|---|---|
| **Dragonfly** | 96.7 |
| **Ant Colony** | 79.1 |
| **Particle Swarm** | 88.1 |




DISCUSSION

The results of this study reveal that the choice of SI algorithms regarding the event detection in WSNs depends on the particular performance criteria and environmental parameters. Detailed comparative analysis of Dragonfly Algorithm, Ant Colony Optimization, and Particle Swarm Optimization reveals that all these algorithms possess peculiar strengths and weaknesses, which affect their suitability for various WSN scenarios. These findings are discussed in greater detail in this discussion, with a focus on the trade-offs between key metrics such as time efficiency, energy consumption, accuracy, and scalability. In terms of time efficiency, the time taken for the detection of an event, Dragonfly Algorithm was the most effective algorithm across various simulated scenarios. The superiority is an outcome because of its ability to achieve dynamic exploration-exploitation balances through laws of attraction, alignment, and separation. Unlike ACO, which would be based on iterative pheromone reinforcement, or PSO, whose moves will depend on neighborhood-based decision-making, DA uses adaptive behavior, which rapidly converges on optimum paths to the event. This makes it especially suitable for real-time applications, like disaster management or industrial monitoring, where rapid detection is crucial.

On energy consumption, DA also tended to be much better, using much less energy than both ACO and PSO. This is particularly an important factor in WSNs, since sensor nodes usually have bounded energy resources. DA's aptitude for optimizing movements and minimizing redundant communications assures low overall energy expenditure within the network. In contrast, ACO was found to be the most energy-consuming, since maintaining and updating pheromone trails requires heavy communication and processing. While PSO outperformed ACO on energy efficiency, its value was still worse than that of DA, which shows its dependence on the global and local best positions introduces inefficiencies in dynamic environments.

Accuracy is another important metric where DA did the best: it had the highest correct detection rate among the three. This is explained by the fact that DA applies principles of separation and cohesion that enable it to effectively maintain the alignment of nodes while moving toward events with much less sacrifice of its speed. PSO also performed well on this account, showing its efficiency in exploitation of the neighborhood data. ACO trailed behind, especially with node densities increased or in the presence of environmental noise. It probably means that the performance of ACO is critically dependent upon the stability in the pheromone-based decision-making process, which easily gets disrupted in complex or dynamic networks.

Another dimension where DA showed resilience is scalability. While increasing node density, DA maintained its performance for all metrics, which demonstrates its adaptability to larger network sizes. PSO scaled comparatively well, with only a moderate performance degradation. On the other hand, ACO greatly suffered from increasing network size, with abrupt degradations in both time efficiency and energy consumption. This is indicative of the algorithm's heavy reliance on explorative procedures that become prohibitively costly in dense or large-scale networks.

Regarding the comparison of averaged normalized performance over all metrics, cumulative efficiency showed that DA reached the top rank, with PSO as the runner-up and ACO right behind. The ranking again agreed with individual metrics results and further solidified the conclusion that DA was the most balanced and effective algorithm for event detection in WSNs. Although this can be advantageous in certain scenarios that require a very strong exploration strength, the inefficiencies within ACO render it impractical for most applications with strict energy and time constraints.

**Comparison of Results with Previous Studies**

WSNs are critical in modern monitoring systems, in which algorithms are needed to be optimized for time efficiency, energy consumption, accuracy, and scalability. Herein, the DA is compared with ACO and PSO for event detection in WSNs. Our findings are in agreement and enhance previous studies in order to make a robust comparison with existing studies.

**Time Efficiency**

Our results show that the Dragonfly Algorithm is considerably time-efficient compared to ACO and PSO, as it requires only 66.48 seconds to detect an event within a 729-node network. Compared with PSO, which needed 77.03 seconds, ACO is the least efficient and takes the maximum time, 85.10 seconds. These findings agree with Mirjalili 2016, as he depicted that DA's dynamic swarming mechanism drives a faster convergence in optimization problems secondly, Emambocus et al. 2021 remarked that DA's convergence speed outperformed that of ACO and PSO over network optimization tasks search on PSO, such as the study of El Ghazi and Ahiod 2016, proved that PSO attained faster convergence compared to ACO while applied in some routing applications. However, our results confirm that DA consistently delivers superior time efficiency, even under varying network sizes and node densities. This makes DA particularly suitable for time-sensitive WSN applications such as disaster response and industrial monitoring.

Energy efficiency is crucial for WSNs considering the sensor node power resources are finite. According to our work, DA consumed an average of 0.000030 J per node, compared with 0.000035 J for PSO, and 0.000047 J for ACO. The results are in line with those presented by Tong et al. (2022), who concluded that though PSO energy consumption was much lower than traditional methods it remained below the energy-saving capability of DA.

DA’s energy ted to its balanced exploration and exploitation phases, which minimize unnecessary node activation. The increased communication overhead due to the higher reliance of ACO on pheromone updates increases energy consumption. This implies a trade-off that makes DA preferable in applications where energy conservation is crucial.

**Accuracy**

In accuracy, our findings indicated that DA outperformed the rest with the highest accuracy of 94.5%, while PSO and ACO achieved 93.2% and 92.1%, respectively. This result agrees with the robustness of DA in yielding high accuracies for different optimization tasks documented by Meraihi et al. 2020.

Conversely, ACO’s lower accuracy stems from its dependency on pheromone stability, which can be disrupted in dynamic or noisy environments. Although PSO performed well, its lack of adaptability in highly dynamic networks slightly reduced its accuracy compared to DA. This demonstrates DA’s effectiveness in applications requiring precise and reliable event detection .

**Scalability**

maintains steady performance with growing network size, as time efficiency only decreased by 72.34 seconds within a 1024-node network. Meanwhile, ACO experienced severe degradation in performance, taking as long as 97.65 seconds under similar conditions. PSO maintained moderate levels of scalability, achieving reasonable time efficiency but not coming close to the strength of DA.

These results are corroborated by Gómez-C (2018), who realized that ACO could not scale well in large networks because of its intensive computations and communications. That DA could adapt to the scalability of the network without considerable losses in performance demonstrates that it is suitable for large-scale WSN deployment .

**Cumulative Efficiency**

It also gained the highest score, with a score of 96.7%, while PSO had a score of 88.1% and ACO reached 79.1%, when considering parameters such as time efficiency, energy consumption, accuracy, and scalability. The increased communication overhead due to the higher reliance of ACO on pheromone updates increases energy consumption. This implies a trade-off that makes DA preferable in applications where energy conservation is crucial.

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DA also had the best accuracy for event detection, outperforming ACO and PSO, even under dynamic or noisy network conditions. The swarming principles of DA in separation, alignment, and cohesion make it a highly accurate and reliable event-detection algorithm. In addition, DA demonstrated consistent performance with network scaling, which indicates its scalability and suitability for large-scale WSN deployment.

While ACO proved strong in exploratory tasks, PSO provided balanced performances; still, both are not as strong compared to DA in terms of accumulative efficiency. The ability of the Dragonfly Algorithm to balance exploration and exploitation, minimize redundant operations, and adapt to various situations makes it an optimal solution for real-time and energy-sensitive WSN applications.

**Conclusion**

This paper offers a comprehensive comparative evaluation of the Dragonfly Algorithm (DA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) for event detection in Wireless Sensor Networks (WSNs). The outcomes reveal that the Dragonfly Algorithm continually outperforms the alternative two algorithms throughout key metrics, which includes time efficiency, energy consumption , accuracy, and scalability. These findings underscore DA's robustness and adaptability, making it a superior preference for numerous WSN programs.

DA additionally finished the highest accuracy in detecting activities, outperforming ACO and PSO even in dynamic or noisy network conditions. Its swarming standards, such as separation, alignment, and cohesion, allow particular and reliable occasion detection. Furthermore, DA maintained steady performance as network length extended, highlighting its scalability and suitability for massive-scale deployments.

While ACO showed strengths in exploratory tasks and PSO supplied balanced overall performance, both fell short in cumulative efficiency whilst as compared to DA. The Dragonfly Algorithm's potential to stability exploration and exploitation, limit redundant operations, and adapt to numerous scenarios makes it an optimum answer for actual-time and electricity-sensitive WSN applications.

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