Enhancing WSN Performance: A Hybrid DA-SA Model for Energy Efficiency Clustering and Data Transmission

Sushil Lekhi[1], Dr. Satvir Singh[2]

[1]*Research Scholar, IKGPTU, India, rieit.cse.sushil@gmail.com*
[2]*Professor, IKGPTU, India, satvir.singh@ptu.ac.in*

Abstract: Wireless Sensor Networks (WSNs) consist of numerous battery-powered sensor nodes, whose limited energy reserves significantly impact the network's lifespan. Prolonging the operational lifetime of WSNs is critical, particularly for energy-efficient data transmission and routing. Clustering, a key technique in WSNs, relies heavily on the optimal selection of cluster heads (CHs) to manage data aggregation and routing efficiently. However, ensuring energy efficiency while maximizing the network's lifespan and minimizing delays remains a formidable challenge in WSN design. In order to address these challenges, a hybrid optimization approach combining the Dragonfly Algorithm (DA) with Simulated Annealing (SA) is proposed. This approach leverages DA's exploration capabilities for identifying potential CHs and SA's exploitation mechanisms for fine-tuning the selection process based on critical constraints such as residual energy, node distance, and packet transmission ratios. The hybrid model ensures centralized cluster formation, with the base station selecting CHs and notifying cluster nodes of their assignments. During data routing, the algorithm evaluates paths based on fitness values, selecting the most energy-efficient and latency-minimized route to the sink node. The proposed DA-SA approach demonstrates improved energy efficiency, prolonged network lifetime, and reduced computational overhead compared to traditional methods

Keywords: Cluster Head, WSN, Dragonfly, PSO, Fuzzy, Base Station

1. Introduction

Wireless Sensor Networks (WSNs) are composed of a large number of spatially distributed sensor nodes that monitor environmental conditions such as temperature, pressure, humidity, and motion. These nodes work collaboratively to collect, process, and transmit data to a centralized base station (BS) or sink. WSNs have become increasingly important due to their wide range of applications, including environmental monitoring, healthcare, industrial automation, and smart cities[1]. Despite their potential, the resource-constrained nature of WSNs poses significant challenges, particularly in terms of energy efficiency, network lifetime, and reliable data transmission. Each sensor node in a WSN is typically powered by a non-rechargeable battery, making energy conservation a critical factor in network design. The energy required for data transmission is substantially higher than that needed for sensing or computation, which makes efficient routing and data aggregation essential for prolonging the network's operational lifespan. Among the techniques developed to enhance energy efficiency, clustering has emerged as a fundamental strategy. Clustering involves grouping sensor nodes into clusters, where a designated Cluster Head (CH) in each cluster manages data aggregation and communication with the BS. This approach reduces redundant data transmissions, optimizes resource utilization, and extends the network's lifetime. However, the efficiency of clustering heavily depends on the selection of optimal CHs, which must balance factors such as residual energy, distance to the BS, and node density. Several protocols and algorithms have been proposed to address these challenges. One of the earliest and most widely used clustering protocols is the Low-Energy Adaptive Clustering Hierarchy (LEACH). LEACH introduced the concept of rotating CH roles among nodes to distribute energy consumption evenly[2]. While effective in reducing energy usage, LEACH suffers from limitations, including a lack of adaptability to varying network conditions and the potential for suboptimal CH placement. To overcome these drawbacks, researchers have turned to metaheuristic optimization techniques, which offer robust solutions for complex and dynamic environments. Among these, the Particle Swarm Optimization (PSO) algorithm has been extensively studied for its ability to explore large search spaces efficiently. PSO, inspired by the social behavior of bird flocks and fish schools, optimizes CH selection by iteratively adjusting the positions of particles (potential solutions) based on their own experience and the collective experience of the swarm[3]. Despite its strengths, PSO can suffer from premature convergence, leading to suboptimal solutions in dynamic WSN environments. The Dragonfly Algorithm (DA)[4] offers an alternative approach, drawing inspiration from the dynamic behaviors of dragonfly swarms, such as attraction, alignment, and cohesion. DA's exploration capabilities make it well-suited for CH selection, as it can adapt to changing network conditions and distribute CH roles efficiently. However, like other metaheuristic algorithms, DA may require additional refinement to achieve optimal performance.

To further enhance the efficiency of clustering in WSNs, hybrid optimization approaches have gained significant attention. In this work the integration of the Dragonfly Algorithm with Simulated Annealing (DA-SA), which combines the strengths of exploration and exploitation. While DA identifies potential CHs by exploring the search space, SA fine-tunes these selections by optimizing critical parameters such as residual energy, distance to the BS, and data transmission efficiency[5]. This hybrid approach ensures centralized cluster formation, where the BS plays a pivotal role in selecting CHs and notifying cluster nodes of their assignments. During data transmission, the DA-SA algorithm evaluates multiple routing paths based on fitness values to identify the most energy-efficient and latency-minimized route to the sink node. This comprehensive approach addresses the limitations of traditional methods such as LEACH and standalone optimization algorithms like PSO and DA. By leveraging the complementary strengths of DA and SA, the hybrid model achieves significant improvements in energy efficiency, network lifetime, and computational overhead. The ongoing advancements in clustering techniques, particularly through the integration of metaheuristic and hybrid optimization algorithms, underscore the importance of innovative solutions in WSN design. These developments not only enhance the performance and reliability of WSNs but also pave the way for their application in increasingly complex and resource-constrained scenarios. As WSNs continue to evolve, addressing challenges such as energy efficiency, scalability, and dynamic adaptability remains a critical focus for researchers and practitioners alike. Leveraging the complementary strengths of DA and SA, this approach enhances the energy efficiency of WSNs, prolongs the network lifetime, and reduces computational overhead compared to traditional methods. This advancement represents a robust solution for overcoming the energy constraints and scalability challenges associated with WSNs.

2. Literature Review

In [6], the author utilized the Ant Colony Optimization (ACO) algorithm, inspired by the foraging behavior of ants, to improve adaptability in dynamic UWSN environments. ACO effectively adapted to changes in network topology and provided optimized routing paths, making it highly suitable for resource-constrained networks. However, the algorithm required extensive computational resources to identify optimal solutions, particularly in large-scale networks. This limitation restricted its real-time applicability, especially in scenarios requiring quick decision-making.

In [7],the authors leveraged the Grey Wolf Optimizer (GWO) algorithm to address optimization challenges in underwater wireless sensor networks (UWSNs). GWO emulates the leadership hierarchy and hunting strategies of grey wolves, enabling efficient exploration and exploitation of the solution space. The methodology successfully balanced these two aspects, making it suitable for solving complex clustering and routing problems. However, the algorithm's heavy dependence on parameter tuning made it less adaptable in scenarios with varying network conditions, which is a common challenge in UWSNs.

In [8], the authors developed the UMOD-LEACH protocol, which enhanced the traditional LEACH protocol by introducing energy-efficient clustering techniques. The proposed method successfully minimized energy consumption across the network by optimizing the selection of cluster heads (CHs). However, the clustering approach was not entirely optimal, leading to uneven resource allocation and inefficiencies in certain network scenarios. This limitation impacted the overall network lifetime, particularly in deployments with high node density.

In [9], the authors proposed TECP-MFO approach to achieve load balancing in UWSNs. By combining the Thermal Energy Consumption Protocol (TECP) with the Moth Flame Optimization (MFO) algorithm, the methodology ensured an even distribution of network loads, prolonging network lifetime. However, the approach lacked specific adaptations for UWSN challenges, such as dynamic topology changes and high latency, reducing its overall effectiveness in underwater deployments.

In [10], the authors employed the Moth Flame Optimization (MFO) technique, which mimics the navigation of moths around flames, for solving optimization problems in UWSNs. MFO demonstrated significant flexibility and robustness in addressing various problem domains, including clustering and routing tasks. However, the algorithm often exhibited premature convergence, failing to escape local optima in complex solution spaces. This shortcoming limited its ability to achieve globally optimal solutions, particularly in scenarios involving intricate and large-scale UWSN deployments.

In [11], the Energy-Efficient Clustering Particle Swarm Optimization (EC-PSO) algorithm was proposed to address the challenges of CH selection and energy hole avoidance WSNs. The algorithm effectively conserved energy by optimizing CH positions and reducing the workload on individual nodes. Despite its benefits, the fitness function used in EC-PSO did not adequately consider the distances between sensor nodes, CHs, and the sink, resulting in suboptimal routing paths and reduced network efficiency in certain cases.

In [12], the authors proposed a hybrid approach combining Fuzzy C-Means (FCM) and Particle Swarm Optimization (PSO) to improve CH selection in WSNs. The methodology aimed to prevent early CH failures by optimizing node selection based on fuzzy clustering. Although this approach effectively enhanced network lifetime, it suffered from slow convergence during CH selection. This drawback made the method less suitable for time-sensitive applications where rapid decision-making is essential.

In [13], the authors presented a hybrid Grey Wolf Optimization (GWO) and Support Vector Machine (SVM) approach to manage congestion in UWSNs. The GWO component effectively controlled network congestion by optimizing routing paths, while the SVM component classified and managed network traffic. Although the method demonstrated significant improvements in congestion management, its high computational complexity posed challenges for implementation in large-scale networks with limited processing power.

In [14], the authors introduced the Dragonfly Optimization (DFO) algorithm, inspired by the social and migratory behaviors of dragonflies, to address large-scale optimization problems in UWSNs. The DFO showed high scalability and effectively handled clustering and routing tasks, ensuring better energy efficiency and network performance. Nevertheless, as the problem size increased, the computational complexity of the algorithm also grew, posing challenges for its deployment in resource-limited to UWSN environments, where energy and processing power are critical constraints.

Table 1: Comparative analysis of various existing protocols

Author [Citation]	Methodology	Features	Challenges
[15]	Firefly Algorithm (FA) with hesitant fuzzy for CH selection	Improved efficiency in CH selection.	Delay was not minimized, and energy efficiency was not improved by FA.
[16]	Particle Swarm Optimization (PSO) for optimal CH selection	Provided an approach for optimal CH selection.	Computational cost was not reduced by the PSO approach.
[17]	Multi-criteria decision-making for CH selection	Considered multiple criteria for CH selection.	Energy efficiency was not at an essential level.
[18]	Double Cluster Head APTEEN routing protocol with PSO (DCA-PSO)	Enhanced CH selection using area double clustering.	Failed to achieve optimal CH selection.
[19]	Fuzzy-based centralized CH selection and distributed cluster formation scheme	Provided centralized CH selection and distributed cluster formation.	Did not minimize clustering time.
[20]	Power-aware routing protocols	Introduced several power-aware routing protocols for WSNs.	Clustering accuracy was not improved by the power-aware routing protocol.
[21]	Fuzzy-based energy-efficient CH selection algorithm	Increased network lifetime through energy-efficient CH selection.	None specifically mentioned in the text.
[22]	ARSH-FATI-based Cluster Head Selection (ARSH-FATI-CHS) algorithm	Minimized energy consumption using	Computational complexity was not minimized.

		advanced selection techniques.	
[23]	Efficient CH election scheme	Rotated CH position among nodes with higher energy levels.	Did not reduce bandwidth use.
[24]	Multi-Objective Taylor Crow Optimization (MOTCO) algorithm	Combined Taylor series and Crow Search Algorithm for effective CH selection.	None specifically mentioned in the text.
[25]	Security system modelling with secure CH selection during data aggregation	Provided cost-effective and simple security modelling for CH selection.	None specifically mentioned in the text.
[26]	Residual energy, node positions, and centrality-based CH selection algorithm	Improved CH selection by considering residual energy and centrality.	None specifically mentioned in the text.
[27]	Hybrid optimization algorithm for energy-aware CH selection	Enhanced CH selection in hierarchical routing using hybrid optimization.	None specifically mentioned in the text.
[28]	Malicious node detection based on gain determination	Provided a method for detecting link failures due to malicious nodes.	None specifically mentioned in the text.
[29]	Defective node identification using Adaptive Neuro Fuzzy Inference System (ANFIS)	Created a classifier to identify defective nodes in the network.	None specifically mentioned in the text.

Through the literature, it is evident that various algorithms have been proposed for clustering, cluster head selection, and optimization in wireless sensor networks to enhance the efficiency of data transmission. While these methods have introduced innovative approaches, challenges remain, such as increased energy consumption and high processing time. For instance, Firefly Algorithm (FA) has been applied for CH selection, demonstrating improved efficiency. However, issues such as delay and lack of significant energy optimization persist.

To address these limitations, integrating Firefly Optimization with Simulated Annealing (SA) is proposed as a potential improvement. This hybrid approach leverages the exploration capabilities of FA and the local search strength of SA to optimize CH selection. By combining these techniques, the efficiency of clustering and data transmission can be significantly enhanced, while simultaneously reducing energy consumption and processing overhead. Such a hybrid model can address the observed gaps in existing methodologies and offer a more robust solution for wireless sensor network optimization.

3. Proposed Methodology

This section provides the proposed methodology where the work combines Dragonfly Algorithm for WSN Optimization incorporated with Simulated Annealing Algorithm.

3.1 The Dragonfly Algorithm (DA) : It is a swarm intelligence technique inspired by the static and dynamic behaviors of dragonflies during hunting and migration. This algorithm effectively balances exploration and exploitation of the search space, making it well-suited for addressing clustering and routing challenges in Wireless Sensor Networks (WSNs).

Dragonfly Behavior Model

Dragonflies exhibit two primary behaviors:

1. Static behavior (hunting): Represented by local exploration.
2. Dynamic behavior (migration): Represented by global exploration.

These behaviors are mathematically modeled through position updates based on three main factors:

- Separation: Avoiding collisions with neighboring individuals.
- Alignment: Matching velocity with neighboring individuals.
- Cohesion: Moving towards the center of neighboring individuals.

The position and velocity of a dragonfly in a multidimensional search space are updated using the following equations:

Separation (S):

The separation factor ensures a dragonfly maintains a minimum distance from its neighbors.

$$S_i = -\sum_{j=1}^{N_i} (X_j - X_i) \qquad (1)$$

where X_i is the position of the i^th^ dragonfly, X_j represents the position of its j^th^ neighbor, and N_i is the number of neighbors.

Alignment (A):

This factor helps dragonflies align their velocity with their neighbors.

$$A_i = \frac{\sum_{j=1}^{N_i} V_j}{N_i} \qquad (2)$$

where VjV_jVj is the velocity of the jthj^{th}jth neighboring dragonfly.

Cohesion (C):

The cohesion factor directs a dragonfly toward the average position of its neighbors.

$$C_i = \frac{\sum_{j=1}^{N_i} X_j}{N_i} - X_i \qquad (3)$$

Attraction Towards a Food Source (F):

The food source represents the optimal solution. The attraction factor is defined as:

$$F_i = X^+ - X_i \qquad (4)$$

where X^+ is the position of the food source.

Distraction From Enemies (E):

The distraction factor helps dragonflies avoid enemy positions:

$$F_i = X^- - X_i \qquad (5)$$

where X^- is the position of the enemy.

Position and Velocity Update

The position and velocity of each dragonfly are updated using a combination of these factors:

1. Velocity Update:

$$V^{(t+1)} = s \cdot S + a \cdot A + c \cdot C + f \cdot F + e \cdot E + w \cdot V^{(t)} \qquad (6)$$

where s,a,c,f,e are the weights for separation, alignment, cohesion, attraction, and distraction, respectively, and www is the inertia weight.

2. Position Update:

$$X^{(t+1)} = X^{(t)} + V^{(t+1)} \qquad (7)$$

To ensure solutions remain within the feasible region, boundary conditions are applied to each dimension of the search space. If a dragonfly exceeds the bounds, it is reinitialized within the permissible range.

3.2 Optimization of clustering and routing

In Wireless Sensor Networks (WSNs), the optimization of clustering and routing is essential for enhancing network performance. The Dragonfly Algorithm (DA) is applied to optimize multiple conflicting objectives, ensuring efficient resource utilization and prolonged network functionality. The key objectives are:

1. Energy Efficiency

Energy consumption is a critical parameter in WSNs due to the limited power supply of sensor nodes. Minimizing energy consumption involves:

- Reducing the transmission energy by selecting cluster heads (CHs) that are closer to sensor nodes.
- Optimizing data routing paths to minimize the distance and energy usage between nodes and the base station.

The energy consumption for a given solution X can be expressed as:

$$E(X) = \sum_{i=1}^{N} \text{ Energy }_{CH}(i) + \text{ Energy }_{\text{Routing}}(i) \qquad (8)$$

where:

- N: Total number of nodes.
- EnergyCH(i): Energy consumed by node iii functioning as a cluster head.
- EnergyRouting(i)\text{Energy}_\text{Routing}(i)EnergyRouting(i): Energy consumed for routing data from node iii to the base station.

2. Network Lifetime

The lifetime of a WSN is defined as the duration until the first sensor node depletes its battery, significantly impacting the overall network performance. Maximizing network lifetime involves:

- Distributing energy usage evenly across nodes to avoid overburdening specific ones.
- Dynamically adjusting CH selection and routing paths based on residual energy.

The network lifetime metric L(X) is inversely proportional to the energy consumption of the most critical node:

$$L(X) = \frac{1}{\max\left(\text{Energy}_{\text{Node}}(i)\right)} \quad (9)$$

where Energy $_{\text{Node(i)}}$ is the residual energy of each node after data transmission.

3. Latency

Latency measures the delay in transmitting data packets from the source to the destination. In critical WSN applications, such as disaster monitoring and healthcare, minimizing latency is crucial to ensure timely responses. The delay D(X) can be represented as:

$$D(X) = \sum_{i=1}^{N} \frac{\text{Distance}_{\text{Node}}(i)}{\text{Transmission Rate}} \quad (10)$$

where:

- DistanceNode(i): Distance between the node and its destination (CH or base station).
- Transmission Rate\text{Transmission Rate}Transmission Rate: Data transfer speed of the network.

3.3 Hybrid Dragonfly and Simulated Annealing Algorithm for WSN

The combination of the Dragonfly Algorithm (DA) and Simulated Annealing (SA) provides an efficient framework for addressing key challenges in Wireless Sensor Networks (WSNs), such as energy efficiency, network lifetime, and latency. DA ensures global exploration of the solution space by mimicking the swarming behavior of dragonflies, while SA refines these solutions through a probabilistic approach, ensuring convergence to an optimal or near-optimal solution. Initially, DA is employed to generate a set of potential solutions by modeling key behaviors like attraction, cohesion, and alignment among nodes. Each dragonfly in the population represents a potential configuration of cluster heads (CHs) and cluster assignments, optimized based on a multi-objective fitness function:

Fitness Function

The fitness function integrates these objectives into a single mathematical expression to evaluate the quality of a solution X. The weighted sum approach ensures flexibility in prioritizing different objectives based on the network requirements:

$$f(X) = w_1 \cdot E(X) + w_2 \cdot L(X) + w_3 \cdot D(X) \quad (11)$$

where:

- E(X): Energy consumption of the current solution.
- L(X): Network lifetime.
- D(X): Latency of the routing paths.
- w1, w2, w3: Weight factors that determine the relative importance of each objective.

Once the solutions are generated, SA is applied to fine-tune the results. Starting with the initial configuration provided by DA, SA introduces small changes to the CH positions or cluster assignments, generating a neighbor solution. The energy difference ΔE between the current and new solutions is evaluated.

$$\Delta E = E_{new} - E_{current} \quad (12)$$

If ΔE<0\Delta E < 0ΔE<0, the new solution is accepted as it represents an improvement. For $\Delta E \geq 0$, the solution is accepted probabilistically using:

$$P = \exp(-\Delta E/T) \quad (13)$$

where T is the current temperature. The temperature decreases iteratively following a cooling schedule, such as $T = \alpha \cdot T$, where α\alphaα is the cooling rate. This hybrid approach leverages the exploration strength of DA and the exploitation capability of SA, providing an effective mechanism for achieving energy-efficient clustering and optimal CH selection in WSNs. The combined methodology ensures reduced energy consumption, prolonged network lifetime, and minimized latency, making it suitable for real-world WSN applications.

3.4 Proposed Algorithm

Input: X[][] = Matrix of Input Layer parameters (Positions, energy, distance, etc.)
Output: CH[][] = Optimal Cluster Head assignments and Network Configuration

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Initialization:
   DA_POP[] = Dragonfly population,   SA_POP[] = Simulated Annealing solutions,
   MaxIter = Maximum number of iterations, T_initial = Initial temperature for SA,
alpha = Cooling rate, X_max = Maximum range of network in X-axis, Y_max =
Maximum   range of network in Y-axis, Fitness[] = Fitness values of solutions

1: Initialize DA_POP[] with random solutions for dragonflies (cluster head candidates)
2: Initialize fitness values for each dragonfly based on distance, energy, and transmission rate
3: for each iteration of DA do:
4:     for each dragonfly d from 1 to population size:
5:         Calculate the attraction, alignment, and cohesion forces based on positions
6:         Update the position of the dragonfly based on calculated forces
7:         Recalculate fitness of dragonfly d after position update
8:     end for
9:     Select the best solutions (cluster heads) based on fitness
10: end for
11: Apply Simulated Annealing for refinement:
12: for each iteration of SA do:
13:     Perturb current CH assignments to explore new configurations
14:     Evaluate fitness for new configuration
15:     if the new configuration is better than the current one:
16:         Accept the new configuration
17:     else if (random chance) accept the configuration based on temperature
18:     Gradually decrease temperature T = T * alpha
19: end for
20: Repeat steps 3 to 19 for the specified number of iterations or until convergence
21: Output: Return the optimal CH assignments and network configuration (CH[][])
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4 Results and Analysis

4.1 Simulation Framework for the Hybrid DA-SA Protocol

The simulation tasks for the hybrid DA-SA protocol are carried out using MATLAB, a robust platform suitable for algorithm development, data analysis, visualization, and numerical computation. The proposed protocol focuses on optimizing cluster formation and data transmission efficiency in Wireless Sensor Networks (WSNs). For this, a random distribution of sensor nodes (SN) is employed within the simulation environment.

4.2 Network Design Assumptions

The deployment of sensor nodes is crucial to understanding the efficiency of the hybrid DA-SA protocol. In this study, 100 SN are distributed within a 100×100 m^2 area, as illustrated in Figure 1. The simulation includes 3500 packet transmission rounds. Notably, the base station (BS) is positioned outside the network's geographical boundary. The probability of selecting a Cluster Head (CH) is fixed at 10%. Among the deployed SN, 10% serve as Application Nodes (AN), while the remaining nodes are designated as Normal Nodes (NN).

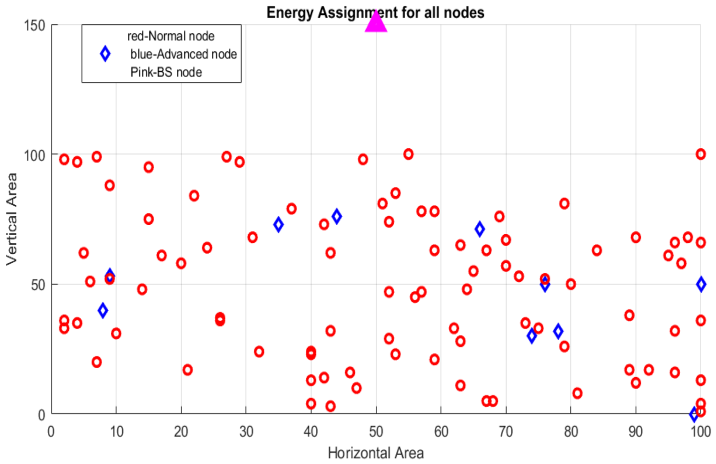

Figure 1: Deployed 100 x 100 m^2 network monitoring area

4.3 Assumptions for the Hybrid DA-SA Protocol

1. Heterogeneous Node Distribution: The network is designed with nodes of varying energy levels and capabilities.
2. Simplified Interference Model: Collisions and noise factors are neglected to streamline simulation analysis.
3. Cluster Head Responsibility: The CHs are responsible for aggregating data from member nodes and forwarding it to the BS.
4. Node Deployment Strategy: Sensor nodes are deployed using a hybrid approach, combining deterministic and random distribution methods to balance uniformity and adaptability.

Table1. Simulation Parameter

Parameter	Values
Number of Sensor Nodes (SN)	100
Network Area	100 × 100 m²
Electronic Energy Consumption (ERX)	50 nJ/bit
Energy for Data Aggregation (EDA)	10 nJ/bit
Initial Battery Energy (E0)	0.5 J
Energy for Free-Space Model (Efs)	10 pJ/bit/m²
Energy for Multipath Model (Eamp)	0.0013 pJ/bit/m⁴

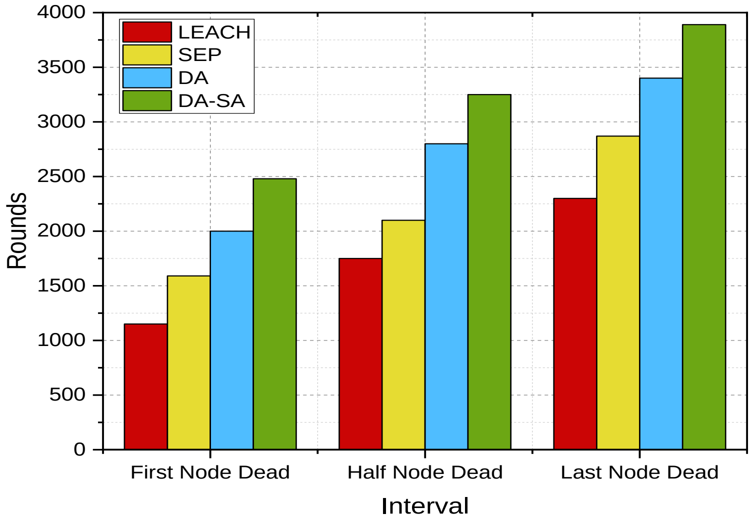

Figure 2: Energy dissipation at different intervals

The simulation for the hybrid DA-SA protocol is conducted over 4000 rounds, with the number of dead nodes tracked at various time intervals, as depicted in Figure 2. The performance of the proposed protocol is evaluated based on key metrics, including the First Node Dead (FND), Half Node Dead (HND), and Last Node Dead (LND). The results demonstrate that the hybrid DA-SA protocol outperforms existing methods, showing a significant improvement in these metrics. Specifically, the protocol delays the occurrence of the first node death, extends the period until half of the nodes die, and further prolongs the network's operational lifetime until the last node becomes inactive.

4.4 Network Lifetime

In Wireless Sensor Networks (WSNs), optimizing routing protocols to achieve energy efficiency is crucial for enhancing the network's lifetime. The lifetime of a WSN is significantly influenced by the operational efficiency of the sensor nodes, which are responsible for sensing, computing, and transmitting data across the network. These activities directly impact the overall endurance of the network. The DA-SA protocol contributes to extending network longevity by optimizing energy consumption through intelligent routing decisions shown in Figure 3. Specifically, the DA-SA approach minimizes the need for long-distance transmissions, reduces control overhead messages, and ensures efficient data aggregation, which prevents data duplication. By strategically managing energy use and reducing congestion within the network, the DA-SA protocol enhances the network's lifetime, allowing it to operate more efficiently over extended periods.

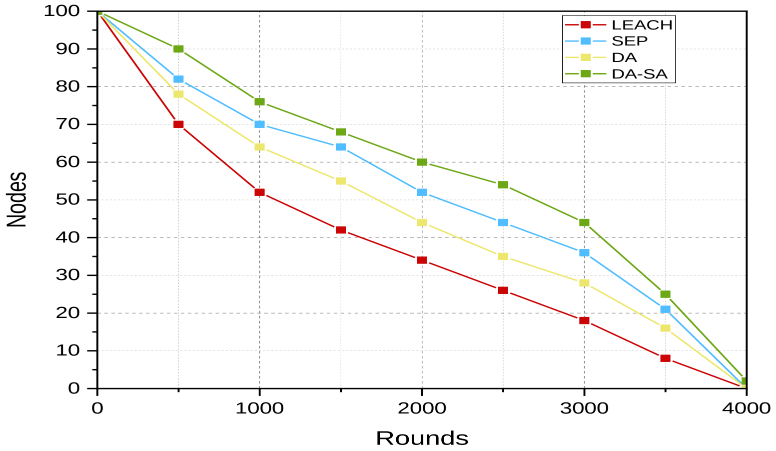

Figure 3. Alive nodes in the Network

End-to-end delay is closely related to latency in wireless sensor networks (WSNs), as it represents the total time taken for a data packet to travel from the source node to the destination, whether it's a cluster head (CH) or base station. Latency, which refers to the delay experienced during data transmission, plays a significant role in determining the efficiency of the network. Several factors contribute to latency, including the distance between nodes, transmission rate, and network congestion. In critical applications like healthcare or disaster monitoring, low latency is essential to ensure real-time data delivery and enable quick responses. Minimizing end-to-end delay, latency can be reduced, leading to enhanced network performance, faster decision-making, and improved reliability in time-sensitive tasks Figure 4 shows that the proposed DA-SA protocol achieved improved results compared to existing protocols.

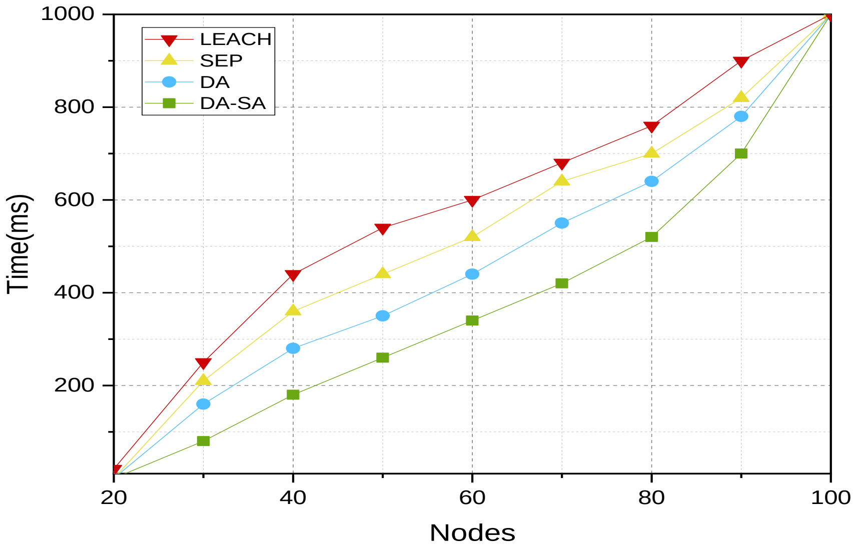

Figure 4. End to End delay

DA-SA achieves lower delays even as the number of nodes increases, which is crucial for maintaining fast data transmission, especially in critical WSN applications.

5. Conclusion

The proposed DA-SA protocol combines the principles of Dragonfly Optimization with Simulated Annihilation based fitness function to enhance energy efficiency and network performance. The proposed DA-SA protocol exhibited remarkable improvements in network lifetime compared to traditional protocols. The proposed DA-SA protocol extended the network lifetime by 64.71% over LEACH, 56.41% over SEP, and 19.05% over DA at 2000 rounds. These consistent enhancements across various rounds emphasize DA-SA's capability to effectively balance energy consumption and prolong the operational duration of WSN. The proposed DA-SA protocol demonstrated significant performance improvements in reducing end-to-end delay compared to traditional protocols. For instance, DA-SA achieved up to 68.75% improvement over LEACH, 42.86% over SEP, and 19.05% over DA for 30 nodes, with similar trends observed across other node counts. These enhancements highlight the protocol's ability to optimize delay reduction effectively, ensuring efficient data transmission in WSNs.

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