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Energy-Efficient Framework Based on Particle Swarm Optimization for Protection of Critical Infrastructures Using Wireless Sensor Networks

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Abstract
Wireless sensor networks (WSNs) have seen increased application in recent years across medicine, the military, and the protection of critical infrastructures. A major challenge in their deployment is limited power supply, which significantly affects its operational lifetime. Several factors such as data transmission latency, packet loss ratio (PLR), and anomalies, also affect the energy-efficiency and by consequence, the lifetime of the WSN. This study proposes an energy-efficient framework based on Particle Swarm Optimization (PSO). The framework is developed in MATLAB, and is capable of detecting anomalies. The model uses Low-Energy Adaptive Clustering Hierarchy (LEACH) to assign cluster heads using k-means while anomaly detection was implemented using isolation forest and statistical z-score. Weibull is used to model wear-out pattern and signal strength while burst errors were modeled using Gilbert-Elliot. The PSO-based routing fitness function considers total energy consumption, packet loss and latency. A cluster of 10 nodes, 15 nodes, 20 nodes, were considered. The performance of these clusters were compared with an unoptimized LEACH-based cluster of 10 nodes. A custom performance metric, energy-latency efficiency index (ELEI) per node is used to assess the performance of each cluster. The ELEI, expressed in Joules per second (J/s), is achieved by the 10, 15, and 20 nodes are 20.866, 11.436, and 78.827 respectively. Another metric, latency-normalized lifetime (LNL) at 215.78 indicates acceptable level of performance. The model performs comparatively well against bacterial foraging Optimization with Harmony Search Algorithm (BFO-HSA) and Trust Index optimized Cluster Head Routing (TIOCHR), for 100 nodes, in terms of latency.

Keywords: *Latency, optimal routing, packet loss ratio, particle swarm optimization, wireless sensor networks.*

1.0 Introduction

The proper functioning of critical infrastructures (CI) such as telecommunication and energy distribution systems are essential to the growth of any society. Failure of any part or the entire system can impact significantly in the socio-economic state of the society thus, ensuring the security and reliability of Cis is essential. Failures may result from natural causes such as disasters or adverse weather, or from physical attacks including tampering and vandalism. WSNs can be deployed on a large scale as a distributed network capability of monitoring, protecting, and sending feedback to complement the traditional methods. WSNs consist of several microsensors connected with each other by self-organization and multi-hop communications (Wang et al., 2018). Each sensor node consists of sensors, a processing unit, a wireless communication module and the battery or power module. They work collaboratively to detect and send information to a sink node (Wang et al., 2018). In the event of an attack or failure, WSNs are less likely to be affected in their entirety. In critical situations, WSNs may still be capable of providing sufficient information or situational report that aids the operator prevent further damage, and begin the recovery process.

WSNs play a crucial role in the surveillance (Gopalan et al., 2024), monitoring, and protection of critical infrastructures (Mani et al., 2024; Basnayaka et al., 2024). Depending on the application, WSNs are capable of threat detection and localization of potential threats (Butt et al., 2024; Li et al., 2022) that could lead to failure through the continuous monitoring of phenomenon such as temperature changes, vibration, pressure etc. Thus, for the protection of critical infrastructures, WSNs provide features such as security, reliability and provides great scalability with possibilities for optimized energy consumption. One drawback of WSNs however is in energy consumption according to Khashan (2024) and Surenther et al. (2024). WSNs usually have battery packs that are irreplaceable (Malisetti and Pamula, 2024; Dass et al., 2023), and a lot of research has gone into developing energy efficient wireless sensor networks to improve WSN applications and deployment. Deployed sensors might be difficult to replace, limiting performance, hence energy-efficient solutions are needed. Other challenges include localization (Wang et al., 2018) needs and cyber-security issues. This study aims to provide a viable solution by incorporating Particle Swarm Optimization (PSO) for efficient packet routing thereby optimizing energy consumption through reduction in latency. Several similar algorithms have been used such as Genetic Algorithm in Bahadur and Lakshmann (2023), improved firefly optimization technique (IFO) (Shankar and Jaisankar, 2021) , Bio-inspired Ant-Cuckoo optimized relay-based energy efficient data aggregation (BACREED) proposed in Ketshabetswe et al. (2024), the hybridized Bacterial Search Algorithm (BSA) and Harmony Search Algorithm (HAS) in Gopalan et al. (2024), Sperm Swarm Optimization (SSO) and Chernobyl Disaster Optimization (CDO) (Shehadah et al., 2018), etc .PSO is implemented here and expected to perform comparatively well. In this paper, a wireless sensor network is developed in MATLAB, primarily with temperature, vibration and intrusion detection sensors for monitoring and protecting critical infrastructures. Figure 1 is a WSN architecture showing the link to the base station

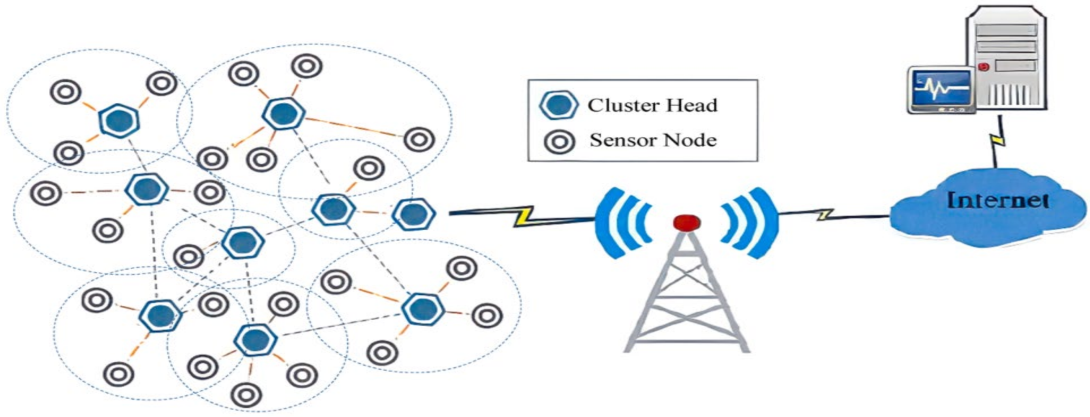

Figure 1: WSN Architecture (Khashan, 2024)

Song et al. (2020) focused on energy saving, improving network performance and extending network lifecycle. In this regard, a hybrid protocol of PSO and evolutionary game theory (EGT) called PSOLB-EGT was developed. This is an efficient clustering and equalization routing protocol. Bhagat et al. (2023) proposed a two-step Neural network - Low-Energy Adaptive Clustering Hierarchy (NN-LEACH) protocol to extend network life and reduce power consumption by clustering and routing sensor nodes using the two-step NN-LEACH protocol. Non-linear energy optimization is achievable in the WSN through the NN-LEACH. The author in Yang (2022), proposed an improved PSO algorithm (improved self-adaptive inertia weight particle swarm optimization [ISAPSO]) to solve issues of poor RSSI (Received Signal Strength Indication). In Cui et al. (2022), the authors developed a localization algorithm assisted by two mobile anchors i.e. MAL (Mobile anchor-assisted localization). This approach was used to balance energy consumption and improve localization accuracy. The authors of Wang et al. (2020), proposed an approach that uses PSO to optimize the coverage control process of wireless sensor networks. The combined mathematics is used to detect the local convergence problem. In Lv and Long (2025), the authors focused on addressing critical issues, such as energy conservation measured through average energy consumption per node, network longevity, and throughput. The paper presented a new scheme for energy-efficient clustering in IoT networks by employing optimized evolutionary rate water cycle algorithm (OERWCA). Xiao et al. (2021) presented an approach, improved adaptive elite ant colony optimization (AEACO) that is proposed to reduce High-density WSN (HDWSN) routing energy consumption. Lizy et al. (2023) focused on solving issues of energy detection efficiency. They proposed a model that forms sensor clusters using k-means clustering algorithm. Chen et al. (2022) proposed the use of an improved ant lion optimizer (IALO) to solve the problem of coverage optimization, and thus improve the network coverage rate and reduce the number of redundant sensors.

2.0 Materials and Methods

The wireless sensor framework is built using MATLAB simulation environment and optimized using Particle Swarm Optimization (PSO). Three separate cases of clusters were considered. They are 10-node cluster, 15-node cluster and the 20-node cluster. The simulated clusters were compared with another un-optimized 10-node cluster based on LEACH. The performance metrics used were custom Energy-latency efficiency index (ELEI) and latency-normalized lifetime (LNL). ELEI shows the trade-off between energy consumption and latency per node while LNL grades the impact on network lifetime. These indices are obtained as follows:

$$\text{ELEI (per node)} = \frac{\text{Energy Remaining (per node)}}{\text{Latency (per node)}} \tag{1}$$

$$LNL = \frac{\sum_{i=1}^{N} T_{life,i}}{\sum_{i=1}^{N} Average\ Latency_i} \tag{2}$$

where $T_{life,i}$ is the projected lifetime of node i and N is the number of nodes in the cluster.

The unit of ELEI is in Joules/second (J/s) showing the amount of energy that can still be expended by the node for packet transmission.

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2.1 Network pseudocode

The pseudocode for the PSO algorithm is outlined below:

1. Network Initialization
i. Define parameters (number of sensors, simulation time, sampling frequency, encryption key, SNR, base station)
ii. Encryption key validation (16-character long)
iii. Initialization of tampered nodes as an array
iv. Generation of sensor data
v. Environmental factors modeling (ambient temperature, humidity and wind speed)
vi. Sensor types assignment and random nodes placement
2. Sensor failure, Channel and Error Modeling
i. Weibull distribution for wear-out patterns
ii. Data normalization
iii. Error detection using CRC (cyclic redundancy check)
iv. Random tampering detection based on encryption and decryption
v. Computation of Rayleigh fading and path loss (free space path loss)
vi. Interference modeling as Gaussian noise
vii. Computation of signal strength using the Weibull distribution.
viii. Packet loss modeling using Shannon Capacity
ix. Implementation of Gilbert-Elliot model for bursty errors
x. Latency modeling based on distance and number of sensors
3. Energy Modeling
i. Modeling re-transmission for failures
ii. Energy consumption modeling for different states (transmission, reception, idle, sleep) and operation (encryption and re-transmission)
4. LEACH Clustering
i. Define number of clusters
ii. Randomly assign coordinates to sensors
iii. Assign cluster heads using k-means and residual energy
iv. Assign cluster members
5. PSO Optimization
i. Define swarm parameters (number of particles, number of iterations, weight, cognitive and social parameter)
ii. Initialization of particle swarm (particle path, particle velocities)
iii. Iterate over particles to evaluate fitness by computing (total energy consumption, packet loss, latency) for routing fitness function
iv. Updating of positions towards the best particle
v. Finalization of optimized routes
6. Anomaly Detection
i. Using statistical z-score and isolation forest
7. Visualization
i. Visualization of parameters (sensor data trends, sensor node, optimal path tracing, energy remaining per sensor, latency distribution, heat-map of sensor data correlation, 3D visualization of network)
8. File Saving
i. Data saving in a file with the columns (sensorID, anomaly, latency, packet loss, SNR, timestamp)
9. Encryption/Decryption

Table 1 shows the network simulation parameters.

Table 1: Network simulation parameters

Parameter	Value

Network Area Size	100m x 100m
Number of Nodes	(10:5:20)
Base Station Location	(0, 0)
Sampling Rate	100Hz
SNR	20 dB
Initial Battery Energy	10000mAh
Number of Particles	30
Maximum Iterations	100
Inertia Weight (w)	0.7
Cognitive Parameter (c_1)	1.5
Social Parameter (c_2)	1.5

Each particle here represents a candidate routing path configuration, which is encoded as a permutation of sensor node identity. The goal of the PSO is to minimize the routing path function in a way that maximizes the energy efficiency, latency, and reliability of the wireless sensor network. The routing fitness function evaluates each particle based on the following parameters:

1. Path length or hop count: This is defined as the number of intermediate nodes in the routing path.
2. Energy consumed (E): This is the total energy consumed by the nodes involved in the routing path.
3. Latency (L): Describes the end-to-end delay during packet transmission on the average.
4. Packet Loss ratio (P): This defines the rate at which packets are lost during transmission. It is a measure of reliability and reflects the quality and congestion of the link.

Considering the aforementioned parameters, the fitness function is defined as:

$$fitness = w_1 E + w_2 L + w_3 P \tag{3}$$

where w_1, w_2 and w_3 are weights that can be adjusted for better performance.

For anomaly detection, the model adopts the unsupervised isolation forest in identifying outliers based on path lengths with a contamination fraction of 10%. This sets a limit to the number of possible anomalies that can be caught. While some anomalous behaviours might be missed, it reduces the possibility of false negatives. As a fallback, a statistical z-score method is implemented. Any data point exceeding 3 standard deviations is caught as anomalous.

3.0 Results and Discussion

MATLAB was used to simulate the wireless sensor network for 10-node, 15-node and 20-node cluster.

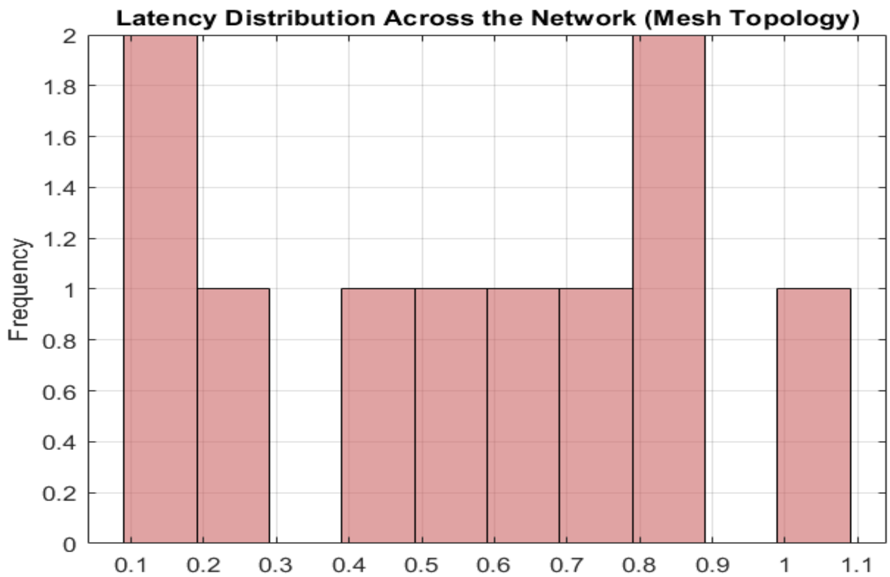

Figure 2: Latency distribution for 10-node cluster (Case One)

In figure 2, the maximum latency recorded is between 1 and 1.1s. The frequency of latency between 0.1 to 0.2s and 0.8 to 0.9s is two (2).

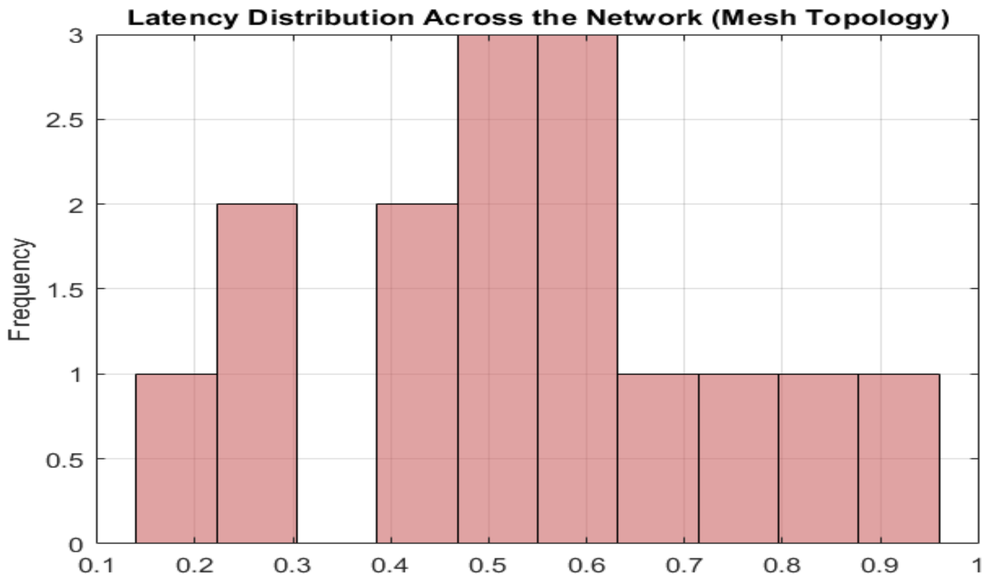

Figure 3: Latency distribution across the 15-node cluster (Case Two)

In figure 3, the maximum latency recorded is between 0.9 and 1s. The frequency of latency between 0.5 to 0.6s is three (3). This indicates variability and could imply inconsistent performances.

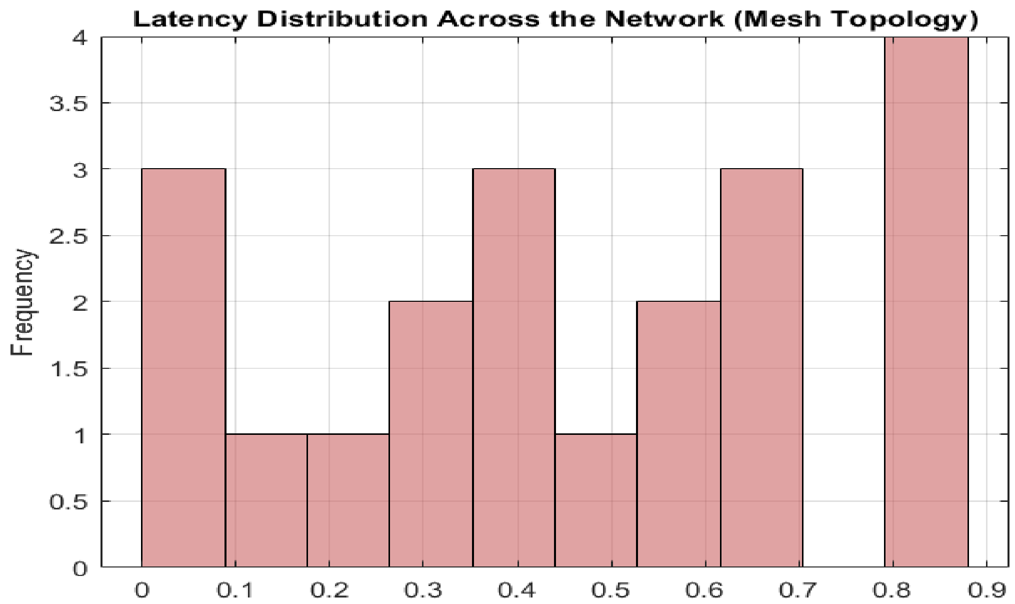

Figure 4: Latency distribution across the 20-node cluster (Case Three)

In Figure 4, the maximum latency recorded is between 0.8 and 0.9s. The frequency of latency at this point is four (4).

As the nodes within a cluster increases, the maximum latency per node tends to drop off indicating reduction in latency. The specific latency of each node for each of the considered clustered cases is pictured in figure 5.

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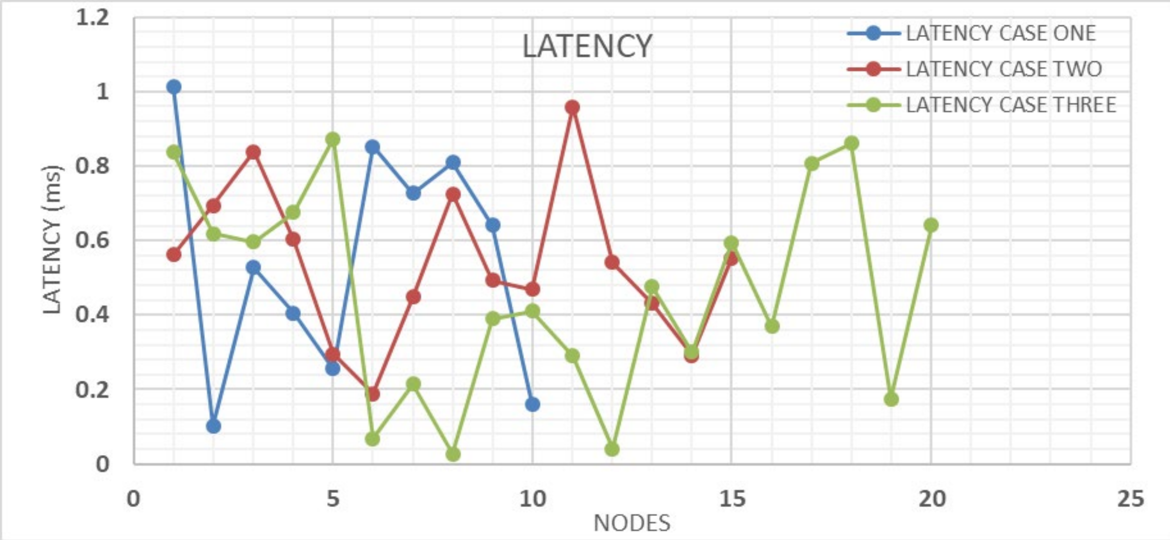

Figure 5: Latency plot

From figure 5, it can be seen that the highest value of latency occurred in the 10-node cluster at 1.014s while for the 20 nodes cluster this is at 0.8732s. Comparing these two values, there is a reduction of 13.88% in latency as the cluster doubled from 10 to 20 nodes. Also, the lowest values are at 0.027s within the 20 nodes cluster and 0.1029s within the 10-node cluster. This amounts to a 73.53% reduction in latency between both clusters.

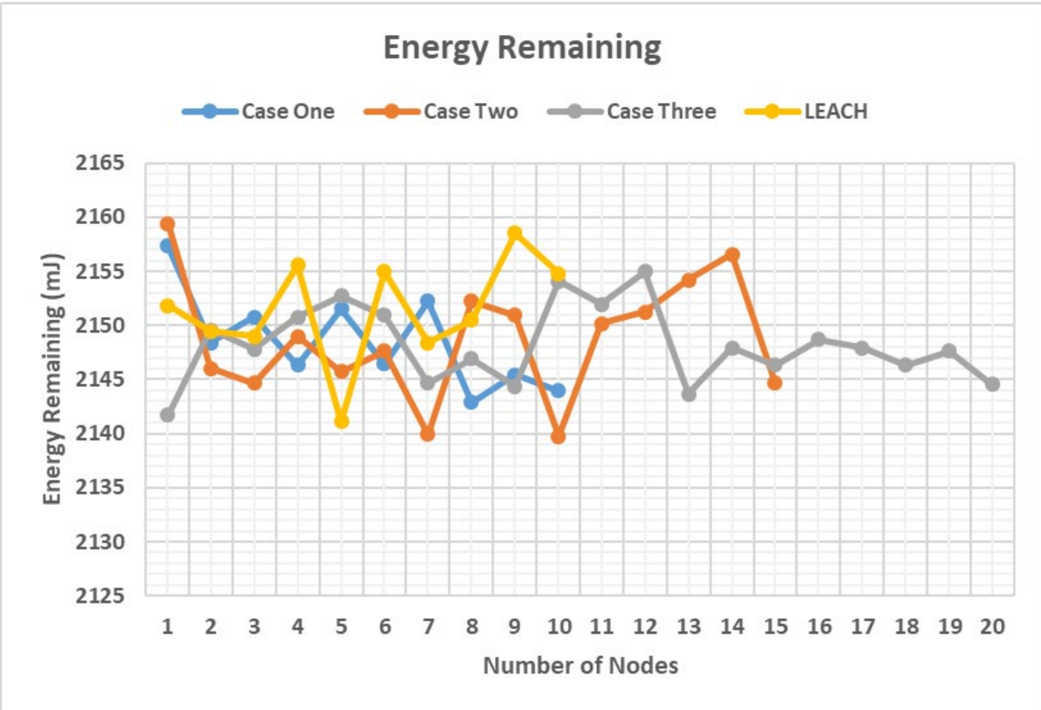

Figure 6: Energy remaining

In figure 6, the baseline LEACH has been included. This plot shows the energy remaining in each individual node after the simulation time elapses with an initial energy of 10 J.

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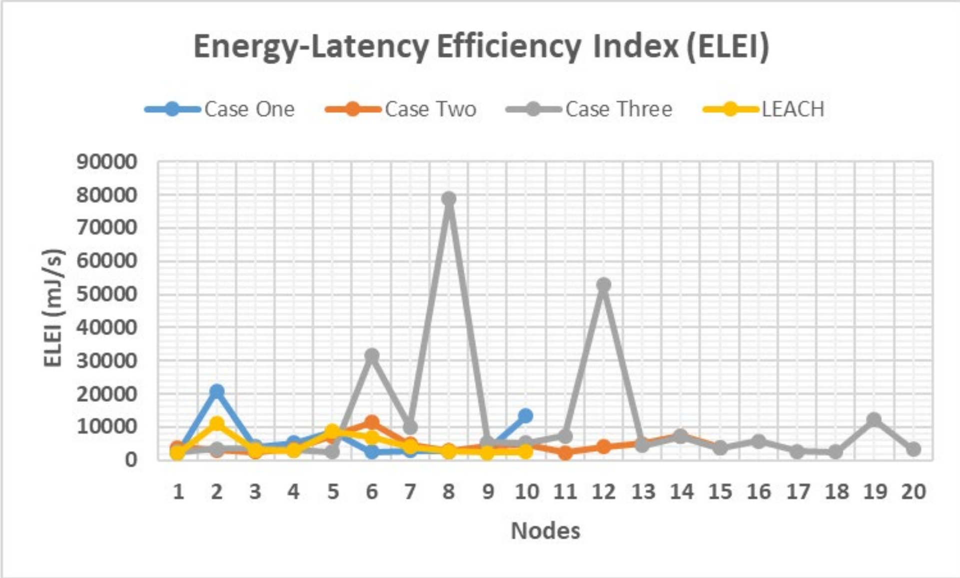

Figure 7: Energy-latency efficiency index per node

In figure 7, the ELEI values of all the simulated clusters are presented. The plot shows the excellent performance of the 20-node cluster over the other three (3) scenarios. The 20-node cluster has a node with an ELEI of 78.827 J/s. Table 2 summarizes the performance values of the simulations.

Table 2: Performance metrics (Average values)

Cluster Type	Metrics			
	Latency (s)	Energy Consumed (mJ)	ELEI (J/s)	LNL
Unoptimized	0.6395	7848.59	4.626	156.37
10 nodes	0.5496	7851.46	6.562	181.97
15 nodes	0.5395	7851.18	4.725	185.34
20 nodes	0.4634	7851.82	12.417	215.78

From table 2, the 20-node cluster has the lowest average latency, the highest average energy consumed and the highest average ELEI value which is desirable. This indicates the superior performance of the 20-node cluster. The LNL value of 215.78 is within acceptable limits for the lifetime

To validate the system, the framework was compared with the approach BFO-HSA (bacterial foraging Optimization with Harmony Search Algorithm) presented by Gopalan et al. (2024) and Babu et al. (2024), for a 100 nodes. Figure 8 shows the latency distribution for the simulated 100 nodes cluster. Most of the nodes have latency 0.2 to 0.6s.

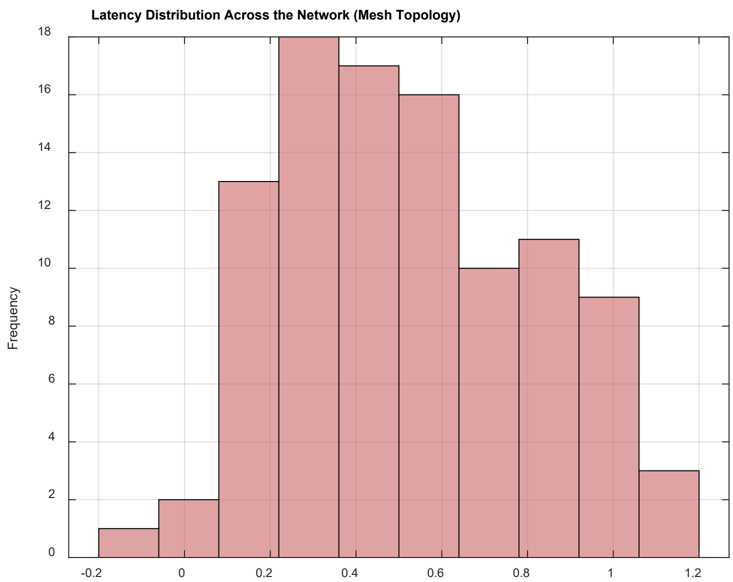

Figure 8: Latency distribution for 100 nodes cluster

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Table 3 compares the latency of the approach used in Gopalan et al. (2024), Babu et al. (2024), and the PSO-based approach in this study.

Table 3: Performance comparison for 100 nodes

Property	Value		
	BFO-HSA	TIOCHR	PSO-based Method
Latency (s)	0.019	9	0.52243

The approach in this study performs relatively better against the TIOCHR though not as efficient in terms of latency reduction as the hybrid BFO-HSA.

4.0 Conclusion

Particle Swarm Optimization (PSO) was adopted in this research and the MATLAB environment, to detect the optimal routing path of data from the sensor nodes. The method showed that the PSO improved the energy consumption by lowering the latency to 0.873s for 20 nodes. This value represents a 13.88% improvement over the 10-node cluster. The 20-node cluster has an average ELEI value of 12.417 J/s and LNL of 215.78 which both indicate good performance or trade-off between latency and energy consumption.

The developed algorithm can be implemented for the protection of critical infrastructures due to its ability to optimize energy consumption and optimal packet routing. The study also shows that increasing the number of nodes in the cluster can further reduce latency.

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