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PSOGWO Algorithm Based Optimized Cluster Head Election In Leach

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Abstract: The advancement of microelectronics and wireless communication technologies has facilitated the widespread adoption of small, networked, and cost-effective sensors in industrial applications and environmental monitoring. Wireless Sensor Networks (WSNs), however, encounter significant challenges due to limitations such as limited processing power, small memory capacity, energy constraints, and network-specific issues like narrow bandwidth and dynamic topology changes. This paper explores the enhancement of WSNs through the implementation of the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol and a hybrid optimization technique, combining Particle Swarm Optimization and Grey Wolf Optimizer (PSOGWO), for cluster head election. Our approach aims to optimize the lifecycle of nodes within the network. Performance metrics such as network lifetime and network throughput are evaluated to demonstrate the effectiveness of the proposed methods. The results indicate a significant improvement in both network longevity and data transmission efficiency, showcasing the potential of optimized cluster head selection in extending the operational lifespan of WSNs.

Index Terms – PSO, PSOGWO, LEACH, WSN.

I. Introduction

Wireless Sensor Networks (WSNs) consist of a large number of sensor nodes deployed in various environments, each powered by a battery. Due to the impracticality of replacing the battery in every node, it is crucial to efficiently manage the limited energy available. Therefore, designing energy-efficient algorithms becomes essential [1]. In WSNs, nodes are spatially distributed and often require multi-hop communication to transmit data to a base station or sink node, especially when the base station is out of direct communication range. This multi-hop data transmission involves multiple intermediate nodes, which consume additional energy by forwarding data from their neighbors, thereby depleting the network's overall energy resources. This challenge motivates the reduction of hops and intermediate nodes in data transmission, achievable through clustering algorithms [2].

In clustering, sensor nodes are grouped into clusters, with each node transmitting data only to its designated cluster head. The cluster head aggregates data from all member nodes and forwards it to the sink or base station, thus minimizing the energy consumption by reducing the number of transmitting nodes [3]. Hierarchical cluster-based routing protocols are especially beneficial due to their energy-efficient nature, data aggregation capabilities, load balancing, and improved network lifetime. These protocols can be centralized or distributed, depending on the cluster head selection process, which typically considers the location and residual energy of nodes within the cluster. One well-known protocol that utilizes this approach is the Low-Energy Adaptive Clustering Hierarchy (LEACH) [4]. LEACH is a chain-based protocol where each node communicates only with its immediate neighbors, thereby further reducing the number of active transmitting nodes and conserving energy [5].

Despite the advantages of hierarchical clustering in Wireless Sensor Networks (WSNs), using a fixed cluster head can be a drawback. This is because all data from member nodes are routed through the cluster head, leading to higher energy consumption at that node, which may cause it to die prematurely. However, this centralized approach can still improve the overall network lifetime. Increasing the size of the cluster head or providing it with more power than the member nodes can extend its operational lifespan. Thus, hierarchical-based clustering remains an effective strategy for enhancing network longevity and energy efficiency [6].

WSNs consist of numerous sensor nodes that communicate wirelessly, each capable of sensing, processing, and transmitting data to neighboring nodes, forming a network. Data packets travel from the source to the destination node via several intermediate nodes. The choice between long and short routes can significantly affect network performance: long routes may lead to network delays and longer simulation times, while short routes generally consume less energy and minimize delays. The selection of routing protocols in WSNs is application-specific, tailored to optimize performance for different use cases [7].

Often described as distributed networks, WSNs feature nodes that operate independently, handling data transmission autonomously. These networks consist of small, randomly dispersed devices, and the size of sensor nodes can vary significantly based on application requirements. Networking topologies in WSNs also vary, with users typically retrieving information by querying the system and receiving the corresponding results.

In proposed research, we perform a comparative analysis between the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol and a variant optimized using the hybrid (Particle swarm optimization and Gray wolf optimization) PSOGWO algorithm for cluster head election. This study aims to identify methods that enhance network lifetime and reduce energy consumption [8].

II. PROPOSED METHODOLOGY

2.1 Low-Energy Adaptive Clustering Hierarchy (LEACH)

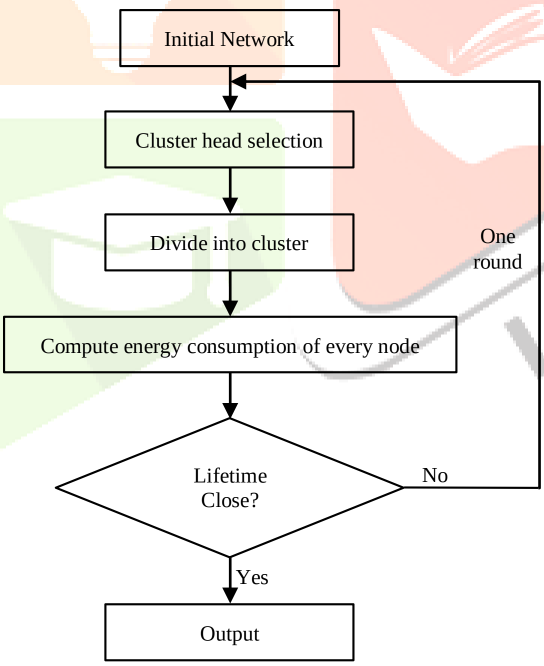

Figure 1: Flow chart for LEACH protocol

During the configuration phase of the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, cluster heads are selected randomly. Each sensor node generates a random number between 0 and 1. If this randomly generated number is less than a predetermined threshold T(n), the node is designated as a cluster head for that round. The threshold T(n) is typically calculated based on factors such as the desired percentage of cluster heads, the current round, and whether a node has been a cluster head recently, ensuring a balanced energy consumption across the network. Formulas of $T(n)$ as follows [9]:

$$T(n) - \int_0^n \frac{p}{1-p\left[r \bmod \left(\frac{1}{p}\right)\right]} \text{ with } n \in G \qquad (1)$$

Where, p is the percentage of the number of cluster headers and the total number of nodes in the network, r is the number of the current round, G is the set of cluster nodes except the cluster head of the last rounds $\frac{1}{p}$. After the cluster head is selected in the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, the chosen cluster head broadcasts a message to the entire network, indicating its status as the cluster head. Nodes decide to join a cluster based on the signal strength of the received message and respond to the appropriate cluster head. In the subsequent phase, each node uses the Time Division Multiple Access (TDMA) method to transmit data to the cluster head. The cluster head then aggregates and forwards the fused data to the base station or sink node. Among different clusters, communication is managed using the Code Division Multiple Access (CDMA) protocol to avoid interference.

After a stable period, the network enters the next round of cluster head selection and data transmission, following a continuous cycle. The random selection of cluster heads helps to distribute energy consumption evenly across the network, thereby extending network lifetime. Data fusion at the cluster heads effectively reduces data traffic, contributing to overall energy efficiency.

However, the LEACH protocol's use of multi-hop communication can present challenges. While transmission delays are minimized, nodes still require high power for communication, limiting the protocol's scalability and making it less suitable for large-scale networks. In smaller networks, nodes farthest from the base station must communicate at higher power levels, potentially shortening their lifespan. Furthermore, the frequent selection of new cluster heads can increase energy consumption, impacting the network's overall energy efficiency and longevity.

2.2 PSOGWO Optimized Cluster Head Election Probability

Let n_{alive} represents the number of alive nodes with residual energy greater then the threshold energy and p be the clusterhead election probability, then the optimum number of CH elected for a given round will be [10]:

$$P_{opt} = n_{alive} * p \qquad (2)$$

Here P_{opt} is optimized using hybrid PSOGWO optimization, which is described as:

This section provides a detailed description of the optimal design process, employing the PSO-GWO hybrid algorithm. The approach integrates the strengths of both PSO and GWO to efficiently explore the parameter space and determine the optimal neural network weight parameters.

2.2.1 Particle Swarm Optimization (PSO)

PSO represents an optimization algorithm grounded in the collective behavior observed in bird flocks or fish schools. Within the PSO framework, a population, termed particles, explores the search space to identify the optimal solution. Every particle adapts its position by drawing insights from its individual experiences and the collective experience of the most successful particle within the population.

The position update equation for each particle in PSO is given by:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \qquad (6)$$

Where:

$X_i^{(t+1)}$ is the updated position of particle i in the t+1 iteration,

$V_i^{(t+1)}$ is the velocity of particle i in the t+1 iteration.

The velocity is updated using both personal best (P_{best}) and global best (G_{best}) information.

2.2.1.1 PSO Algorithm:

Initialize constants and variables $(T, S, c_1, c_2, x_i^0, v_i^0)$
for i=1 to S do
    $pbest_i^0 \leftarrow x_i^0$
end for
for $i = 1$ *to S do*
    Update $gbest_i^0$
end for
for t=1 to T do
    for i=1 to S do
        Update v_i^t *and* x_i^t

$\quad\quad Evaluate\ f(x_i^t)\ and\ update\ pbest_i^t$
$\quad end\ for$
$\quad for\ i = 1\ to\ S\ do$
$\quad\quad Update\ gbest_i^t$
$\quad end\ for$
$end\ for$
$return\ gbest \leftarrow min_{gbest_i}\{f(gbest_i^T)\}$

2.2.2 Grey Wolf Optimization (GWO)

GWO is inspired by the hunting behaviour of grey wolves and is a metaheuristic optimization algorithm. In GWO, three types of wolves (alpha, beta, and delta) are assumed to lead the pack. Wolves adjust their positions based on the positions of these leaders.

The position update equation for each wolf in GWO is given by:

$$X_i^{(t+1)} = X_\alpha^{(t)} - A \cdot D_i^{(t)} \tag{7}$$

Where:
$X_i^{(t+1)}$ is the updated position of wolf i in the $t+1$ iteration,
$X_\alpha^{(t)}$ is the position of the alpha wolf in the t iteration,
A is a coefficient,
$D_i^{(t)}$ is a random vector.

2.2.3 PSO-GWO Hybrid Optimization

The hybrid optimization technique, combining the PSO and GWO algorithms, harnesses the unique strengths inherent in each. In every iteration, the PSO algorithm steers the population toward promising sectors within the search space. Subsequently, the GWO algorithm comes into play, strategically exploiting these identified regions for enhanced performance.

The comprehensive hybrid optimization unfolds through the following sequential steps:

Initialization: Kick-start the particle population with randomly assigned positions and velocities.

Fitness Evaluation: Gauge the fitness of each particle by applying the objective function, wherein, for neural network design, the MSE method is employed.

PSO Update: Refine the position and velocity of each particle through the application of the PSO algorithm.

GWO Exploitation: Transition to GWO after a predefined number of iterations or upon meeting specific criteria, intensifying the exploitation of promising regions pinpointed by PSO.

Optimal Solution: Determine the optimal solution by assessing the best-performing outcome achieved throughout the entirety of the hybrid optimization process.

The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

III. Simulation and Results

The Simulation is carried out using MATLAB 2019a.

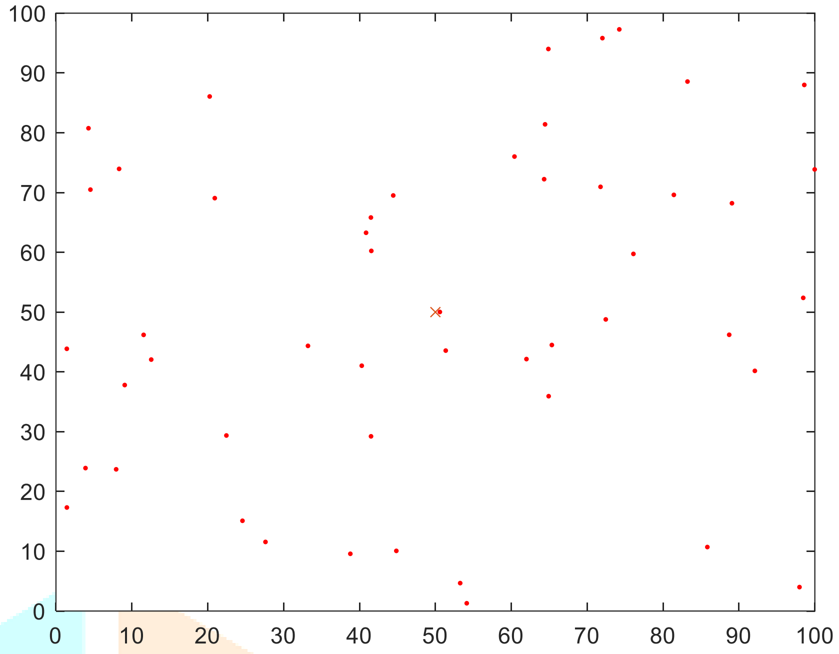

Figure 2: Node execution PSOGWO optimized Leach

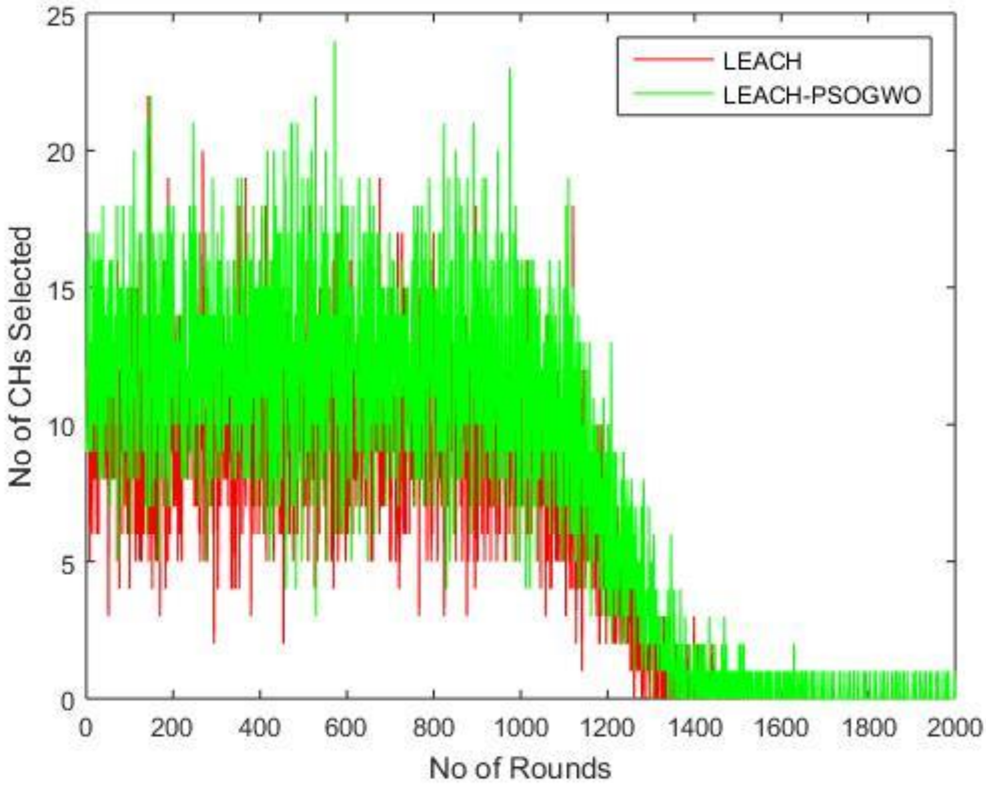

Figure 3: Cluster head formation vs Number of round

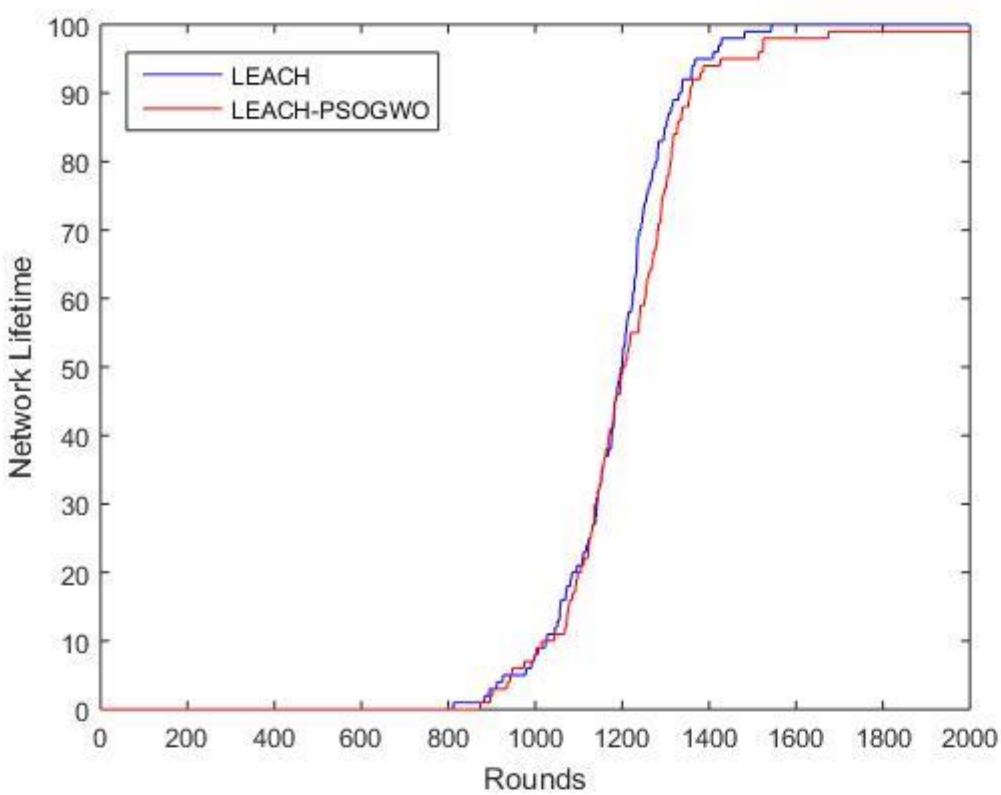

Figure 4: Network lifetime comparison between LEACH and LEACH-PSOGWO for 100 nodes and 5000 rounds

Figure 4 illustrates the network lifetime comparison between the LEACH protocol and the PSOGWO-LEACH approach. The simulation considers a field with dimensions of 100 meters in both the x and y directions. The network comprises 100 sensor nodes, with a 10% probability for each node to become a cluster head. The initial energy for each node is set at 0.5 Jules. Performance was evaluated over 5000 iterations. The results clearly demonstrate that the proposed PSOGWO-LEACH approach significantly outperforms the traditional LEACH protocol in terms of extending the network's lifetime. Lifetime comparison is as shown in table 1. The stable period is increased by 9.25% and overall lifetime of the network is increased by 27%.

Table 1: Network lifetime comparison of LEACH and LEACH-PSOGWO

	FND(1st node dead)	HND(50% node dead)	LND(100% Node Dead)
LEACH	810	1200	1547
LEACH-PSOGWO	875	1207	1970

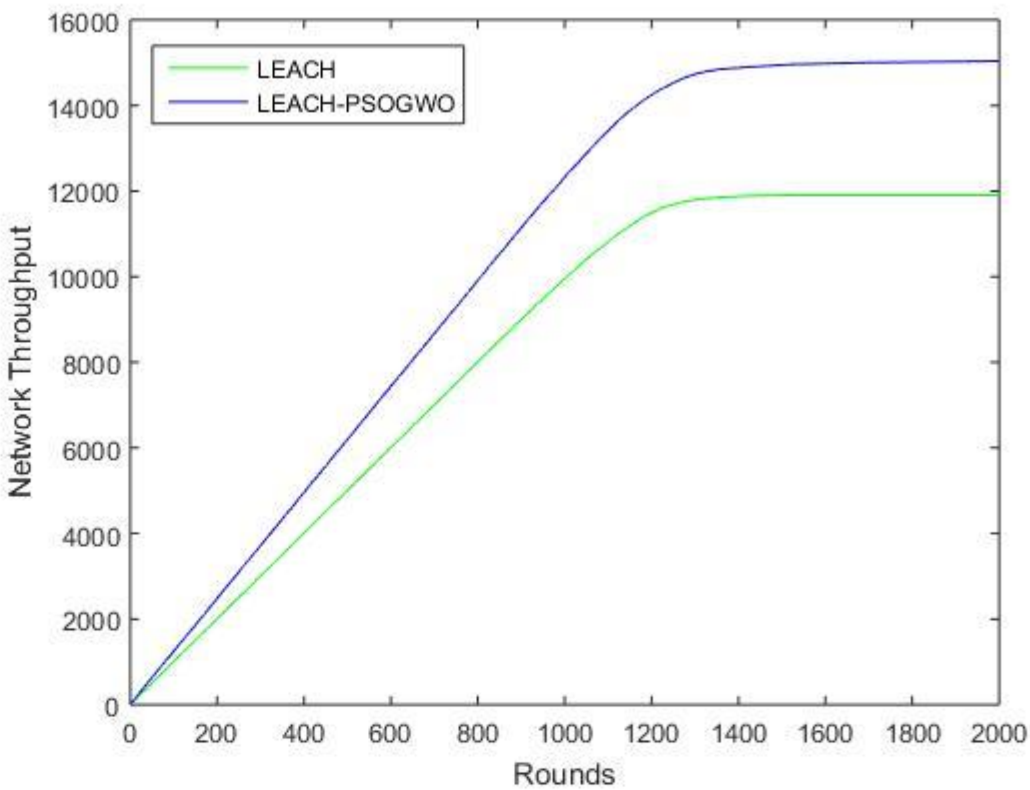

Figure 5: Throughput comparison between LEACH and PSOGWO-LEACH for 100 nodes and 5000 rounds

The **Figure 5** presents a comparison of network throughput between the LEACH protocol and the PSOGWO-LEACH approach. The simulation setup involves a field measuring 100 meters in both the x and y directions. The network consists of 100 sensor nodes, with each node having a 10% probability of becoming a cluster head. Each node starts with an initial energy of 0.5 units. The throughput performance was measured over 5000 rounds. The results indicate that the PSOGWO-LEACH approach significantly outperforms the traditional LEACH protocol, achieving higher network throughput. Throughput comparison is as shown in table 2. The throughput in stable period is increased by 33.57%% and overall throughput of the network is increased by 26.02%.

Table 2: Throughput comparison of LEACH and LEACH-PSOGWO

	Throughput at FND(1st node dead)	Throughput at HND(50% node dead)	Throughput at LND(100% Node Dead)
LEACH	8115	11490	11910
LEACH-PSOGWO	10840	14290	15010

IV. CONCLUSION

In this research, we evaluated routing protocols for Wireless Sensor Networks (WSNs) with a focus on enhancing energy efficiency and network performance. We structured our study into two scenarios: one using the standard LEACH protocol and the other utilizing an optimized version, PSOGWO-LEACH. Various network topologies were implemented to conduct a comparative analysis.

The proposed energy management framework, utilizing the PSOGWO-LEACH algorithm, demonstrated superior performance compared to the traditional LEACH protocol. Our findings indicate that PSOGWO-LEACH significantly improves both network lifetime and throughput, thereby making it a more effective solution for energy management in WSNs. This research contributes to the ongoing efforts to optimize WSN protocols for better resource utilization and longevity.

REFERENCES

[1] Daanoune, Ikram, Baghdad Abdennaceur, and Abdelhakim Ballouk. "A comprehensive survey on LEACH-based clustering routing protocols in Wireless Sensor Networks." Ad Hoc Networks 114 (2021): 102409.

[2] Mohammed, F. A., Mekky, N., Suleiman, H. H., & Hikal, N. A. (2022). Sectored LEACH (S-LEACH): An enhanced LEACH for wireless sensor network. IET Wireless Sensor Systems, 12(2), 56-66.

[3] Daanoune, I., Baghdad, A., & Ballouk, A. (2021). Improved LEACH protocol for increasing the lifetime of WSNs. Int. J. Electr. Comput. Eng. IJECE, 11(4), 3106-3113.

[4] Nasr, S., & Quwaider, M. (2020, April). LEACH protocol enhancement for increasing WSN lifetime. In 2020 11th International Conference on Information and Communication Systems (ICICS) (pp. 102-107). IEEE.

[5] Radhika, M., & Sivakumar, P. (2021). Energy optimized micro genetic algorithm based LEACH protocol for WSN. Wireless Networks, 27, 27-40.

[6] Lasisi, I. O., Gbolagade, K. A., & Asaju-Gbolagade, A. W. (2023). GWO Optimized LEACH CRT-Based Forwarding Scheme for Wireless Sensor Networks Energy Optimization. European Journal of Computer Science and Information Technology, 11(4), 34-50.

[7] Prithi, S., & Sumathi, S. (2021). Automata based hybrid PSO–GWO algorithm for secured energy efficient optimal routing in wireless sensor network. Wireless personal communications, 117, 545-559.

[8] Ahmadi, R., Ekbatanifard, G., & Bayat, P. (2022). BioWSN: A Bio-Inspired Method for Optimization of Routing in Wireless Sensor Networks. Mathematical Problems in Engineering, 2022(1), 4826388.

[9] Yadav, R., Sreedevi, I., & Gupta, D. (2022). Bio-inspired hybrid optimization algorithms for energy efficient wireless sensor networks: a comprehensive review. Electronics, 11(10), 1545.

[10] Bharany, S., Sharma, S., Alsharabi, N., Tag Eldin, E., & Ghamry, N. A. (2023). Energy-efficient clustering protocol for underwater wireless sensor networks using optimized glowworm swarm optimization. Frontiers in Marine Science, 10, 1117787.