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facilitate multimedia pathways in wireless sensor networks using GWO and learning techniques

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Abstract:

To improve the performance and extend the operational lifetime of wireless sensor networks (WSNs), this thesis presents a novel two-stage hybrid approach based on energy efficiency and resource constraints. In the first stage, a GWO-based optimization is applied to the cluster head selection, which is assisted by K-means clustering to provide better starting solutions and increase the convergence speed. This form of hybridization increases the energy consumption efficiency along with improving the overall energy efficiency. The second stage focuses on optimizing the multi-hop routing between cluster heads. In order to achieve energy-optimized routing, PSO is combined with Prim's minimum spanning tree (MST) algorithm. Since the implementation of PSO is computationally very intensive, the optimal paths generated by PSO are learned by an LSTM neural network. The weighted routing prediction inferred by LSTM enables independent PSO inference during routing without comprehensive optimization, eliminating computational overhead, thereby saving time and energy. The computational efficiency of the proposed GWO-LSTM method comes at a negligible cost to routing performance.

Keywords: Wireless sensor. networks, particle swarm optimization, gray wolf algorithm,

Introduction:

The development of Wireless Sensor Networks (WSNs) has taken place in recent years and is especially impactful for scientific and industrial fields. WSNs are networks made of small sensor nodes that are capable of gathering specific environmental data and transmitting it wirelessly to a central computer or any other nodes. The IoT-based automation systems of today facilitate the real time

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tracking and monitoring of environmental factors, thus making WSNs significantly useful in sectors such as agriculture, healthcare, industry and IoT as well as smart transportation systems, environmental monitoring smart agriculture, intelligent security, and even in warning systems [1].

Although there are many advantages, wireless sensor networks (WSN's) have to deal with very strict limitations like with: low processing capacity, limited memory, and most importantly, lack of a power supply. Out of all of the challenges within WSNs, optimizing energy consumption and extending the network's lifetime are the most crucial research concerns. These networks' performance and stability can be greatly enhanced by optimizing energy consumption [2].

A major way to reduce energy consumption is to improve the design of clustering structures and the data routing techniques between the nodes and the base station. In these structures, some nodes are chosen as cluster heads which are responsible for gathering data from the cluster members and send it to the destination. Selecting these cluster heads and the way the paths of data transmission are designed so that energy consumption is minimal has been one of the focal points in WSN for a long time [3].

Research method:

This research proposes a hybrid method for optimizing energy utilization and extending the lifespan of wireless sensor networks (WSNs). This method is carried out in two stages: the first stage focuses on carrying-out clustering-by picking the best cluster heads and in the second stage, multi-hop routing is refined to transfer data from cluster heads to the base station.To enhance the effectiveness of the system, optimal cluster head selection is done using Grey Wolf Optimizer (GWO), while communication route optimization is done by combining Particle Swarm Optimization (PSO), Recurrent Neural Network (RNN), and Minimum Spanning Tree (MST) algorithms. This approach achieves

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reduced energy consumption, prolonged network lifetime, and improved stability of communication pathways[4].

In the initial phase, the nodes of the network are organized into a collection of independent clusters. Each cluster has a designated cluster head which is tasked with gathering and transmitting sensor data. The residual energy of the nodes, their distance from the rest of the node members in the cluster, as well as their position with respect to the base station are some of the factors that will be considered when applying the Grey Wolf Optimizer to define the optimal cluster heads. To perform this optimization, the network nodes are randomly initialized, creating a set of initial solutions, with each solution being one possible set of cluster heads. Subsequently, the GWO algorithm employs the three roles of wolves: alpha, beta and delta, to explore optimal solutions. These wolves influence the solution by applying the objective function which includes residual energy, distance to member nodes, and uniform energy utilization within the network[5]. This enables iterative refinement of the cluster head selection until the optimal set is achieved. Upon completion of this optimization, the non-cluster head nodes join the previously identified cluster heads at minimal distance and energy expenditure, and a layered clustering topology is structured.

In the second stage, it is essential to transmit the gathered data from cluster heads to the base station. Due to the energy constraints inherent in wireless sensor networks (WSNs), this transmission is done through multi-hop routing. Initially, the routing problem is addressed as an optimization issue, applying the PSO (Particle Swarm Optimization) algorithm to establish communication routes between the cluster heads[6]. In this approach, each particle represents a potential routing path, and its position is adjusted according to criteria such as minimum energy expenditure, shortest distance, and a balanced load among the cluster heads. After some iterations, an optimal set of paths is achieved for data transmission to the base station. However, due to the high computational demand of executing PSO at each time interval, a predictive model leveraging a Long Short-Term Memory (LSTM) recurrent neural network is trained to forecast

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optimal routes based on the current state of the network. This neural network is provided with data on the positions of the cluster heads, their remaining energy levels, and the status of network connections to make predictions on the optimal routing paths, thereby eliminating the need to re-run the PSO algorithm[7].

Stages of the Grey Wolf Optimization Algorithm

The GWO algorithm seeks to detect the optimal solution to a given problem by emulating the wolf-pack hunting technique. Its operation is cycle based, improving the solution in steps, as illustrated below [8]:

1. **Representation of Wolf Positions** : Each GWO wolf has its distinct optimization problem solution serving as a position, and the wolf's location is indicative of a possible solution in relation to the search space. By keeping a diverse population of wolves, the algorithm explores the search space to hunt for the best solution.
2. **Position Update** : The location of every wolf is updated according to algorithms that simulate their hunting behavior and movement towards the best possible solutions. This method is broken down into three stages:
   - **Alpha, Beta, and Delta Wolves**: These wolves' locations are modified according to their contacts with the leader wolves, mimicking collective decision making over a hunt.
   - **Omega Wolves**: The wolves reposition themselves by moving towards the leaders, aligning their decisions to converge on the optimal strategies.

With the GWO algorithm, there is construction of formulas to update the position so that a balance between exploration and exploitation is achieved in the search space. The algorithm successively focuses the search on the most promising solutions and narrows down the search using this method [9].

1. **Position Update for Alpha, Beta, and Delta Wolves**:

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$$\vec{D}_\alpha = |\vec{C}_\alpha.\vec{X}_\alpha(t) - \vec{X}(t)|$$

$$\vec{D}_\beta = |\vec{C}_\beta.\vec{X}_\beta(t) - \vec{X}(t)|$$

$$\vec{D}_\delta = |\vec{C}_\delta.\vec{X}_\delta(t) - \vec{X}(t)|$$

Here, $\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta$ are the distances from the current position to the position of Alpha, Beta and Delta wolves, respectively. $\vec{X}(t)$ is the current position of the wolf. $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ are the position of the Alpha, Beta and Delta wolves. $\vec{C}_\alpha, \vec{C}_\beta, \vec{C}_\delta$ are vectors that simulation the hunting behavior and randomly generated within a specific range:

2. Update the position of Each Wolf:

$$\vec{X}(t+1) = \vec{X}(t) + \vec{A}.\vec{D}$$

Here, $\vec{A}$ is a vector used to control the step size of the movement it is randomly chosen within the range of [-2,2]. $\vec{D}$ is the distance vector calculated above, determining where the wolf should move?

3. Position Updates

Wolves modify their locations at every iteration based on the positions of the best leaders found so far within the decided bounds. This continues until the stopping conditions such as the maximum number of iterations or a desired results is achieved.

Formulas and Functionality

Vectors C and A: These vectors are randomly generated and control the movement of wolves.

$$\vec{A} = 2.\vec{r}_1 - 1$$

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$\vec{C} = 2.\vec{r}_2$

Here, $\vec{r}_1$ and $\vec{r}_2$ are random numbers within the range [0,1].

Simulation Results:

To validate the performance of the proposed method, extensive simulations were conducted in a MATLAB environment under realistic wireless sensor network (WSN) conditions. The WSN was deployed over a $200\,\text{m} \times 200\,\text{m}$ two-dimensional sensing area, with 100 sensor nodes randomly distributed within this region. The base station (BS) location was varied to test performance under different topological conditions. The maximum number of cluster heads (CHs), denoted as K, was set to 10, a reasonable upper bound for a network of 100 nodes to ensure balanced clustering without excessive energy overhead. All sensor nodes were initialized with 1 J of energy. The packet size for both transmission and reception was set to 500 bytes, and the data aggregation ratio (ρ) was fixed at 0.01 to simulate energy-efficient data fusion at the CH level. The radio energy dissipation model followed the widely accepted free-space and multipath fading channel models, with energy consumption parameters as listed in Table 1. These include the electronic energy per bit (e_{elec}), energy required by the transmitter amplifier in free space (e_{fs}), and the multipath fading coefficient (e_{mp}). The energy cost for data aggregation (e_{da}) was also considered to reflect realistic CH operations. The optimization and deep learning components of the method were configured as follows: the population size and number of iterations for the Gray Wolf Optimizer (GWO) were set to 30 and 50, respectively, while the Particle Swarm Optimization (PSO) used 50 particles with 150 iterations. The deep learning model, based on a Long Short-Term Memory (LSTM) network, was trained using 30 hidden units, a learning rate of 0.001, and a batch size of 64, for a total of 600 epochs. The trade-off coefficient (β) between energy consumption and energy distribution in the cost function was set to 0.5, ensuring both terms contribute meaningfully to the optimization process.

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In addition, the coefficient α used in the ideal energy distribution function was experimentally determined to be 0.00125 based on preliminary tuning. The final configuration parameters are summarized in Table 1.

Table 1. Simulation Parameters and Configuration

Parameter	Value
WSN Area	200m×200m
Number of nodes	100
Maximum Number of Cluster Heads	10
Data Aggregation Ratio	0.01
Data Packet Size	500 bytes
e_{elec}	50 nJ/but
e_{fs}	10 pJ/bit/m^2
e_{mp}	0.0013 pJ/bit/m^4
e_{da}	10 nJ/bit/signal
Population Size of GWO	30
Maximum Iterations of GWO	50
Population Size of PSO	50
Maximum Iterations of PSO	150
Number of LSTM Hidden Units	30
Maximum Number of Epochs	600
Batch Size	64
Learning Rate	0.001
α	0.00125
β	0.5

This experimental setup establishes the foundation for a rigorous evaluation of the proposed method under varying conditions. The next section introduces the scenarios under which the performance is tested and the rationale behind their selection.

Performance of GWO-PSO-Based Optimization:

This part showcases the results from the first step of the approach that implements GWO-based clustering and PSO integrated with Prim’s algorithm for energy-aware routing. This step is crucial in creating the best cluster and routing map for training the LSTM model, effectively serving as the ceiling for system performance. The analysis begins with an extensive visual and quantitative descriptive for the chosen routing and clustering schemes and continues to compare system wide lifetime performance against the baseline LEACH protocol in three different deployment scenarios.

Figures 1, 2, and 3 illustrate the three scenarios mentioned previously, demonstrating the impact of routing optimization on energy efficiency with dedicated plots. Each plot includes three typical cases where clustering is shown on the left and routing on the right. These visualizations are important for demonstrating the improvement in the clustering baseline due to the routing structure which rebalances the communication load among cluster heads (CHs), resulting in lower transmission cost. In the figures, CHs are marked with red circles, regular sensor nodes with yellow dots, and the base station (BS) is indicated by a blue triangle. It is evident from the figures that the proposed routing technique always improves the single-hop clustered structure to a more symmetrically distributed multi-hop topology. This transformation is subtle when the BS is located centrally but becomes considerably more impactful in asymmetric layouts. In Scenario 1, where the BS is placed at the center of the monitored region, the routing refinement leads to slight yet consistent reductions in energy consumption. The energy loss after applying PSO-Prim routing is reduced from 0.046487 to 0.046455 in the first example, from 0.046219 to 0.046145 in the second, and from 0.045757 to 0.045344 in the third. While these changes may appear marginal, they are significant given the already balanced nature of this configuration. The optimization manages to preserve structure while fine-tuning inter-CH connections to eliminate redundant paths and reduce overlap. The advantage of the routing layer becomes more apparent in Scenario 2, where the BS is placed at the edge of the sensing field. In such layouts, certain CHs must communicate over longer distances, which, without optimization, leads to rapid energy depletion in specific regions. After routing, energy losses are considerably reduced—0.051852 to 0.048972 in the first example, 0.051607 to 0.048991 in the second, and 0.051906 to 0.049020 in the third. The resulting

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topologies more effectively distribute the communication load among CHs, minimizing the burden on distant nodes and reducing the risk of early node death in critical zones. In Scenario 3, where the BS is situated at the far corner of the network, the clustering alone yields significantly unbalanced energy consumption due to long-distance direct transmissions from peripheral CHs. The PSO-Prim routing mechanism demonstrates its adaptability by rerouting paths through intermediate CHs closer to the BS. This rerouting leads to the most pronounced reductions in energy loss: from 0.054289 to 0.0492, 0.053794 to 0.048085, and 0.054168 to 0.048898 in the three respective examples. These findings confirm that the proposed routing mechanism substantially enhances energy efficiency in topologically challenging deployments, compensating for increased path lengths and asymmetry by creating low-cost and loop-free communication trees.

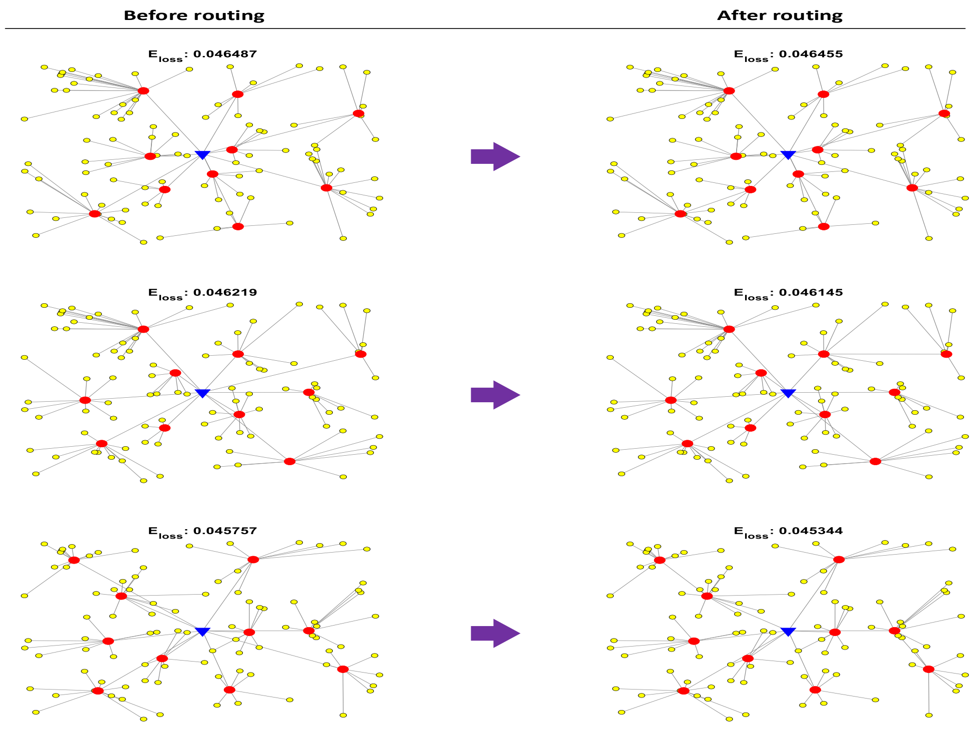

Figure1: The clustering and following routing refinement results for three example rounds of the first scenario.

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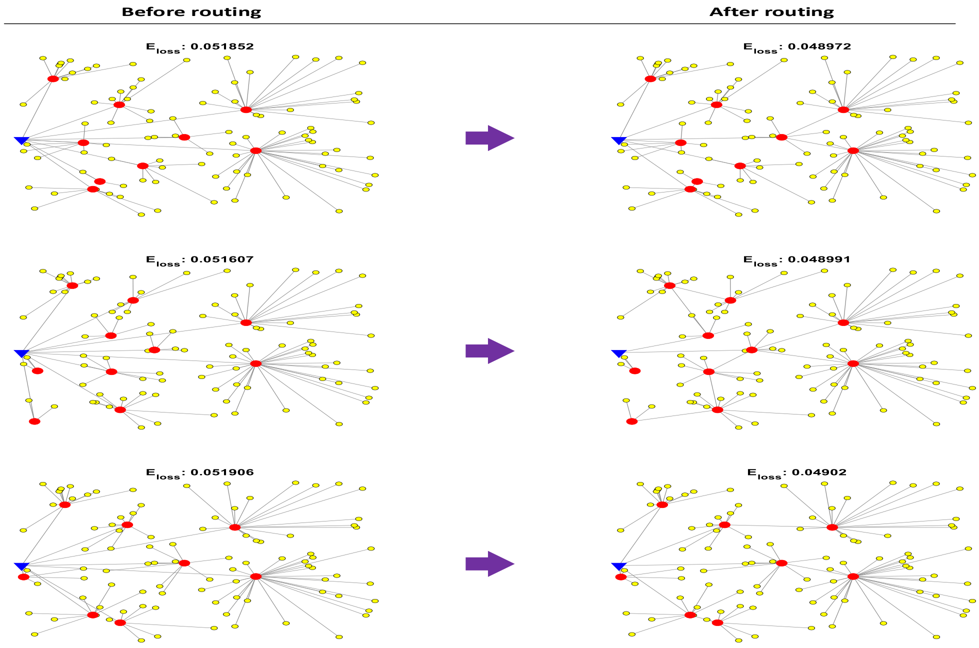

Figure 2: The clustering and following routing refinement results for three example rounds of the second scenario.

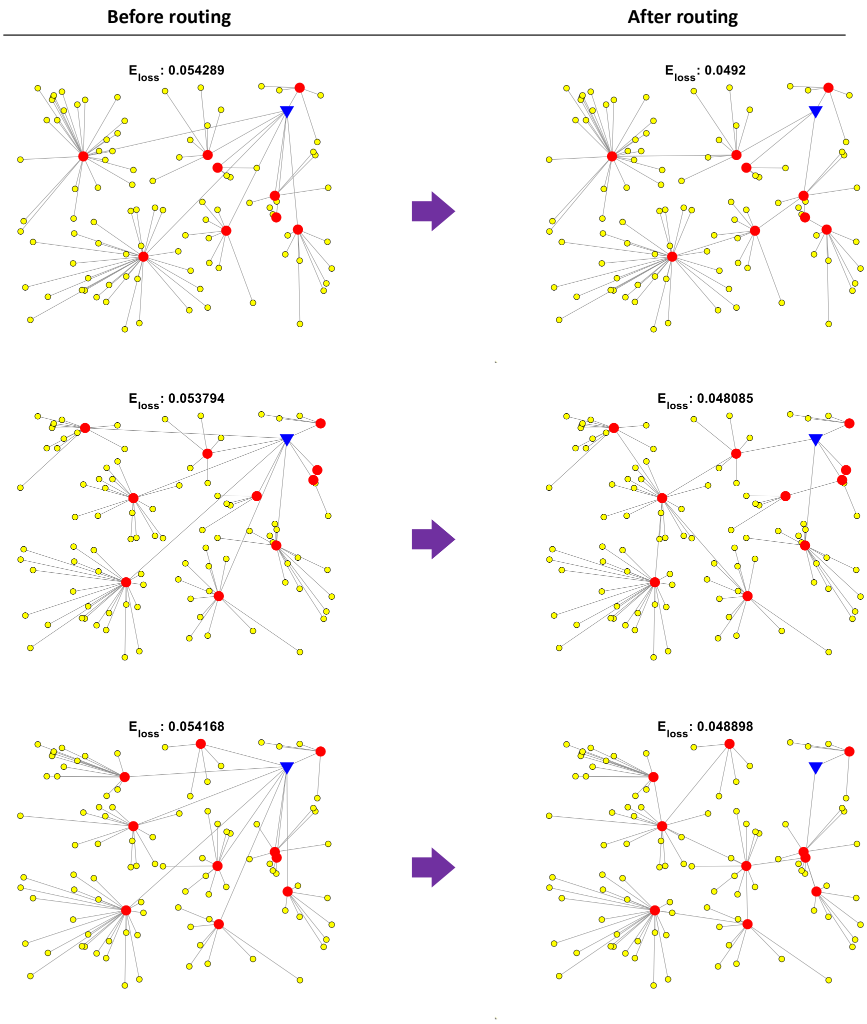

Figure 3: The clustering and following routing refinement results for three example rounds of the third scenario.

In Scenario 1 (Figure 4), where the BS is centrally located, both approaches yield their best results. However, with the use of GWO-PSO, the FND is delayed to 2468 rounds from 539 in LEACH, and LND is pushed to 3553 from 2300. That is a 357% increase in network lifespan prior to first node failure and over 54% improvement in full network longevity. Also, the extended HND at 3053 rounds proposed by GWO-PSO as opposed to 1447 with LEACH demonstrates its ability to postpone mass node depletion even further.

In Scenario 2, shown in Figure 5, where the BS is positioned at the edge of the field, the enhancements are even more pronounced. Here, LEACH performs poorly in retaining communication due to node burnout, resulting in failures. For LEACH, the FND is reached at 152 rounds, but with our method it is improved to 722 rounds. In the same manner, LND improves from 1869 to 3081 rounds which is over 64% improvement in lifetime. The balance point provided with default parameters turns into a strong advantage for all the three metrics as we merge cluster quality obtained from GWO and route optimization from PSO-Prim.

Scenario 3 (Figure 6) poses significant challenges, but it is here where the advantages of the proposed methodology stand out the most. LEACH encounters a rapid reduction in performance because of the increased distance for data transmission, yielding an FND of 113 rounds and LND of 1415 rounds. GWO-PSO, on the other hand, increases both the FND and LND to 695 and 2318 rounds respectively. There is also an increase in HND from 824 to 1765 rounds. The nearly twofold increase in the lifetime metrics illustrates how strongly and effectively the proposed method can deal with adverse conditions through optimizing not just the CH selection, but also the hierarchical links between them.

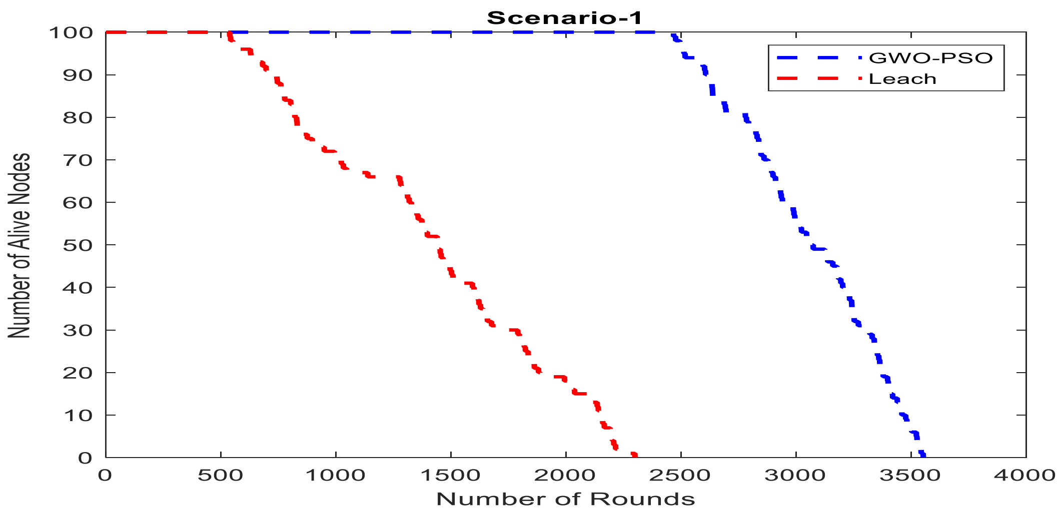

Figure 4: Comparing the network lifetime of proposed method and LEACH for the first scenario

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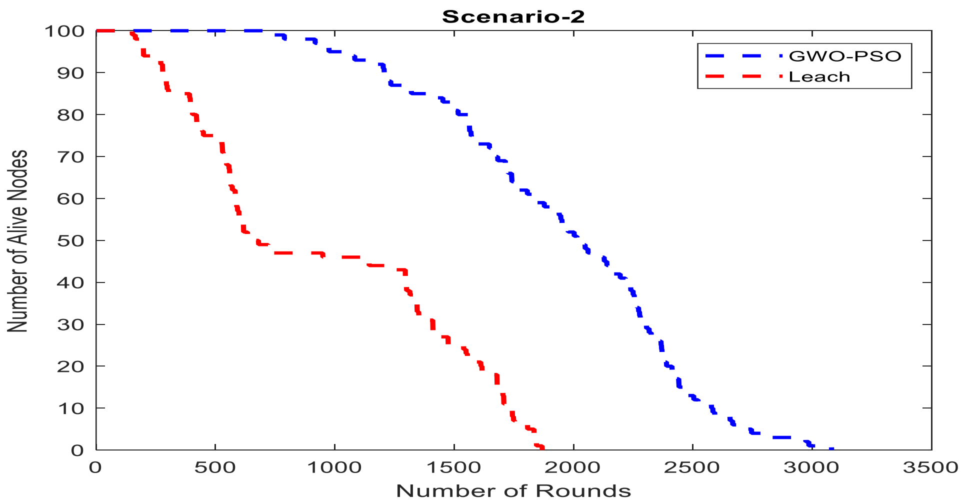

Figure 5: Comparing the network lifetime of proposed method and LEACH for the second scenario

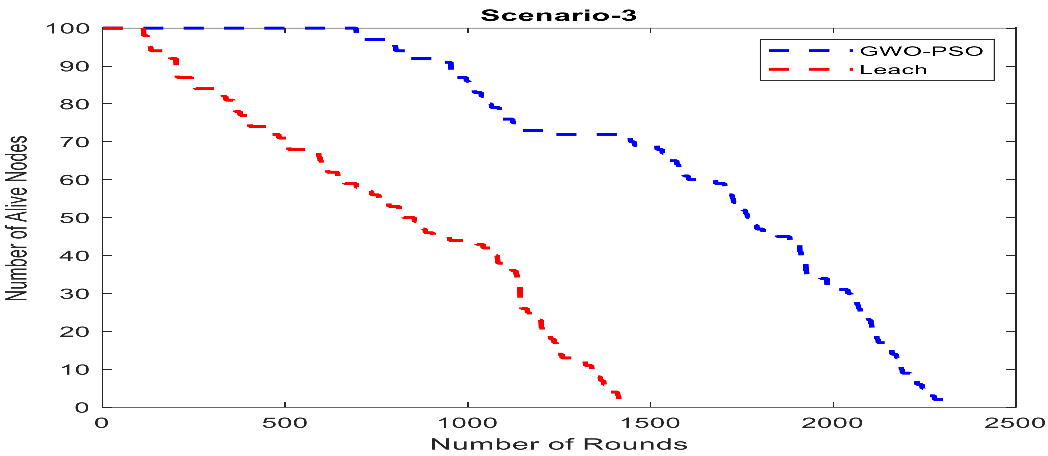

Figure 6: Comparing the network lifetime of proposed method and LEACH for the third scenario

<u>Conclusion:</u>

Two-stage approach with the aim of increasing the lifetime and improving the energy efficiency of wireless sensor networks. In the first stage, a combination of the Gray Wolf (GWO) algorithm and K-means was used to cluster nodes, which led to the creation of balanced clusters and reduced communication costs. By creating a uniform energy distribution among the nodes, this stage prevented the rapid energy depletion of some nodes and provided more stable conditions for the second stage. In the second stage, multi-hop routing between cluster heads was optimized. In this section, the PSO algorithm was used to extract the optimal path weights, and then the LSTM model was replaced with the iterative optimization process. Thus, the optimal routing was predicted by LSTM in real time without the need for heavy PSO calculations, which reduced computational complexity and saved energy.

Simulation results in three different base station location scenarios (center, edge, and corner of the field) showed that the proposed GWO-LSTM method always performed close to GWO-PSO and significantly outperformed the reference protocol LEACH. In the first scenario (base station in the center), the network lifetime metrics including FND, HND, and LND for GWO-LSTM were almost equivalent to GWO-PSO and significantly better than LEACH. In the second scenario (base station at the edge), the main challenge was creating long and asymmetric paths that led to unbalanced energy consumption.

Analysis of the residual energy trend in all scenarios showed that GWO-LSTM provides stability in the network by distributing energy evenly and reducing the rate of sudden drops. In contrast, LEACH experienced rapid energy drops and premature node deaths due to uneven energy consumption at cluster heads. On the other hand, the ability of LSTM to predict optimal routing weights allowed energy-conscious and efficient decisions to be made without repeatedly executing heavy optimization algorithms.

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