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Energy Efficient Wireless Sensor Networks Through PUMA Based Clustering and Grid Routing

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Abstract

Energy efficiency and prolonged network lifetime remain key challenges in wireless sensor networks. Clustering, cluster head selection, and routing are central to addressing these issues since they directly affect energy consumption, data delivery, and overall network stability. In this work, we introduce a novel hybrid protocol named PUMA-GRID, which uniquely integrates the recent Puma Optimization Algorithm with a grid-based multi-hop routing framework. Unlike traditional schemes, PUMA-GRID adaptively balances exploration and exploitation during cluster head selection while learning optimal data forwarding paths through grid-based routing. This combination provides improved adaptability, scalability, and load balancing, key strengths that distinguish it from earlier AEO, LEACH, and static PUMA variants. The fitness function for cluster head election incorporates intra cluster distance, distance to the base station, and residual energy, with adjustable weights that allow flexible adaptation to deployment scenarios. Simulation experiments were performed under different base station placements and weight configurations to assess the influence of each factor. The results show that the effect of the weights depends strongly on base station location, and that careful tuning is required to balance efficiency and fairness. Across all scenarios, PUMA-GRID demonstrated superior performance compared to LEACH, AEO based schemes, and other PUMA variants Overall, PUMA-GRID demonstrates an effective and scalable solution for sustainable and energy-aware operation of wireless sensor networks.

Keywords: wireless sensor networks; energy efficiency; network lifetime; puma optimization algorithm; cluster head selection; grid-based routing; multi-hop communication; metaheuristic optimization; base station deployment; weighted fitness function

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1. Introduction

In recent decades, computer networks, particularly wireless communications, have undergone remarkable expansion due to continuous technological progress. Advances in microelectronics and transducer design have enabled the development of compact, efficient, and low-cost devices capable of detecting and measuring diverse physical quantities with high accuracy. These innovations have paved the way for Wireless Sensor Networks (WSNs), a transformative technology widely recognized by researchers and industry analysts [1–4]. A WSN consists of numerous sensor nodes distributed across a geographical area, each capable of sensing, processing, and transmitting information to a central Base Station (BS) [5]. However, transmitting large volumes of data consumes significant energy, directly limiting network lifespan, particularly since nodes rely on small batteries and are often deployed in hard-to-reach areas.

In addition to limited energy and transmission range, wireless sensor networks (WSNs) face several other inherent challenges. These include signal interference from co-channel or adjacent wireless systems, low memory and processing capabilities of sensor nodes, narrow communication bandwidth, constrained transmission range, and heightened vulnerability to environmental disturbances and cyberattacks. For example, Kenyeres et al. [6] detail how narrow bandwidth, limited memory, and constrained transmission range degrade WSN reliability and increase susceptibility to noise and external interference. Likewise, Ahmad et al. [7] highlight how these resource constraints amplify security challenges and make nodes vulnerable to attacks and faults.

To overcome this limitation, various routing strategies have been proposed, each aiming to balance energy consumption and extend network lifetime [8–10]. These strategies are generally classified into four families based on logical topology. In flat-based routing [11], all nodes share equal roles, but flooding often leads to redundancy and overhead. Chain-based routing [12] reduces transmissions by forming sequential links but increases delay. Tree-based routing [13] establishes a parent–child hierarchy for data aggregation, while cluster-based routing [14] organizes nodes into clusters managed by a Cluster Head (CH) that aggregates and forwards data to the BS, directly or via other CHs. The main challenge lies in selecting optimal CHs, forming balanced clusters, and maintaining efficient communication routes [15]. Clustering therefore remains central to improving energy efficiency in WSNs.

The pioneering Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol [14] and its variants—LEACH-C [16], LEACH-1R [17,18], V-LEACH [19], TL-LEACH [20], and E-LEACH [21]—introduced improvements such as centralized control, fixed clustering, backup cluster heads (CHs), hierarchical communication, and energy-aware CH election. Despite these enhancements, they still suffer from unbalanced energy consumption and limited network lifetime. Machine learning-based clustering methods, including k-means [22,23] and DBSCAN (Density-based spatial clustering of applications with noise) [24,25], have also been investigated. However, k-means requires prior knowledge of the optimal number of clusters, while DBSCAN is highly sensitive to parameter settings. These limitations highlight the need for more adaptive and robust clustering approaches.

Since their emergence in the early 1980s, metaheuristic algorithms have advanced considerably, offering innovative strategies to enhance computational efficiency, solve complex large-scale optimization problems, and provide robust solutions. They have achieved notable success in addressing diverse combinatorial optimization tasks [26,27], with examples including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Grey Wolf Optimizer (GWO). A recently proposed population-based metaheuristic, the Puma Optimizer Algorithm (PO) [28], is inspired by the hunting instincts and territorial behaviors of pumas, effectively modeling their exploration and exploitation strategies to solve optimization problems.

Despite extensive research on energy-efficient clustering and routing, many existing protocols still face key limitations. Traditional methods often use fixed clustering structures that fail to adapt to node energy variations, while optimization-based algorithms frequently overlook spatial balance or introduce excessive control overhead. Moreover, the interaction between cluster formation and routing remains loosely coupled, leading to uneven energy depletion and reduced coverage over time. To address these challenges, this study introduces a unified clustering and routing framework that integrates the adaptive exploration–exploitation capability of the Puma Optimization Algorithm with grid-based multi-hop routing. The novelty lies in combining optimization-driven cluster head selection with topology-aware routing, enabling dynamic energy balancing, improved scalability, and extended network lifetime.

The major contributions of this paper are summarized as follows:

- A novel clustering protocol, PUMA-GRID, designed to optimize energy consumption and extend network lifetime.
- Exploiting the adaptive balance between exploration and exploitation: exploration identifies diverse CH candidates, while exploitation refines them into energy-efficient selections. The dynamic switching between these phases prevents premature convergence, improves robustness, and ensures high-quality clustering solutions.

- CH selection is guided by a fitness function based on three parameters: residual energy of candidate CHs, distance to the BS, and distance from each node to its CH.
- Several experiments were conducted by varying the weight values of the fitness function to evaluate their impacts under three different BS placements.
- Performance was assessed using multiple metrics, including residual energy, number of packets sent to the BS, First Node Death (FND), Half Node Death (HND), Last Node Death (LND), energy consumption per round, and the coverage fairness index (measuring the impact of node deaths on coverage).
- The proposed protocol was compared against AEO, LEACH, PUMA-SH, and grid-enhanced versions such as AEO-GRID.

Compared with previous studies, this paper addresses several limitations observed in existing clustering and routing approaches. Traditional protocols such as LEACH and MR-LEACH provide simple probabilistic or static cluster-head selection but lack adaptability to energy dynamics. Optimization-based schemes like AEO, SHO-CH, and AVOACS incorporate heuristic search but often ignore spatial routing balance. The proposed PUMA-GRID protocol distinguishes itself by combining the adaptive exploration–exploitation behavior of the Puma Optimization Algorithm with grid-based multi-hop routing, achieving enhanced load balancing, energy preservation, and coverage fairness across varying deployment scenarios.

The remainder of this paper is organized as follows. Section 2 reviews clustering protocols that employ metaheuristics for CH selection. Section 3 presents the PUMA algorithm, while Section 4 describes the proposed PUMA-GRID protocol. Section 5 discusses the simulation setup along with the results and analysis. Finally, Section 6 concludes the paper.

2. Related Work

In AEOWSNC [29], a clustering protocol inspired by the Atomic Energy Optimization (AEO) algorithm [30] was introduced to extend the operational lifespan of WSNs. The protocol selects optimal CHs to minimize energy consumption while maintaining clustering efficiency. Each atom represents a candidate CH set, initialized randomly with a predefined number of CHs and assigned an energy level indicating its effectiveness. Through iterative operations such as energy transfer and dissipation, atoms evolve toward improved solutions. The objective function evaluates each solution based on the total distance from nodes to their CHs and from CHs to the BS, with the best solution yielding the lowest value. Strong solutions are preserved, while weaker ones lose energy and are replaced, ensuring a balance between exploration and exploitation. The protocol operates centrally, with CHs transmitting data directly to the BS. Simulations confirm its efficiency over other protocols. However, since the objective function considers only distance and not residual energy, CHs remain in that role until depletion, leading to unbalanced energy usage and reduced coverage. This limitation highlights the need for energy-aware optimization to further enhance performance.

The SHO-CH protocol [31] was proposed as an energy-efficient, cluster-based routing scheme for heterogeneous WSNs. Its goal is to extend network lifetime while balancing energy consumption across nodes. Inspired by the cooperative hunting strategies of spotted hyenas, the protocol balances exploration and exploitation to select CHs that are both energy-efficient and strategically positioned. CH selection is guided by a fitness function incorporating residual energy, distance between nodes and their CHs, and distance from CHs to the BS. After aggregating data from members, CHs transmit either directly to the BS or via intermediate CHs located closer to it. Simulation results demonstrate that SHO-CH improves network lifetime and achieves more equitable energy distribution compared to existing approaches.

The African Vulture Optimization Algorithm-based Energy Efficient Clustering Scheme (AVOACS) [32] applies the scavenging and foraging behaviors of vultures to optimize CH selection. Each vulture represents a candidate CH configuration, evaluated using a fitness function that considers residual energy, distance to the sink, intra-cluster distance, and a communication mode decider (CMD). After evaluation, the best two vultures guide the others, which update their positions relative to these leaders. A dynamic hunger rate controls the balance between exploration and exploitation: initially promoting wide exploration and later encouraging intensive exploitation. Two exploitation strategies are applied: refining searches via siege-fighting and spiral flight or intensifying them by averaging around leaders or making aggressive jumps. This adaptive mechanism ensures a smooth transition from global search to local refinement, preventing premature convergence. Results show that AVOACS distributes energy more evenly, improves stability, and extends network lifetime compared to conventional protocols.

The EEM-LEACH-ABC protocol [33] combines LEACH with the Artificial Bee Colony (ABC) algorithm for energy-efficient clustering and routing. Initially, each node computes a fitness score based on residual energy and distance to the BS to determine its suitability as a CH. Only high-fitness nodes are considered candidates. The ABC algorithm then refines CH selection, with worker, onlooker, and scout bees exploring and introducing new candidates to avoid local optima. To reduce the transmission cost of distant CHs, a multi-hop relay mechanism is applied. Selected CHs are ordered by weight to form a hierarchical relay tree. Each CH broadcasts advertisements, allowing nearby nodes to join its cluster, and generates a TDMA schedule for organized transmissions. During operation, CHs aggregate data and forward it either to the BS or through relay CHs. This adaptive clustering and routing approach significantly delays the FND and extends overall network lifetime.

The Binary Dragonfly Algorithm (BDA)-based protocol [34] introduces a four-phase clustering process. First, after deployment, each node sends a hello message to the BS containing its ID, location, and residual energy. Second, CHs are selected using the Dragonfly Algorithm, with candidate solutions evaluated by a fitness function integrating residual energy, distance to the BS, and neighborhood degree (number of nearby nodes). Continuous solutions are mapped to binary values using transfer functions. Third, cluster formation is performed through a fuzzy inference system considering residual energy, distance to CHs, and neighborhood degree. Finally, data transmission is achieved through path discovery, where nodes identify shortest routes to the CH, and CHs forward aggregated data to the BS either directly or via other CHs in multi-hop fashion. This protocol extends network lifetime by balancing energy usage, though reliance on fuzzy logic and multi-hop forwarding through normal nodes can increase energy burden on some nodes, potentially affecting long-term performance.

A hybrid protocol combining K-means and ACO [35] was also proposed. Initially, K-means forms clusters based on spatial proximity, after which ACO selects CHs and determines optimal routing paths. Decisions are guided by residual lifetime and energy efficiency (energy consumed in transmission). This hybridization exploits the strengths of K-means in forming compact clusters and ACO in optimizing routing. However, K-means alone is less effective in WSNs since it emphasizes Euclidean distance to centroids, overlooking irregular node distributions and resulting in imbalanced clusters and suboptimal energy usage.

Another hybrid approach combining K-means, PSO, and fuzzy logic [36] was introduced. K-means first generates initial clusters, and its result is used as one particle in PSO, while the others are generated randomly. After optimization, the best particle defines the final clusters. CHs are then elected using fuzzy logic: Primary CHs are selected based on residual energy, distance to the BS, and distance to the centroid; Secondary CHs are chosen considering residual energy, distance to the centroid, and distance to the Primary CH. While this multi-layered selection improves clustering efficiency, executing fuzzy logic at every node increases computational overhead and accelerates energy depletion.

Zheng et al. [37] proposed a relay selection and deployment approach for non-orthogonal multiple-access (NOMA) enabled multi-AAV-assisted wireless sensor networks. Their study jointly optimizes relay placement and selection to enhance throughput and spectral efficiency under energy and coverage constraints, demonstrating the growing research interest in deployment-aware WSN optimization.

Table 1 summarizes the reviewed protocols in terms of CH selection methods, considered variables (residual energy, distance to BS, intra-cluster communication), and routing strategies.

Overall, energy minimization in WSNs is achieved not only through metaheuristic-based CH selections, such as evolutionary and swarm-intelligence algorithms, but also via classical clustering, adaptive thresholding, and energy-aware multi-hop routing. These complementary approaches balance network load, prolong node lifetime, and reduce communication overhead, leading to more sustainable WSN deployments.

Table 1. Comparison of clustering protocols in WSNs.

Protocol	CH Selection Method	Parameters Considered	Routing Type	Main Strengths	Limits
AEOWSNC	AEO	Distance(Node, CH) Distance(CH, BS)	Single-hop	Simple implementation and efficient CH distance minimization	Lacks energy-awareness in CH rotation and scalability
SHO-CH	Hyenas	Residual energy Distance(Node, CH) Distance(CH, BS)	Multi-hop Single-hop	Balances exploration and exploitation for better CH selection	High computational cost and limited scalability
AVOACS	African Vulture	Residual energy Distance(Node, CH) Distance(CH, BS) Communication mode decider	Single-hop	Adaptive switching between exploration and exploitation phases	Increased overhead and slow convergence in large networks
EEM-LEACH-ABC	ABC	Residual energy Distance(CH, BS)	Multi-hop Single-hop	Reduces control overhead and improves network lifetime	Random CH initialization may cause imbalance
BDA	Dragonfly	Residual energy Distance(CH, BS) Neighborhood degree	Multi-hop Single-hop	Maintains network connectivity and energy balance	Sensitive to parameter tuning and dense topologies
KPSOFL	K-means and PSO	Residual energy Distance(CH, BS) Distance to centroid	Single-hop	Combines clustering accuracy with adaptive optimization	Dependent on initial cluster centroids and PSO randomness

3. Preliminaries: Puma Optimizer

The Puma Optimizer is inspired by the natural predatory strategies of pumas, which combine learning, exploration, and exploitation behaviors to maximize hunting success [26]. The algorithm emulates the gradual transition of pumas from inexperienced hunters to skilled predators through a series of interconnected phases that adaptively balance global search and local refinement. This design maintains population diversity in the early stages to promote exploration and gradually intensifies the search around promising regions as convergence progresses. If the population diversity decreases too rapidly, premature convergence may occur, causing the algorithm to settle around local optima and leading to suboptimal cluster-head selection and energy imbalance. The severity of this issue depends on the chosen control parameters, such as population size, learning rate, and movement coefficients, which influence the exploration–exploitation balance. In the proposed implementation, these parameters are adaptively tuned to preserve diversity and stability. It is also noted that exploration and exploitation durations are measured in algorithmic iterations rather than real-time units, as they depend on the internal convergence dynamics of the optimizer rather than clock time.

3.1. Unexperienced Phase

At the start of the optimization, pumas are considered inexperienced hunters. This phase, typically lasting only a few iterations, activates both exploration and exploitation simultaneously. By combining wide roaming of the search space with initial local improvements, the algorithm mimics the trial-and-error learning of young pumas. This balance provides an initial diversity of solutions before specialization begins.

3.2. Experienced Phase

After the unexperienced stage, the algorithm assumes that pumas have gained hunting experience. In this phase, the decision to favor exploration or exploitation is made adaptively, based on their relative effectiveness in previous iterations. This adaptive behavior is governed by two reinforcement counters: $Score_{\text{Explore}}$ and $Score_{\text{Exploit}}$. If exploration has yielded better improvements, the algorithm emphasizes global roaming; otherwise, it prioritizes local exploitation. This mechanism reflects the natural ability of experienced pumas to choose the most effective hunting strategy.

3.3. Exploration Phase

Exploration represents the roaming of pumas over wide territories in search of prey. In the algorithm, candidate solutions are perturbed around the global best and other agents, modulated by trigonometric functions such as cosine. This introduces nonlinear trajectories that expand the search space, helping avoid stagnation and maintain diversity across the population.

3.4. Exploitation Phase

Exploitation simulates the stalking and chasing of prey once it has been detected. Here, agents are drawn toward elite and neighboring solutions using sine-based functions, narrowing the search to promising local regions. By reducing randomness and refining solution quality, exploitation accelerates convergence while ensuring the final solutions are highly optimized.

3.5. Parameter Definitions

The PO algorithm relies on several key parameters and functions:

- f_1: Exploration Function, which governs roaming behavior:

$$f_1(X_i^t) = X_i^t + r_1 \cdot \cos(r_2) \cdot (X^{Best} - X_i^t) \quad (1)$$

where $r_1, r_2 \in [0,1]$ are random numbers, and X^{Best} is the elite solution.

- f_2: Exploitation Function, which models local pursuit around promising solutions:

$$f_2(X_i^t) = X^{Best} + r_3 \cdot \sin(r_4) \cdot \left(X_j^t - X_k^t\right) \quad (2)$$

where $r_3, r_4 \in [0,1]$ are random numbers, and X_j^t, X_k^t are random solutions.

- f_3 (Adaptive Balancing Term): A time-varying coefficient that gradually decreases exploration strength while increasing exploitation with iterations.
- $Score_{\text{Explore}}$ and $Score_{\text{Exploit}}$: Reinforcement counters that track the relative success of each phase. If exploration produces improvements, $Score_{\text{Explore}}$ is incremented; otherwise, exploitation is rewarded. Phase selection is determined by comparing the two scores.
- N: Population size.
- $[LB, UB]$: Lower and upper bounds of the search space.
- T_{max}: Maximum number of iterations.

The choice of *cosine* and *sine* functions in equations (1) and (2) is intentional and reflects the different objectives of the two phases. In the exploration phase, cosine provides a push–pull oscillatory effect with larger displacements, allowing agents to roam widely and escape local minima. In contrast, the exploitation phase uses sine, which generates smaller, smoother oscillations around zero, enabling precise local adjustments. This asymmetric design ensures that exploration remains disruptive and diverse, while exploitation is fine-grained and convergent.

The key functions in PO algorithm govern the balance between exploration and exploitation and directly influence convergence behavior and optimization performance. Specifically, the position update and hunting functions control how pumas move through the search space, while the fitness evaluation function determines the quality of each solution. These mechanisms together define the algorithm's capacity to avoid local optima and converge toward high-quality solutions.

3.6. PO Pseudocodes

The operational flow of the PO can be summarized in the following pseudocodes:

It is important to note that the global best solution X^{Best} is explicitly updated at the end of the exploitation phase (Algorithm 3) but not during exploration (Algorithm 2). This design reflects the different goals of the two phases: exploration aims to diversify the population by generating wide, trial solutions, while exploitation focuses on refining and improving the elite solution. Updating X^{Best} during exploration could prematurely bias the search toward unstable exploratory candidates, whereas updating it during exploitation ensures that only robust, locally improved solutions influence the global best.

Algorithm 1: Puma Optimizer (PO)

Input: Population size N, maximum iterations T_{max}, parameter settings

Output: Best solution X^{Best} and fitness value

Initialize a population of N pumas X_i within $[LB, UB]$

Evaluate fitness of all pumas

Identify the best solution X^{Best}

// Unexperienced Phase

For $t = 1$ to 3 **do**

  Apply *Exploration Phase*

  Apply *Exploitation Phase*

End For

// Experienced Phase

For $t = 4$ to T_{max} **do**

  If $Score_{\text{Explore}} > Score_{\text{Exploit}}$

    Apply *Exploration Phase*

    If new solution improves X^{Best}

 Update X^{Best}

    End If

  Else

    Apply *Exploitation Phase*

    If new solution improves X^{Best}

      Update X^{Best}

    End If

  Update control parameters $(f1, f2, f3)$

  Recompute $Score_{\text{Explore}}$ and $Score_{\text{Exploit}}$

End For

Return X^{Best}

Algorithm 2: Exploration Phase

Input: Population X_i^t, best solution X^{Best}

Output: Updated solutions X_i^{t+1}

For each puma $i = 1$ to N **do**

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Generate random $r_1, r_2 \in [0,1]$
$X_i^{new} = X_i^t + r_1 \cdot \cos(r_2) * (X^{Best} - X_i^t)$
If X_i^{new} is out of bounds
Reinitialize X_i^{new} within $[LB, UB]$
End If

Evaluate fitness of X_i^{new}
If fitness(X_i^{new}) better than fitness(X_i^t)
$X_i^{t+1} = X_i^{new}$
Else
$X_i^{t+1} = X_i^t$
End If
End For

Algorithm 3: Exploitation Phase
Input: Population X_i^t, best solution X^{Best}
Output: Updated solutions X_i^{t+1}

For each puma $i = 1$ to N **do**
Select two random distinct pumas X_j, X_k
$X_i^{new} = X^{Best} + r_3 \cdot \sin(r_4) * (X_j - X_k)$
If X_i^{new} is out of bounds
Reinitialize X_i^{new} within $[LB, UB]$
End If

Evaluate fitness of X_i^{new}
If fitness(X_i^{new}) better than fitness(X_i^t)
$X_i^{t+1} = X_i^{new}$
Else
$X_i^{t+1} = X_i^t$
End If
End For
Update X^{Best} if any X_i^{t+1} is better

4. The PUMA-GRID Protocol: Clustering with Grid-Based Multi-hop Routing

The proposed protocol, PUMA-GRID, introduces an advanced clustering and routing framework to address the critical challenge of energy efficiency in WSNs. It leverages the Puma Optimizer, a metaheuristic known for its adaptive balance between exploration and exploitation, to dynamically optimize CH selection across the network. By navigating the complex combinatorial space of possible CH assignments, PUMA explores diverse clustering configurations during the early search stages and gradually intensifies its focus on promising regions of the solution space. This adaptive tuning enables efficient convergence toward high-quality, energy-aware clustering solutions.

In this study, PUMA-GRID assumes a single BS located either inside or at the edge of the monitored area, which serves as the central data collection point. This assumption aligns with most benchmark WSN configurations and facilitates consistent performance comparison. Although deploying multiple BSs could further reduce communication distances and balance network load, the proposed framework was designed and evaluated under a single-BS scenario.

To complement clustering, the approach incorporates a grid-based, machine-learning-inspired multi-hop routing mechanism. Grid-based routing divides the wireless sensor network into uniform virtual cells, facilitating energy-efficient data forwarding through structured multi-hop paths and localized packet transmission. As highlighted in [38], this approach enhances scalability and ensures predictable communication costs, although its performance depends on appropriate grid configuration to prevent problems such as empty cells and uneven node distribution.

4.1. Initialization

In the initialization phase, the clustering process is prepared by setting up candidate solutions for CH selection. In the proposed protocol, the CH selection process is not predetermined within each grid cell but dynamically optimized through the PUMA algorithm. All sensor nodes are initially eligible to become CHs, and their selection depends on the fitness function that considers residual energy, distance to the base station, and intra-cluster communication distance.

After random deployment of nodes in the target area, each node transmits its position information to the BS, which then begins executing the PUMA algorithm. A population of m individuals (candidate solutions) is generated, where each individual is represented as an n-length binary vector. In this encoding, a value of 1 denotes that the node is selected as a CH, while 0 indicates a regular sensor node. The desired number of CHs is specified as a user-defined percentage of the total nodes. This binary representation, consistent with classical metaheuristic clustering approaches, enables flexible exploration of CH configurations and establishes a solid foundation for the optimization process.

4.2. PUMA-Based Clustering and Fitness Evaluation

PUMA balances exploration and exploitation through adaptive control mechanisms embedded in its search dynamics. During the exploration phase, candidate solutions undergo wide, randomized position adjustments that preserve diversity and help the algorithm avoid premature convergence. As optimization progresses, PUMA transitions into the exploitation phase, where updates become more focused, favoring local improvements around the current best solution. The number of CHs is not strictly enforced during this process, allowing the search to flexibly explore a broader range of configurations. This hyper-heuristic switching mechanism, as demonstrated in recent applications of the Puma Optimizer, dynamically adjusts the exploration–exploitation ratio according to the optimization context, enabling progressive refinement of clustering results while avoiding local optima.

The fitness function in PUMA-GRID integrates three key metrics: (1) the total distance between each regular node and its nearest CH, (2) the distance from each CH to the base station (BS), and (3) the residual energy of the selected CHs. These components are combined using weighted coefficients w_1, w_2, and w_3, all in the range [0-1].

$$w_1 + w_2 + w_3 = 1 \tag{3}$$

Additionally, a penalty term is introduced to discourage solutions where the number of CHs deviates significantly from the desired count. This mechanism ensures a balance between flexibility in exploration and compliance with user-defined network constraints. The objective function is therefore formulated as follows:

$$Cost = w_1 \times \sum_{i \in N \setminus CH} \min_{j \in CH} Dist(i,j) + w_2 \times \sum_{j \in CH} Dist(j,BS) - w_3 \times \sum_{j \in CH} Energy_j + \alpha \times |NumCH - K_{opt}| \tag{4}$$

where:

- $Dist(i,j)$ is the Euclidean distance between node i and its associated CH j.
- $Dist(j,BS)$ is the Euclidean distance between CH j and the base station.
- $Energy_j$ is the residual energy of CH j.
- $NumCH$ is the number of CHs in the current solution.
- K_{opt} is the desired number of CHs.

After evaluating all candidate solutions in the PUMA population using the objective function, the individual with the minimum cost value is chosen as the best solution. This puma represents the

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most energy-efficient clustering configuration for the current round, achieving the optimal trade-off among intra-cluster communication, CH-to-BS transmission, residual energy, and the cluster count penalty. In this context, a round refers to a complete operational cycle consisting of cluster formation, data sensing, aggregation by CHs, and data transmission to the BS. Algorithm 4 illustrates how PUMA operates in selecting CHs.

Algorithm 4: Binary Puma Optimization Algorithm for WSN Clustering

Input: Number of sensors N; sensor positions (X_i, Y_i); residual energy; base station position (BS_x, BS_y); maximum iterations T_{max}; weighted coefficients w_1, w_2, and w_3
Output: Optimal binary vector of cluster heads (CHs); best fitness value
Initialize a population of pumas $X_i (i = 1, 2, \dots, N)$ as binary vectors (1 for CH, 0 for normal node)
Evaluate the fitness of each puma using a weighted combination of residual energy, distance to cluster center, and distance to base station (Equation 2)
Identify the best local solution as the leader
For each iteration $t = 1$ to 3 **do**
  For each puma X_i **do**
    Apply *exploration phase*: roaming and searching for locally optimal CH positions
    Apply *exploitation phase*: refining CH selection using ambush/attack strategies
    Ensure updated positions remain binary (1 or 0)
  End For
  Evaluate fitness of all pumas
  Update the leader (best solution so far)
End For
For each iteration $t = 4$ to T_{max} **do**
  For each puma X_i **do**
    Update positions using exploration and exploitation with adaptive coefficients
    Ensure updated positions remain binary (1 or 0)
  End For
  Evaluate fitness of all pumas
  Update the leader (best solution so far)
End For
Return the leader as the optimal CH selection vector and its fitness value

4.3. Grid-Based Multi-Hop Routing via A-Inspired Logic*

After clustering, PUMA-GRID proceeds with a grid-based routing phase that employs a machine-learning-style decision mechanism. The network field is divided into uniform grid cells of user-defined size, with each CH residing in a specific cell. When forwarding aggregated data, a CH selects its next-hop relay from an adjacent grid cell that lies closer to the BS. The forwarding rule works like this: a CH will only choose another CH as a relay if going through it makes the total path to the BS shorter than sending data directly. In short, if the detour is shorter, the CH forwards through the relay. This heuristic emulates intelligent path selection, progressively routing data through energy-efficient multi-hop corridors while avoiding unnecessary long-range transmissions. Figure 1 illustrates how the next CH is elected, and the detailed mechanism is provided in Algorithm 5.

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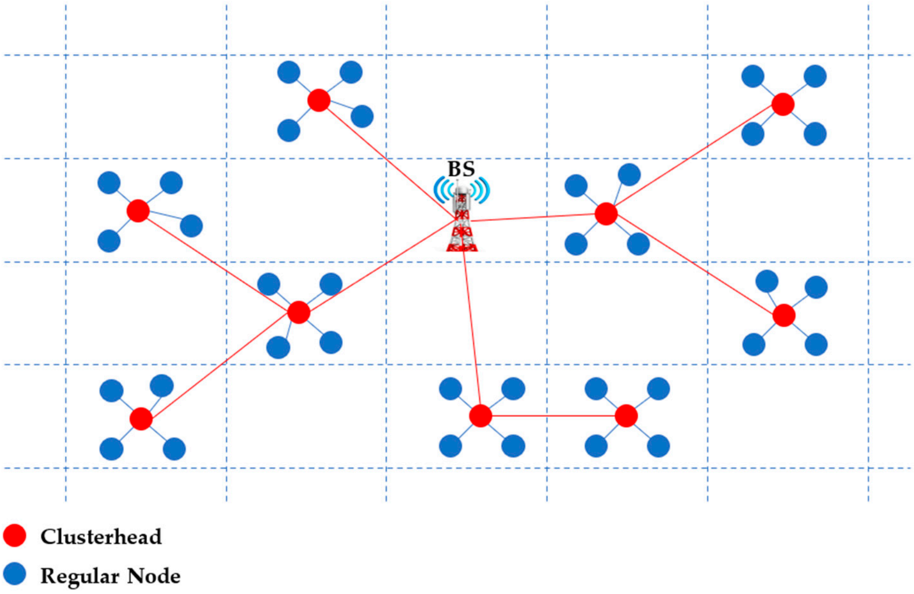

Figure 1. Grid-based routing.

The grid size and number were determined empirically according to the network area and the average communication range of sensor nodes. The objective was to balance routing accuracy with computational and communication overhead. A smaller grid size allows finer routing granularity and shorter transmission distances but increases the number of control decisions, while larger grids simplify routing at the cost of suboptimal paths. In this work, the grid dimension was chosen to achieve a moderate balance between these factors. Future extensions will consider adaptive grid resizing to optimize performance dynamically under different network conditions.

Algorithm 5: Grid-Based Cluster Head Routing

```
Input: Set of CHs, BS, grid structure
Output: Optimal multi-hop routing paths for data forwarding
For each clusterhead CH_i do
    If CH_i and BS are in the same grid
        Send data directly to BS
    Else If BS is in a directly adjacent grid
        Send data directly to BS
    Else
        Search adjacent grid(s) in the direction of the BS
        If one or more CHs exist in adjacent grids
            Select CH_j = argmin_{CH_k}(Dist(CH_i, CH_k) + Dist(CH_k, BS)), where CH_k
            belongs to adjacent grids
            Forward data to CH_j
        Else
            Extend search to next-level adjacent grids
            If BS is found
                Send data directly to BS
            Else If one or more CHs exist
                Select CH_j = argmin_{CH_k}(Dist(CH_k, BS)), where CH_k belongs to
                adjacent grids
                Forward data to CH_j
        End If
```

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21: **End If**
22: **End If**
23: **End For**
24: Return final routing paths for all CHs

4.4. Adaptive Operation and Steady-State Execution

Once the best individual (lowest-cost solution) is identified, PUMA-GRID organizes clusters by enabling CHs to broadcast advertisements. Ordinary nodes then join their nearest CH, and a time-division schedule is established. During the steady-state phase, regular nodes sense data and transmit it to their CH, which aggregates the data and forwards it through the grid-based multi-hop path toward the BS. Re-clustering is triggered when the residual energy of CHs falls below defined thresholds or when load imbalance occurs, thereby maintaining sustained energy-aware operation.

4.5. Complexity Analysis of PUMA-GRID

The computational complexity of the proposed PUMA-GRID protocol can be analyzed by considering its two main components: CH selection based on PO and grid-based multi-hop routing. In the clustering phase, PO operates over a population of P pumas, each representing a possible CH configuration among N sensor nodes. During each iteration, the algorithm evaluates the fitness of all individuals using the defined weighted objective function. This process involves computing intra-cluster distances, CH-to-base-station distances, and residual energies. The cost of evaluating one solution is $O(N)$, leading to an overall clustering complexity of $O(P \times N \times I)$, where I denotes the number of iterations. This level of complexity is typical for metaheuristic-based clustering algorithms and remains acceptable for moderate network sizes due to the algorithm's parallelizable structure and convergence efficiency.

In the routing phase, the grid-based multi-hop routing mechanism partitions the monitored area into G grids, where each CH searches for the next-hop relay among adjacent grids. Assuming each grid contains a small constant number of CHs, the selection of the next-hop node for each CH requires a limited search over neighboring grids, resulting in a routing complexity of approximately $O(G)$ for a single transmission round.

Consequently, the total computational complexity of PUMA-GRID per clustering round is dominated by the POA component and can be expressed as $O(P \times N \times I + G)$ which scales linearly with the number of nodes and grids. The memory complexity is $O(P \times N)$, as the algorithm stores the position vectors and fitness values for all candidate solutions.

5. Simulation Setup, Results, and Discussion

In practical deployments, sensor nodes can estimate their geographical positions through various localization techniques depending on the application and cost constraints. Common approaches include Global Positioning System (GPS) modules for outdoor environments, or signal-based localization methods such as Received Signal Strength Indication (RSSI), Time of Arrival (ToA), and Time Difference of Arrival (TDoA). In cases where GPS is not feasible, anchor-based or centroid localization algorithms can be applied using a limited number of reference nodes with known coordinates. The position of the base station is typically predefined and broadcast once to all nodes during network initialization, enabling each node to store this information locally and use it for cluster formation and routing decisions.

In the simulation study, we employed the first-order radio model for energy consumption as presented in [39]. In this model, a radio transmits an L-bit data packet to a receiver at distance d meters by dissipating an energy amount $E_{TX}(L, d)$. Similarly, a sensor node's radio consumes $E_{RX}(L)$ energy to receive an L-bit message.

The free-space channel (ε_{fs}) is applied when $d < d_0$, while the multi-path channel (ε_{mp}) is applied when $d \geq d_0$. Equation (3) expresses the energy required to transmit a packet of L-bit across a distance d.

$$E_{TX} = \begin{cases} L * E_{elec}(L, d) + L * \varepsilon_{fs} * d^2, d < d_0 \\ L * E_{elec}(L, d) + L * \varepsilon_{mp} * d^4, d \geq d_0 \end{cases} \quad (5)$$

where: $E_{elec}(L, d)$ is the energy needed to transfer a single bit over d meters, both ways. The threshold distance at which the amplification factors begin to shift is known as d_0:

$$d_0 = \sqrt[4]{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (6)$$

For the receiver to receive a packet of L bits, energy $E_{RX}(L)$ must be consumed as follows:

$$E_{RX}(L) = L * E_{elec} \quad (7)$$

The simulations were conducted in MATLAB using a network model to evaluate sensor node performance. Energy consumption was analyzed both at the node level and across the entire network using a standard radio energy model. A set of n sensor nodes was randomly deployed within the monitored area, where they continuously gathered and exchanged data before transmitting it to the BS after aggregation by the CHs. The CHs forwarded the data either directly to the BS or through other CHs using multi-hop transmission. Table 2 summarizes the simulation characteristics and the different BS positions.

Table 2. Simulation parameters for optimal PUMA-GRID weight selection.

Simulation Parameters	Values/Ranges
Network Size	100×100 (m^2)
BS Position	(0, 0), (50, 50)
Number of Nodes	100
Node's Initial Energy	0.1 $(Joules)$
Percentage of Clusterheads	5 %
Packet Size	500 $(Bytes)$
E_{elec}	50 $(nJoule/bit)$
ε_{fs}	10 $(pJoule/bit/m^2)$
ε_{mp}	0.0013 $(pJ/bit/m^4)$
d_0	10 (m)
Grid Size	$10 - 40$ (m)

The simulation parameters listed in Table 2 were selected based on widely adopted configurations in WSN studies to ensure fair comparison and reproducibility. The network size of $100 \times 100\ m^2$ and node count of 100 provide a moderate-density scenario suitable for evaluating scalability. The percentage of cluster heads was fixed at 5%, as this value is commonly used in protocols such as LEACH and its variants to maintain an optimal balance between energy consumption and communication overhead. The initial energy (0.1 J) and packet size (500 bytes) follow standard benchmarks used in energy-efficient routing simulations. The energy model parameters (E_{elec}, ε_{fs}, and ε_{mp}) correspond to the first-order radio model, while the threshold distance $d_0 = 10\ m$ differentiates free-space and multipath propagation regions. The grid size (10–40 m) range was tested to assess the effect of spatial partitioning on routing performance.

Before execution, all nodes are initialized with basic network information, including the total number of nodes, grid dimensions, and the position of the base station, which is broadcast once during setup. These parameters are required to compute distances and support clustering and routing operations. Although this study uses static weight values for the fitness function, the same framework can support adaptive weight adjustment, where weights are dynamically updated in real time according to network conditions such as average residual energy, node density, or communication cost.

5.1. Choosing the Optimal Weights for the Fitness Function

To improve the energy efficiency of the proposed PUMA-GRID protocol, a multi-objective fitness function was employed, combining three key factors with associated weights: the distance from sensor nodes to their respective CH (w_1), the distance from CHs to the BS (w_2), and the residual energy of the CH (w_3). An additional penalty term with a fixed coefficient $\alpha = 10$ is applied to penalize deviations from the optimal number of CHs. The fitness function is minimized, and the PUMA solution with the lowest cost is considered the optimal configuration for that iteration.

To identify the most suitable weight combinations, extensive simulations were conducted under three BS deployment scenarios:

1) Located at the center of the sensor field,
2) Situated outside the network boundary.

Although a full factorial exploration would involve 36 weight combinations, only a representative subset is reported here to avoid redundancy, while all possible combinations were simulated and analyzed. Each configuration was evaluated using the following performance indicators:

1) FND, HND, LND — the rounds when the first, half, and last nodes die, used to estimate network lifetime and stability;
2) Live Nodes per Round — tracking the network's vitality throughout the simulation;
3) Number of Packets Sent to the BS— reflecting data delivery capability;
4) Coverage Fairness Index (CFI) — defined as

$$CFI = \frac{Occupied\ Cells}{Total\ Number\ of\ Cells} \tag{8}$$

which measures the fraction of grid cells containing at least one live node, where $CFI = 1$ indicates perfect spatial fairness and values near 0 reflect poor distribution; and

5) Residual Energy per Round — quantifying the energy dissipated by the entire network in each round.

5.2. Impact of Weight Combinations on Different Metrics (BS Inside the Network)

Figure 2 illustrates the FND, HND, and LND of the same network under different weight combinations when the BS is located inside the network. A higher value of w_1 directs the optimization process to prioritize assigning nodes to nearby CHs. This reduces transmission energy, balances load distribution, and delays the FND, thereby prolonging the initial operational phase of the network. In contrast, a low w_1 neglects proximity, forcing some nodes to transmit over longer distances, consume more energy, and die earlier.

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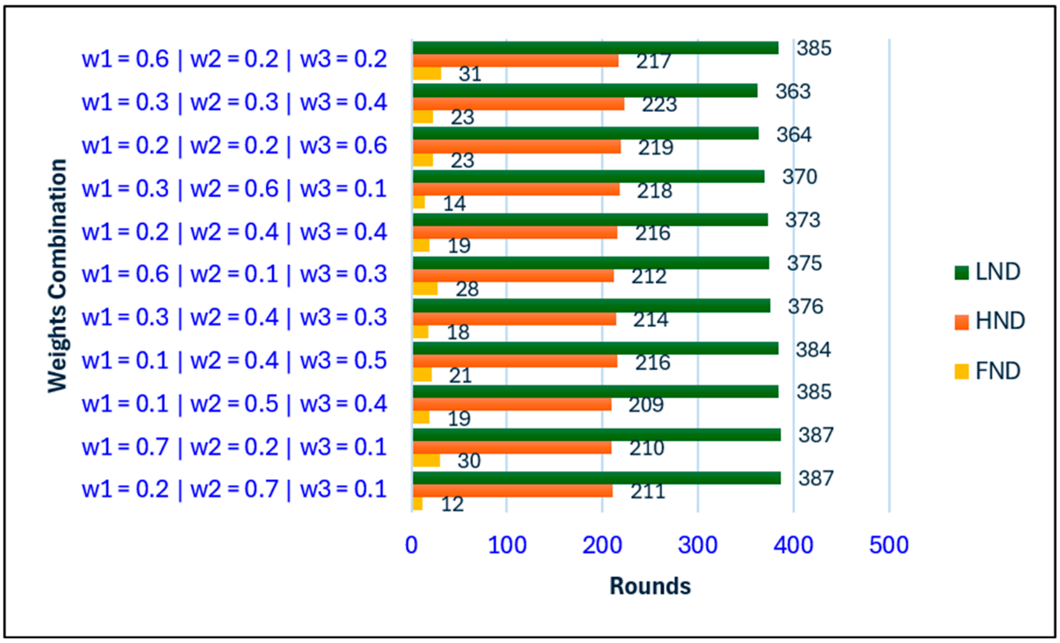

Figure 2. Effect of weight combinations on FND, HND and LND with BS inside the network.

The influence of w_2 on FND, HND, and LND is relatively minor when the BS is located at the center of the network. Since the CH-to-BS distance remains short across all configurations, variations in w_2 do not significantly affect energy consumption or network lifetime. Thus, minimizing CH-to-BS distance is less critical in this deployment scenario.

A lower w_3, which reduces emphasis on CH residual energy, generally results in a longer LND. This is because CH selection becomes more diversified and less biased toward high-energy nodes, enabling more nodes to remain active over time. Conversely, a high w_3 favors repeated selection of energy-rich nodes, which may initially appear beneficial but eventually accelerates their depletion due to overuse, thereby reducing LND.

When w_1 and w_2 differ significantly, even a high w_3 can still produce an extended LND. This demonstrates that the interaction among weights plays a decisive role, and certain imbalanced combinations can nevertheless enhance overall energy efficiency.

Figure 3 shows the number of packets sent to the BS under different weight combinations when the BS is located inside the network. The analysis reveals that the choice of weights (w_1, w_2, w_3) has a significant effect on the volume of data successfully delivered. A higher value of w_1 substantially increases the number of packets, emphasizing the importance of prioritizing intra-cluster distance in CH selection. This improves local communication efficiency and ensures more reliable data forwarding.

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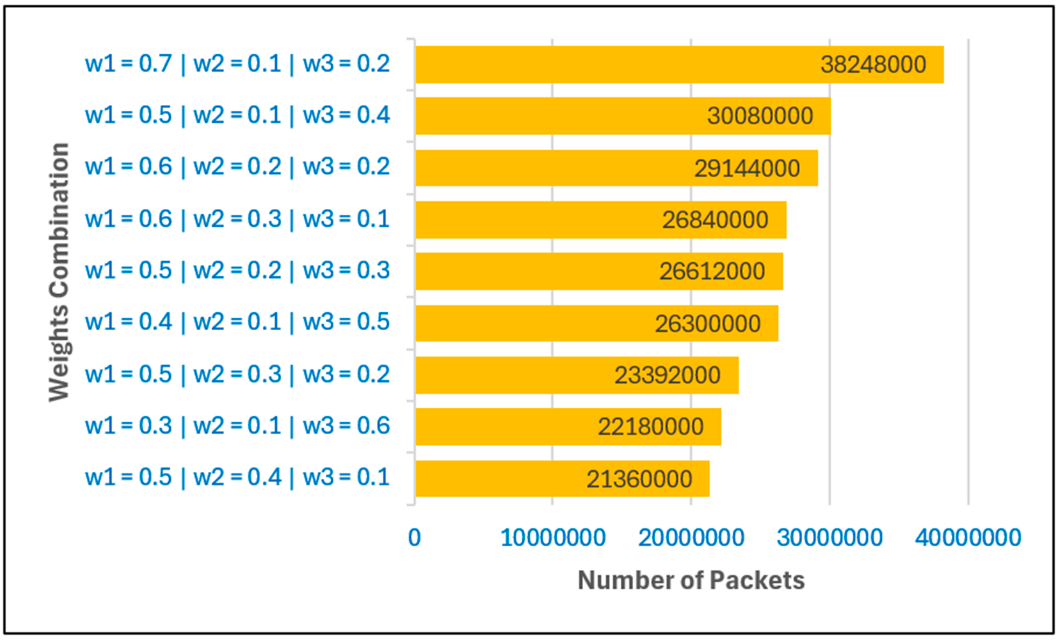
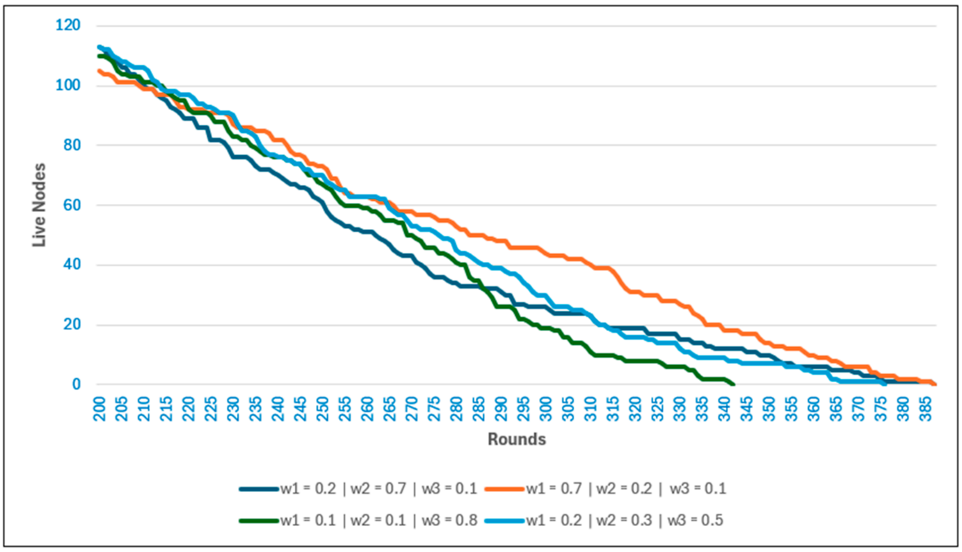


Figure 3. Effect of weight combinations on data delivery with BS inside the network.

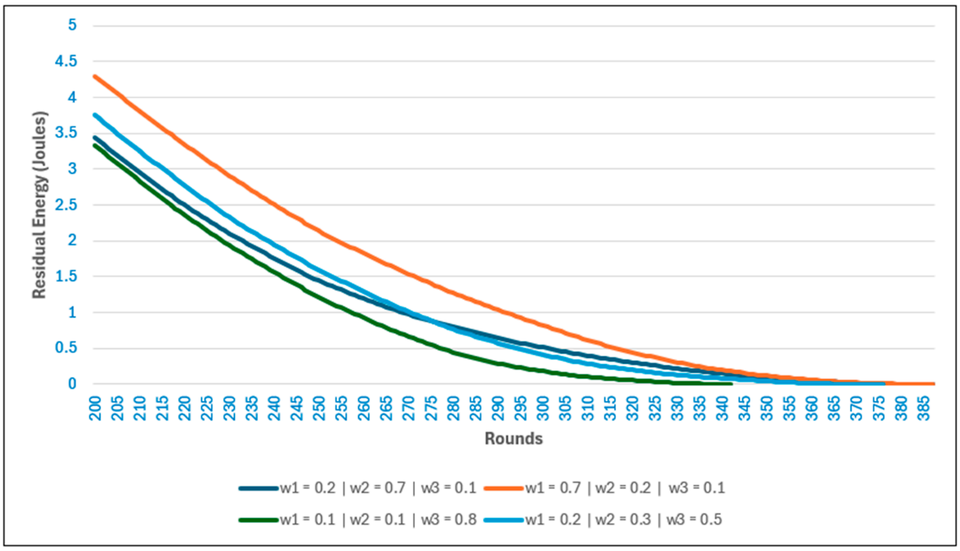
In contrast, lower values of w_2 are associated with higher packet counts. This indicates that giving excessive weight to the distance between CHs and the BS can reduce throughput, particularly when the BS is located within the network where CH-to-BS distances are already short. Thus, minimizing the emphasis on w_2 in such scenarios helps preserve higher packet delivery rates.

The role of w_3 is also evident: lower values, which reduce the influence of residual energy in CH selection, tend to yield more packets. This outcome suggests that excessive reliance on energy-rich nodes can lead to their overuse, while a moderate level of randomness or fairness in CH rotation distributes the forwarding load more evenly and supports sustained throughput.

Figure 4 illustrates the effect of different weight combinations on three performance metrics when the BS is located inside the network: (a) number of live nodes, (b) residual energy, and (c) the CFI.



(a)



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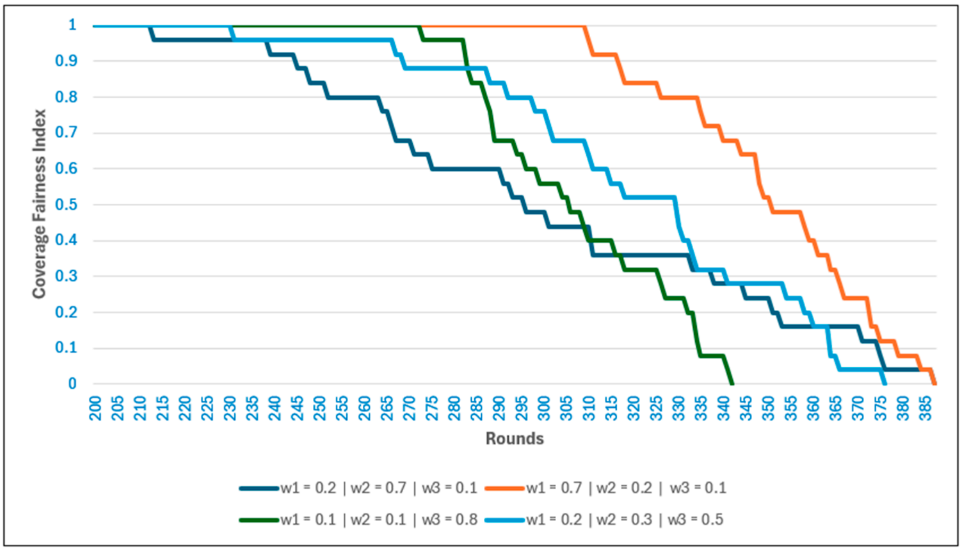


(c)

Figure 4. Effect of weight combinations on live nodes (a), residual energy (b), and CFI (c) with BS inside the network.

A higher value of w_1 generally extends the number of live nodes and preserves residual energy for longer rounds. This is because prioritizing the distance between nodes and their CHs reduces transmission costs, balances energy consumption across nodes, and delays early depletion. Consequently, higher w_1 values also correlate with improved coverage fairness, as nodes remain distributed and active for longer. In contrast, a lower w_1 accelerates node death and energy dissipation due to longer communication distances, which results in uneven coverage and reduced fairness over time.

The effect of w_2 is comparatively limited in this scenario since the BS is centrally located, and CH-to-BS distances are already short across all configurations. As a result, increasing w_2 does not significantly alter node survival, energy consumption, or fairness. Nonetheless, excessive emphasis on w_2 can slightly reduce throughput and energy efficiency by constraining CH selection unnecessarily.

For w_3, the results show that a moderate value contributes to more balanced performance across all three metrics. A lower w_3, which reduces emphasis on CH residual energy, helps sustain node activity and fairness by diversifying CH selection, but it can accelerate overall energy depletion. Conversely, a very high w_3 biases the algorithm toward repeatedly selecting energy-rich nodes, which may appear beneficial initially but leads to concentrated energy usage, faster depletion of those nodes, and lower fairness.

5.3. Impact of Weight Combinations on Different Metrics (BS Outside the Network)

Figure 5 presents the effect of different weight combinations on FND, HND, and LND when the BS is located outside the network. The results highlight that the placement of the BS substantially changes how the weights influence network lifetime.

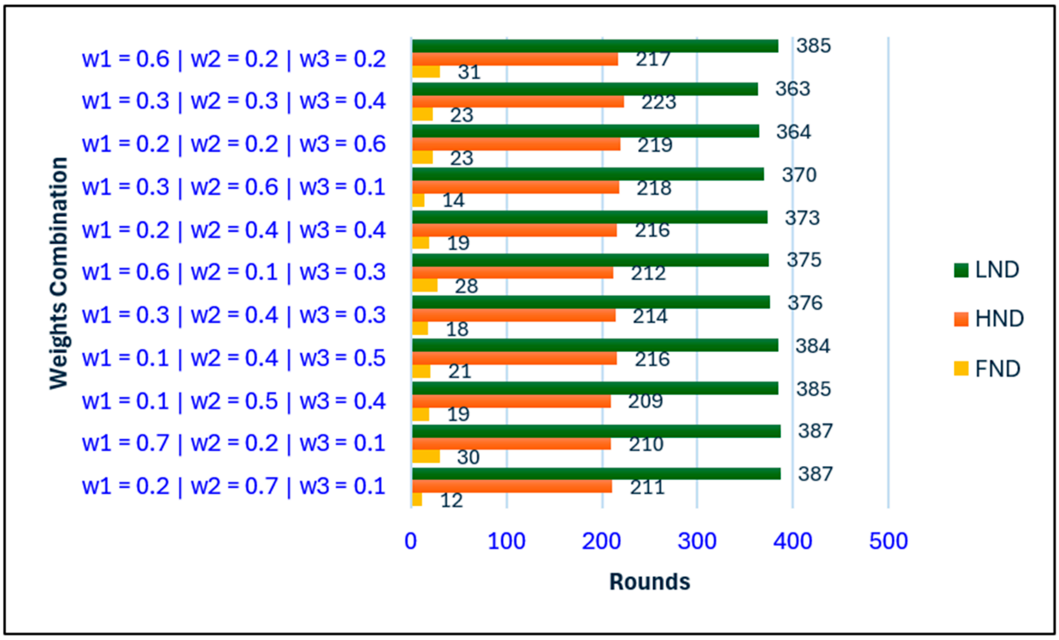


Figure 5. Effect of weight combinations on FND, HND and LND with BS outside the network.

A higher value of w_1 continues to delay FND by emphasizing proximity between nodes and their CHs. This reduces intra-cluster energy costs and prevents early depletion of distant nodes. However, the improvement in HND and LND is less pronounced compared with the BS-inside scenario, since a larger proportion of energy is consumed in long-range CH-to-BS transmissions, regardless of efficient clustering.

The role of w_2 becomes more significant when the BS is external. Higher w_2 values extend both HND and LND, as prioritizing shorter CH-to-BS distances helps reduce the energy cost of long-range transmissions. In contrast, very low w_2 values degrade overall performance because CHs are sometimes selected without regard for their distance to the BS, leading to higher energy consumption and earlier node death.

The influence of w_3 remains consistent with earlier findings: moderate values provide balanced performance, while very high values lead to repeated use of energy-rich nodes, causing faster depletion and reduced LND. Conversely, very low w_3 improves fairness in CH rotation but may accelerate energy consumption across the network.

Figure 6 presents the effect of different weight combinations on the number of packets delivered to the BS when the BS is located outside the network. The results show that the role of weights shifts compared with the BS-inside scenario, reflecting the higher energy cost of long-range CH-to-BS communication.

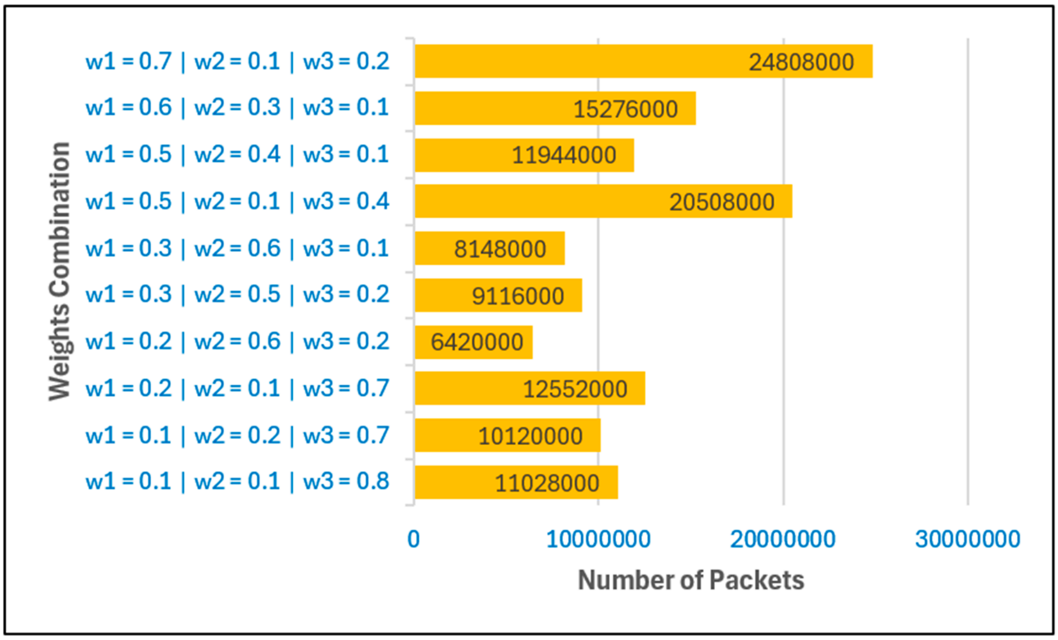


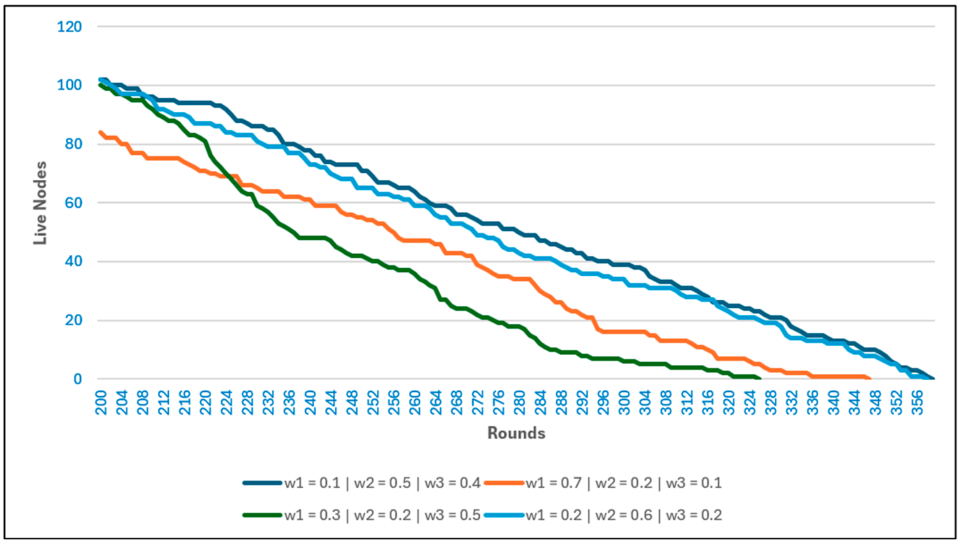
Figure 6. Effect of weight combinations on data delivery with BS outside the network.

A higher value of w_1 significantly improves packet delivery, as prioritizing intra-cluster distance reduces energy consumption during local transmissions and leaves more residual energy available for forwarding data to the distant BS. This effect is particularly evident for combinations where w_1 dominates, leading to the highest packet counts.

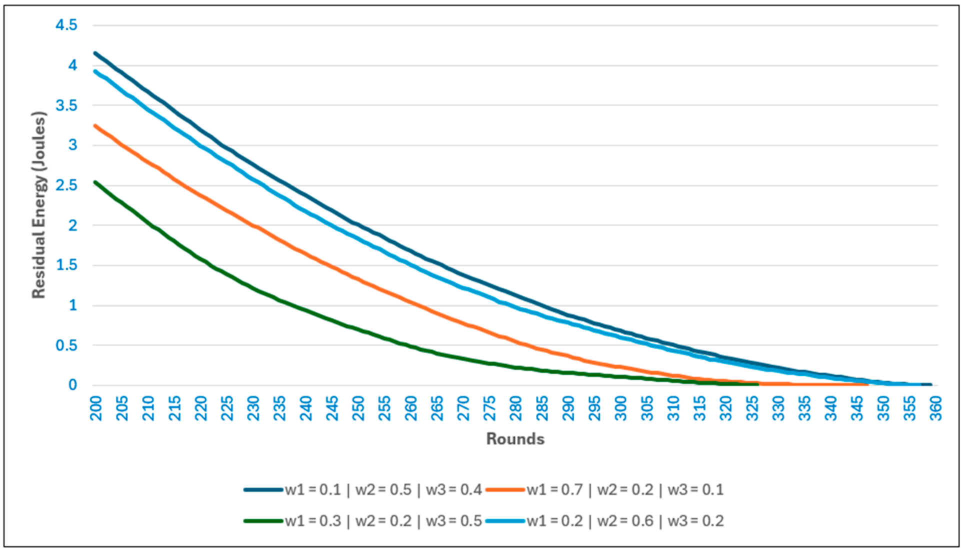
The influence of w_2 becomes more pronounced with the BS outside the network. Lower values of w_2 often correspond to higher packet counts, indicating that assigning excessive weight to CH-to-BS distance can restrict CH selection without substantially reducing long-range transmission costs. Conversely, when w_2 is kept moderate, it contributes positively by preventing inefficient CH placements.

The effect of w_3 is more nuanced. Lower to moderate values support higher packet delivery rates by diversifying CH selection and preventing the repeated overuse of energy-rich nodes. In contrast, very high w_3 values limit CH rotation, concentrating energy demands on a few nodes and reducing the overall number of packets delivered.

Figure 7 shows the effect of different weight combinations on (a) the number of live nodes, (b) residual energy, and (c) the CFI when the BS is located outside the network. The results emphasize how weight selection affects network longevity and energy balance under the more demanding external BS setting.



(**a**)



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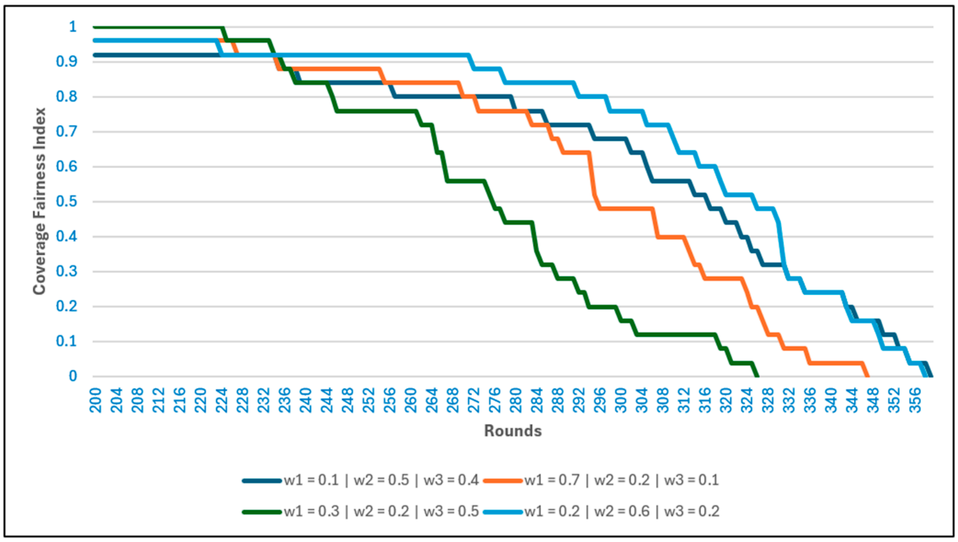

(**c**)

Figure 7. Effect of weight combinations on live nodes (a), residual energy (b), and CFI (c) with BS outside the network.

A higher value of w_1 supports longer node survival by prioritizing intra-cluster proximity. As seen in Figure 7(a), configurations with high maintain a greater number of live nodes over time,

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which translates into slower residual energy depletion in Figure 7(b). In contrast, lower w_1 values accelerate node deaths due to increased transmission distances, leading to earlier energy exhaustion and a faster decline in fairness.

The role of w_2 is more critical when the BS is external. Configurations with moderate to high w_2 exhibit extended residual energy and a slower decline in live nodes, as prioritizing CH-to-BS distance mitigates the cost of long-range transmissions. Figure 7(c) confirms this, where higher w_2 values sustain higher CFI levels for longer periods, ensuring more balanced spatial coverage.

The influence of w_3 is evident in fairness outcomes. Moderate w_3 values help diversify CH selection and balance the workload, contributing to extended CFI stability. However, very high w_3 risks over-relying on energy-rich nodes, which may initially improve residual energy but ultimately accelerate fairness degradation as these nodes deplete more quickly.

5.4. Discussion

The analysis of weight combinations under both deployment scenarios—BS inside and BS outside the network—provides important insights into the role of w_1, w_2, and w_3 in optimizing network lifetime, energy efficiency, and fairness.

When the BS is located inside the network, a higher emphasis on w_1 consistently improves performance across most metrics. Prioritizing intra-cluster distance minimizes transmission costs, delays FND, and sustains a larger number of live nodes, ultimately extending LND. In this scenario, the effect of w_2 is minimal, as the distance between CHs and the BS is already short and does not significantly impact energy consumption or throughput. Meanwhile, moderate values of w_3 prove beneficial by balancing the reuse of high-energy nodes with fairness in CH rotation, thereby supporting longer coverage and stable CFI.

In contrast, when the BS is outside the network, the influence of w_2 becomes critical. Long-range CH-to-BS transmissions dominate energy consumption and assigning higher weight to w_2 helps select CHs closer to the BS, reducing transmission costs and improving HND, LND, and residual energy utilization. While w_1 remains important for sustaining intra-cluster efficiency and supporting high packet delivery, its relative dominance is reduced compared with the BS-inside case. As before, moderate values of w_3 yield more balanced performance by preventing overuse of energy-rich nodes and maintaining fairness in coverage.

Across both scenarios, packet delivery results confirm that the highest throughput is achieved when w_1 is high, w_2 is kept low to moderate, and w_3 remains moderate. However, fairness metrics such as CFI suggest that purely maximizing throughput may compromise spatial coverage unless residual energy is also considered. Thus, configurations with overly low w_3 improve packet counts but reduce coverage balance over time, while excessively high w_3 shorten LND by exhausting selected nodes prematurely.

Synthesizing these findings, the best overall weight configuration emerges as a combination where w_1 is high (0.5–0.7), w_2 is low to moderate (0.1–0.3 when the BS is inside, and 0.2–0.4 when the BS is outside), and w_3 is moderate (0.2–0.3). This setup ensures efficient intra-cluster communication, controlled CH-to-BS distance, and fair utilization of residual energy, resulting in extended network lifetime, sustained packet delivery, and improved coverage fairness across both deployment scenarios.

5.5. Comparison of Different Routing Protocols

To validate the effectiveness of the proposed PUMA-GRID protocol, its performance was evaluated against several well-established clustering and routing schemes, including LEACH, AEO-based variants, and different implementations of PUMA (single-hop, multi-hop, and grid-based). The comparison considered a range of performance metrics that collectively capture both network longevity and efficiency: the stability period expressed through the rounds of first, half, and last node deaths; the total number of packets successfully delivered to the base station; the evolution of live nodes over time; the residual energy trends; the overhead in terms of control packets exchanged; and the coverage fairness index, which reflects the spatial distribution of active nodes. Simulations were conducted under two deployment scenarios, with the base station placed either inside or outside the sensor field, to assess protocol behavior under varying communication constraints.

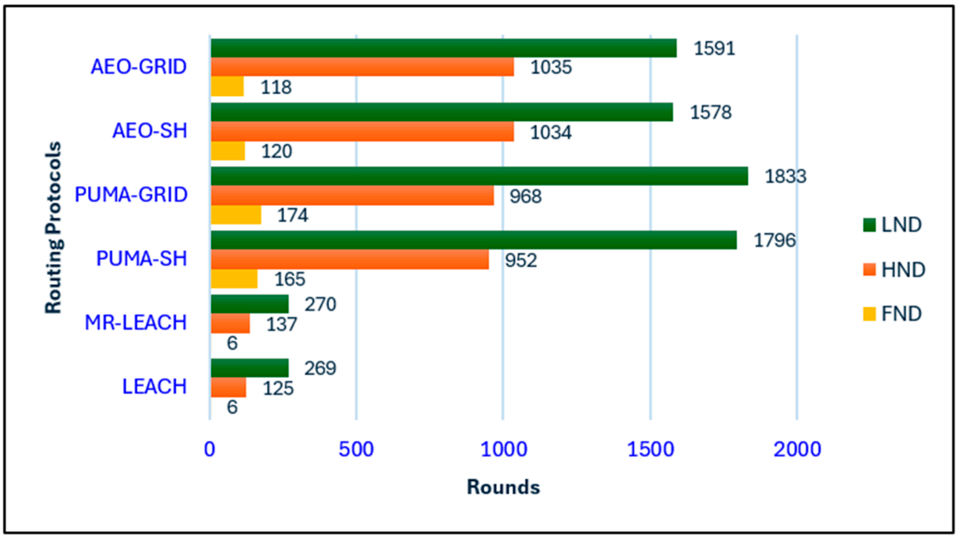
For the simulation parameters (Table 3), we extended the network to $200 \times 200\, m^2$, and increased the initial energy of each node to 0.5 joules. In addition, parameters values are set for grid size, w_1, w_2, and w_3.

Table 3. Simulation parameters for comparing routing protocols.

Simulation Parameters	Values/Ranges
Network Size	$200 \times 200\ (m^2)$
BS Position	(0, 0), (100, 100)
Number of Nodes	300
Node's Initial Energy	0.5 $(Joules)$
Percentage of Clusterheads	5 %
Packet Size	500 $(Bytes)$
E_{elec}	50 $(nJoule/bit)$
ε_{fs}	10 $(pJoule/bit/m^2)$
ε_{mp}	0.0013 $(pJ/bit/m^4)$
d_0	10 (m)
Grid Size	40 (m)
w_1	0.7
w_2	0.2
w_3	0.1

In Figure 8(a), where the base station is located inside the network, LEACH and MR-LEACH show the weakest results. Both suffer from extremely early FND and a rapid progression to HND, which indicates highly unbalanced energy consumption. Their LND values are also much shorter than those achieved by optimization-based methods, confirming that their probabilistic cluster-head selection does not provide adequate energy distribution, even under the relatively favorable condition of a centrally placed BS.

The AEO-based protocols offer a noticeable improvement over LEACH and MR-LEACH, extending the HND and LND considerably. Between the two, AEO-GRID performs slightly better, benefiting from its structured multi-hop forwarding, which helps to alleviate the energy burden of long transmissions. Nevertheless, both variants still experience relatively early FND compared with PUMA-based methods, limiting their stability phase in the initial part of the network's lifetime.



(a)

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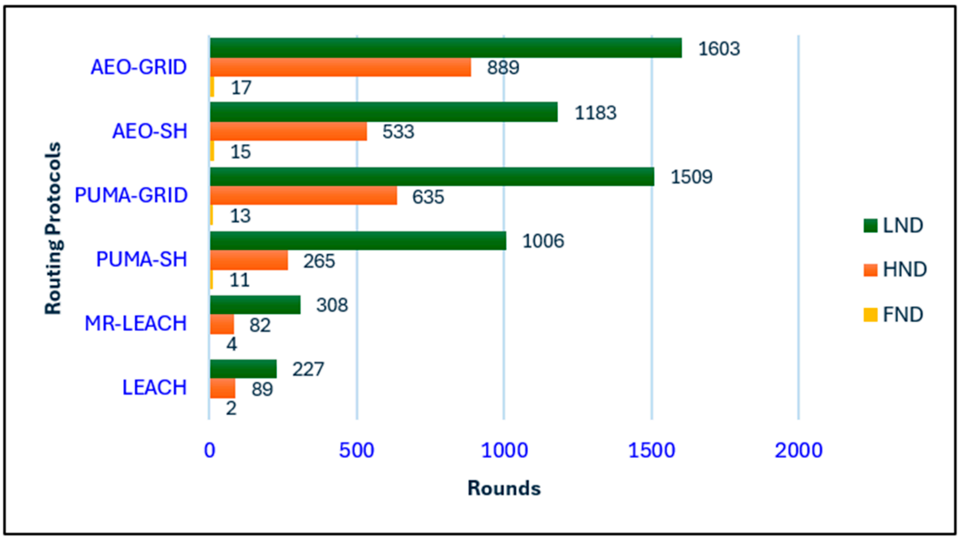


(**b**)

Figure 8. Comparison of FND, HND, and LND across different routing protocols with BS inside (a) and outside (b) the network.

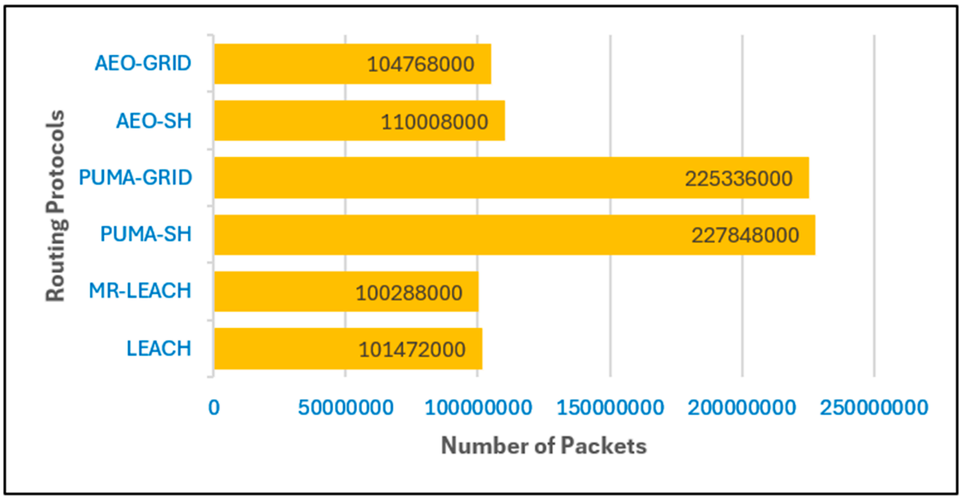
PUMA-SH and PUMA-GRID achieve the best overall performance in the BS-inside scenario. PUMA-SH delays FND significantly while maintaining a strong stability period, and PUMA-GRID further extends LND, achieving the longest lifetime among all protocols. This outcome demonstrates the benefit of combining PUMA's adaptive clustering with grid-based routing, which balances traffic loads and prevents energy hotspots. As a result, PUMA-GRID delivers the most balanced and long-lasting operation when the BS is positioned inside the sensor field.

In Figure 8(b), where the base station is located outside the monitored area, the performance trends change noticeably. LEACH and MR-LEACH degrade further, with extremely short lifetimes and minimal stability. Nodes in these protocols consume excessive energy when transmitting to the distant BS, leading to very early network collapse.

Interestingly, under this more challenging deployment, the AEO-based protocols outperform all others. AEO-SH and particularly AEO-GRID achieve the longest HND and LND, clearly showing their strength in distributing energy fairly when longer communication distances are involved. The fitness-driven clustering of AEO, combined with grid-based routing, enables the network to adapt effectively to the harsher conditions, sustaining activity longer than both PUMA-based and classical approaches.

The PUMA protocols still maintain competitive results, especially in terms of delaying FND, but their lifetimes are shorter than those of the AEO-based methods in this scenario. PUMA-SH provides moderate stability, while PUMA-GRID achieves a balanced performance but cannot match the endurance of AEO-GRID. This indicates that while PUMA excels under central BS placement, AEO is better suited for external BS deployments, where its clustering and routing strategies better handle the additional communication overhead.

In Figure 9(a), where the base station is located inside the network, LEACH and MR LEACH achieve the lowest packet delivery, reflecting their limitations in balancing energy and sustaining communication. The probabilistic cluster head election of LEACH and the multi-hop variation of MR LEACH result in nodes depleting their energy too early, which reduces the overall throughput. AEO-SH and AEO-GRID perform better, with noticeable gains in packet delivery compared to LEACH, but their performance remains moderate and unable to match the more advanced designs. In contrast, the PUMA based approaches clearly dominate. Both PUMA-SH and PUMA-GRID deliver more than twice the number of packets compared to AEO and LEACH, with PUMA-GRID producing the highest values among all protocols. This emphasizes the advantage of combining PUMA's adaptive cluster head election with grid based multi-hop routing, which reduces energy consumption and ensures more balanced utilization of resources.



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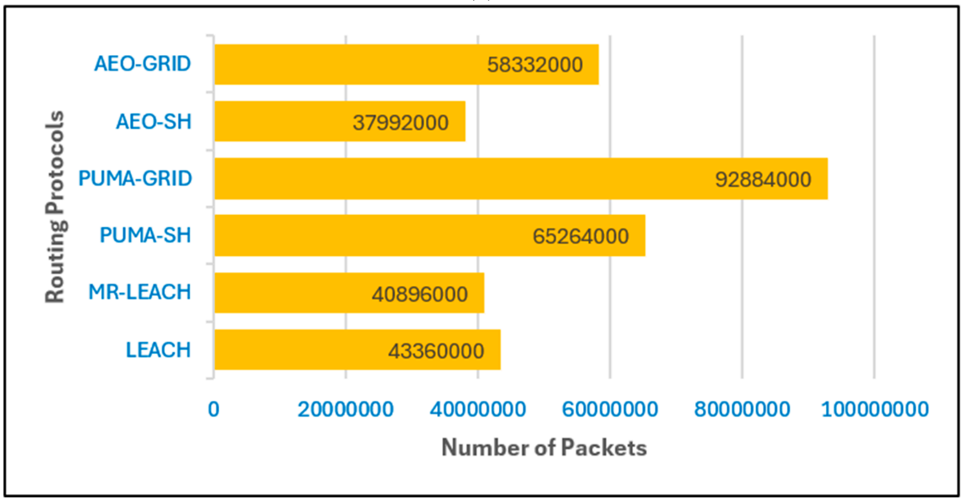
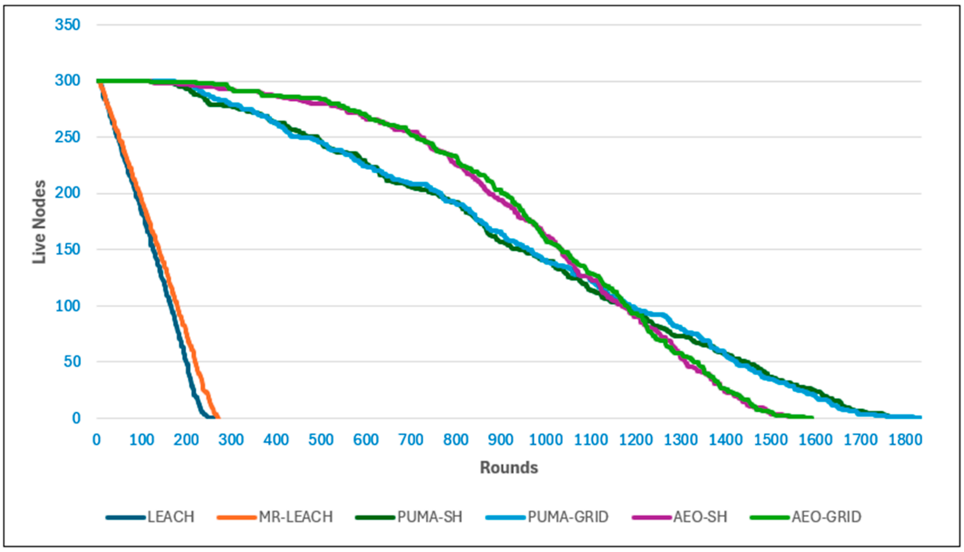


(b)

Figure 9. Comparison of the number of packets delivered to the base station across different routing protocols with BS inside (a) and outside (b) the network.

In Figure 9(b), when the base station is placed outside the network, packet delivery declines across all protocols because of the higher transmission energy required for long distance communication. LEACH and MR-LEACH remain the weakest performers, again highlighting their inability to adapt to challenging deployment conditions. AEO-SH and AEO-GRID manage to sustain a moderate level of throughput, but their improvement is still limited. The PUMA based protocols once again provide the best results, with PUMA-GRID achieving the highest number of packets followed closely by PUMA-SH. This consistent superiority across both scenarios highlights the robustness of the PUMA design, which successfully integrates residual energy awareness, node proximity, and efficient data forwarding mechanisms to maintain reliable communication even under more demanding conditions.

In Figure 10(a), which shows the results with the base station located inside the network, the LEACH and MR-LEACH protocols exhibit very short lifetimes, with both the first and last nodes dying much earlier than in other protocols. This outcome is consistent with their limited energy-awareness and reliance on probabilistic cluster head selection. In contrast, the AEO protocols (both single hop and grid-based) extend the network lifetime considerably, with the last node surviving much longer than in LEACH and MR-LEACH. However, while AEO demonstrates strong stability and balanced performance, the PUMA-based protocols, particularly PUMA-GRID, show the best performance overall. PUMA-GRID maintains live nodes for the longest duration, indicating that the combination of adaptive cluster head selection and grid-based routing significantly reduces energy imbalance and delays node deaths. PUMA-SH also performs strongly, maintaining a higher number of live nodes than AEO protocols, though it falls slightly behind PUMA-GRID in sustaining the final rounds of operation.



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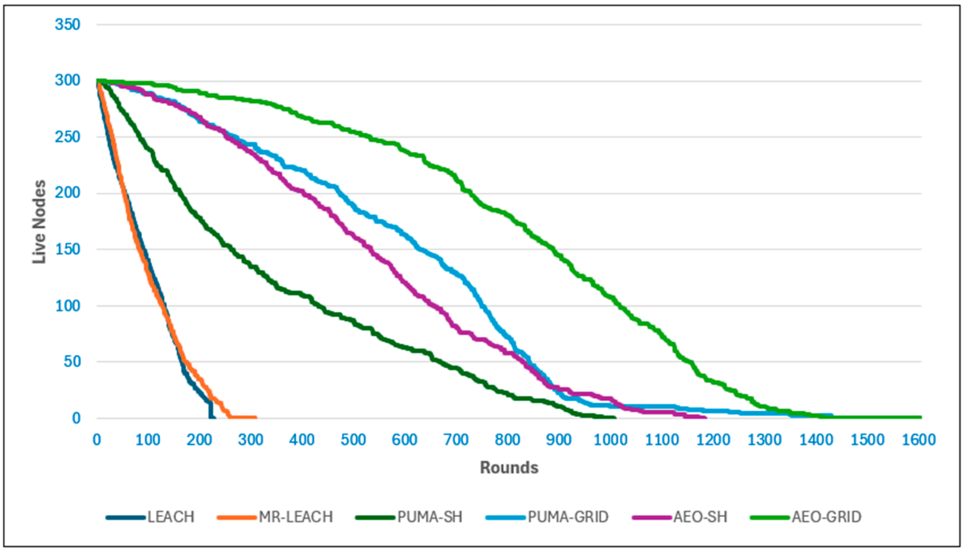
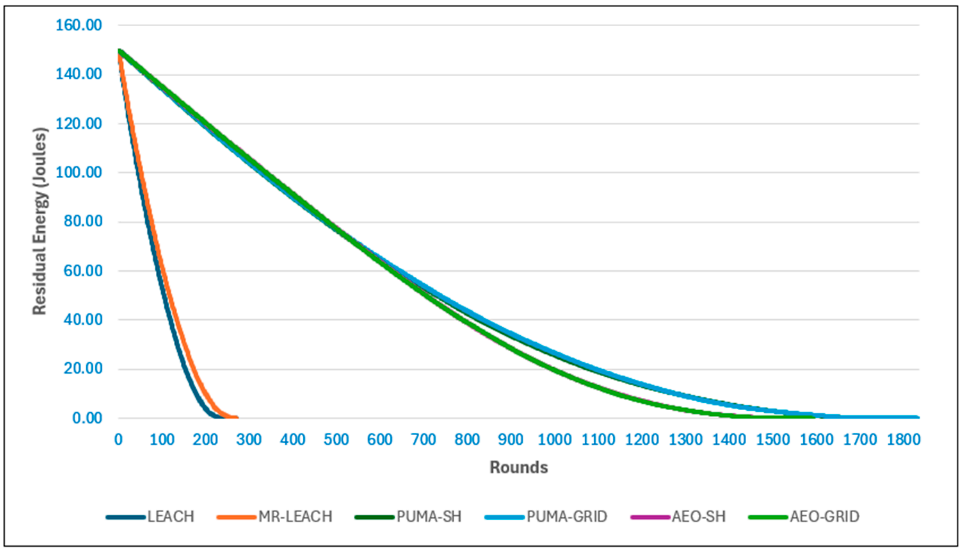


(**b**)

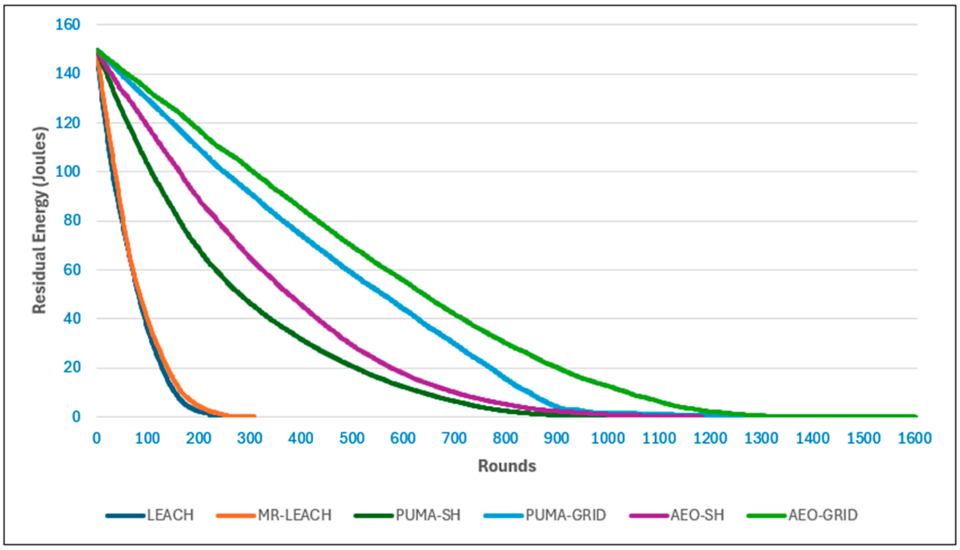
Figure 10. Comparison of the number of live nodes across different routing protocols with BS inside (a) and outside (b) the network.

In Figure 10(b), when the base station is positioned outside the network, the performance differences between protocols become more pronounced. LEACH and MR-LEACH again show the shortest lifetime, confirming their inability to cope with the higher communication burden imposed by longer distances to the base station. AEO-SH and AEO-GRID perform considerably better, demonstrating resilience in maintaining active nodes for a longer time compared to LEACH. However, the PUMA protocols remain superior under this scenario. PUMA-SH shows the longest stability period, maintaining the largest number of live nodes until the later rounds, while PUMA-GRID also achieves a significantly extended lifetime compared to AEO. These results confirm that PUMA's optimization-driven cluster head election, combined with efficient routing, ensures more balanced energy consumption, making it the most effective approach for sustaining network operations regardless of the base station placement.

In Figure 11(a), where the base station is located inside the network, the residual energy trends highlight clear differences between the protocols. LEACH and MR-LEACH deplete their energy rapidly, confirming their limited capacity to distribute communication loads evenly across the network. Both protocols reach near-zero energy in significantly fewer rounds, reflecting their vulnerability to hotspot issues and lack of energy-aware clustering. In contrast, AEO-SH and AEO-GRID extend energy sustainability further, with nodes maintaining moderate reserves across more rounds. This outcome is consistent with their energy-oriented cluster formation, which postpones full depletion. However, the best performance is observed in PUMA-based protocols, especially PUMA-GRID and PUMA-SH, which conserve energy most effectively. The balanced incorporation of residual energy, intra-cluster distance, and grid-based routing mechanisms enables slower depletion, maintaining higher energy levels through later rounds. This indicates that PUMA's design succeeds in spreading energy consumption evenly while preventing premature exhaustion of cluster heads.



(a)



(b)

Figure 11. Residual energy comparison across different routing protocols with BS inside (a) and outside (b) the network.

When the base station is placed outside the network, as shown in Figure 11(b), the disparities become more pronounced. LEACH and MR-LEACH remain the weakest performers, exhausting energy reserves very early, which underscores their inability to handle the longer transmission distances imposed by external base station placement. AEO-SH and AEO-GRID perform better, especially AEO-GRID, which manages to conserve energy longer due to its grid-based structure. Nonetheless, PUMA again demonstrates superior performance. PUMA-GRID shows the most stable

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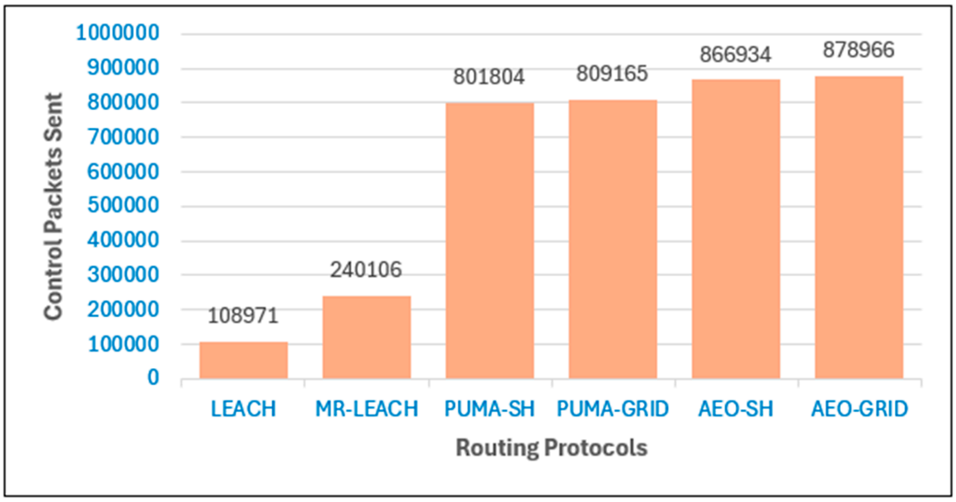
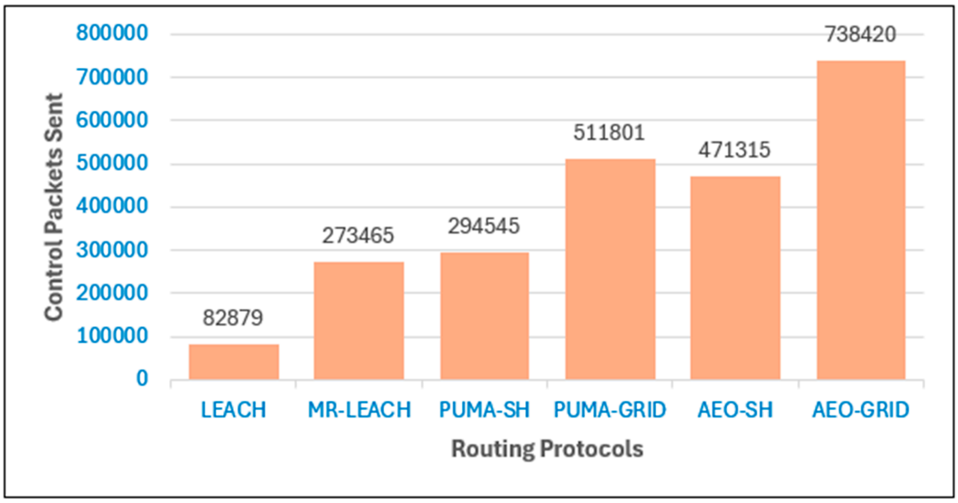
and gradual decline in residual energy, with PUMA-SH following closely. These results reveal that PUMA's adaptive strategies are resilient under harsher transmission conditions, ensuring that energy dissipation is minimized and reserves last significantly longer than in competing protocols.

In Figure 12, the number of control packets highlights the overhead introduced by each routing protocol. LEACH consistently shows the lowest control overhead in both scenarios, with BS inside and outside the network, since it relies on simple probabilistic clustering without frequent energy-aware adjustments or sophisticated routing mechanisms. MR-LEACH increases the overhead slightly due to its multi-hop extension, which requires additional control messaging for route setup.



(**a**)



(**b**)

Figure 12. Comparison of control packet overhead across different routing protocols with BS inside (a) and outside (b) the network.

In contrast, the PUMA-based protocols generate a considerably higher number of control packets compared to LEACH and MR-LEACH. This overhead stems from the energy-aware cluster head selection and adaptive routing strategies that require additional coordination between nodes. While this increases control packet exchange, it directly contributes to improved energy balance and longer network lifetime, as observed in earlier figures. Between the two, PUMA-GRID typically introduces slightly more overhead than PUMA-SH, owing to the additional routing logic used in grid-based forwarding.

The AEO-based protocols exhibit the highest overhead across both scenarios. Their complex optimization-driven clustering demands intensive control messaging to exchange node state information and maintain optimal configurations. This ensures strong energy distribution but comes

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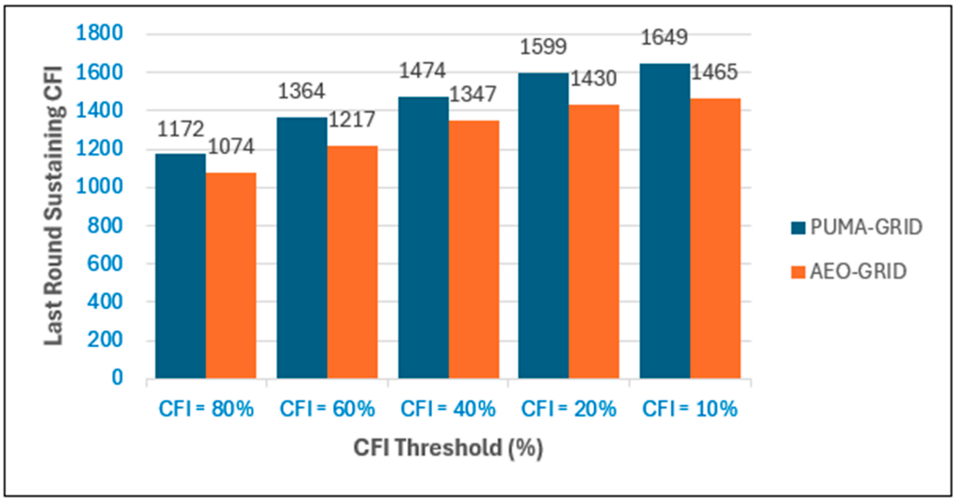
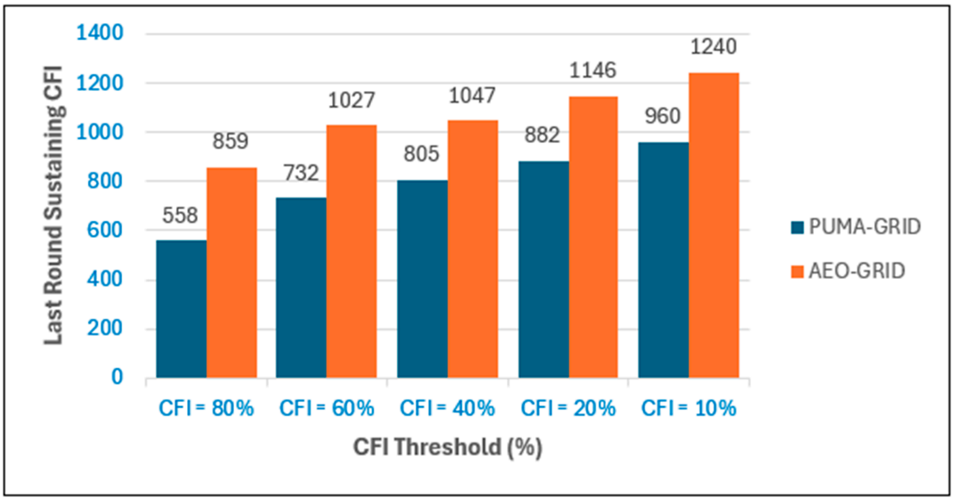
at the cost of higher overhead. Notably, AEO-GRID further increases the number of control packets compared to AEO-SH, reflecting the added cost of maintaining grid-based routing paths.

In Figure 13(a), with the base station placed inside the network, PUMA-GRID consistently outperforms AEO-GRID in maintaining higher coverage fairness over longer periods. At high CFI thresholds such as eighty and sixty percent, PUMA-GRID achieves a larger number of rounds before the fairness level drops, demonstrating its ability to sustain widespread spatial coverage across the grid. As the fairness requirement becomes less strict, both protocols extend their network lifetimes, yet PUMA-GRID maintains a steady advantage, confirming its strength in balancing energy consumption while ensuring even node distribution.



(a)



(b)

Figure 13. Network lifetime in terms of the last round sustaining different Coverage Fairness Index (CFI) thresholds for PUMA-GRID and AEO-GRID, with BS inside (a) and outside (b) the network.

In Figure 13(b), where the base station is located outside the monitored area, the trend is reversed. AEO-GRID shows better resilience in sustaining higher CFI levels for longer rounds compared to PUMA-GRID. This is particularly evident at stricter thresholds such as eighty and sixty percent, where AEO-GRID achieves later last-round values. At lower fairness thresholds, such as twenty and ten percent, AEO-GRID still maintains its advantage, highlighting its efficiency in scenarios where longer-distance transmissions dominate.

5.6. General Discussion

The comparative analysis across Figures 8 to 13 highlights not only which protocols perform better but also why these differences emerge, offering deeper insights into energy-aware routing for wireless sensor networks. The results confirm that network lifetime extension depends strongly on how effectively protocols balance energy among nodes. LEACH and MR-LEACH, with their probabilistic or static cluster head assignments, suffer from severe imbalance: some nodes deplete energy very early, leading to short stability periods. By contrast, optimization-based protocols such as PUMA and AEO explicitly consider residual energy and distances in their objective functions, which directly improves stability. PUMA-GRID achieves superior performance because it combines the adaptive exploration-exploitation mechanism of the Puma Optimizer with grid-based multi-hop routing. The optimizer dynamically refines cluster-head selection to avoid premature node depletion, while the grid structure shortens transmission distances and balances inter-cluster loads. This synergy minimizes redundant transmissions, preserves residual energy, and maintains spatial coverage more effectively than LEACH, AEO-based, or earlier PUMA variants.

Throughput analysis provides further evidence of these differences. The number of packets delivered to the base station reflects both stability and how well a protocol manages congestion and redundancy. LEACH and MR-LEACH deliver very few packets because many nodes die early and surviving nodes face high transmission costs. AEO protocols improve throughput but remain limited by their sensitivity to initial cluster head assignments. PUMA protocols, especially PUMA-GRID, achieve the highest throughput in both scenarios, confirming that adaptive exploration–exploitation and efficient forwarding maximize sustained delivery. The improvement in PUMA-GRID is not only quantitative but also qualitative: by maintaining diverse cluster head distributions and structured forwarding paths, the network avoids congestion around central nodes, ensuring that throughput is steady rather than collapsing rapidly after a short period.

The live node and residual energy trends provide complementary insights. LEACH and MR-LEACH show sharp drops in both metrics, which reveals two main shortcomings: poor energy balancing and lack of residual energy consideration. AEO protocols distribute energy more effectively, reflected in smoother declines, but they still concentrate some load on selected cluster heads, leading to earlier depletion than PUMA. PUMA's balance between exploration and exploitation ensures that cluster head roles rotate across different candidates, which distributes energy use more evenly and prevents premature exhaustion of high-energy nodes. Grid-based routing amplifies this effect by minimizing long direct transmissions, reducing the steep decline seen in other methods. These findings also show that the metric of residual energy alone can be misleading: although AEO maintains relatively high reserves at certain points, its coverage and fairness degrade earlier, indicating that spatial distribution of energy is as important as total reserves.

The analysis of control packet overhead reveals another trade-off. LEACH achieves low overhead but at the expense of stability and fairness, showing that minimal control traffic is not useful when it results in early collapse. AEO incurs the highest overhead because of frequent information exchange for clustering and routing optimization. PUMA strikes a middle ground, requiring more control packets than LEACH but significantly fewer than AEO, while still achieving superior lifetime and fairness. This demonstrates that optimal protocol design is not about minimizing overhead but about maximizing utility per control packet. PUMA achieves this by linking its overhead directly to measurable lifetime gains, while AEO sometimes introduces overhead that outweighs the benefits, particularly when the base station is inside the field.

Coverage fairness adds another dimension to the evaluation. A network that survives longer but collapses coverage in large regions may be unsuitable for applications such as environmental monitoring or surveillance. The Coverage Fairness Index results show that PUMA-GRID sustains higher fairness levels for longer when the base station is inside the network, reflecting its ability to spread cluster heads evenly and avoid clustering bias. Conversely, when the base station is outside, AEO-GRID maintains fairness for longer, indicating that its clustering strategy is more robust under asymmetric energy demands. This suggests that protocol suitability depends on deployment context and application requirements: for dense monitoring tasks where coverage uniformity is critical, PUMA is more effective with central base stations, whereas AEO is better suited for external placements where energy burdens are unevenly distributed.

Taken together, the findings show that PUMA-GRID provides the most consistent improvement across metrics when the base station is inside the network, combining high throughput, extended stability, balanced energy consumption, and strong fairness. When the base station is outside, AEO-GRID performs competitively and often surpasses PUMA in fairness and energy distribution, although PUMA remains stronger in throughput. LEACH and MR-LEACH remain consistently weak across all scenarios, underscoring the necessity of energy-aware and adaptive clustering strategies. The results highlight that effective protocol design requires not only extending lifetime but also balancing energy, maintaining fairness, and managing overhead, with the choice of protocol ultimately depending on the deployment environment and application objectives.

5.7. Limitations

Although the proposed PUMA-GRID protocol achieves notable improvements in energy efficiency, stability, and coverage fairness compared with existing approaches, several limitations should be acknowledged.

First, the study was carried out in an idealized simulation environment where effects such as interference, packet loss, retransmissions, and signal fading were not modeled in detail. The use of the free space propagation model provided a simplified baseline for evaluating the optimization behavior of the algorithm, but it does not capture the full complexity of real wireless environments. Incorporating more realistic communication stacks and physical channel models will be an important step in future experimental work.

Second, the grid-based routing structure was designed mainly to complement the PUMA optimization mechanism rather than to serve as a new routing method. While the grid approach effectively reduces long distance transmissions and balances the load among cluster heads, it does not adapt dynamically to variations in node density, node failures, or irregular spatial distributions. Empty grid cells or uneven deployments can cause routing inefficiencies or temporary disconnections. However, the simplicity and scalability of the grid model make it appropriate for evaluating the energy optimization capability of PUMA based clustering. Future studies will consider adaptive grid resizing and density aware routing mechanisms to improve resilience in heterogeneous network conditions.

Third, the proposed approach assumes that all nodes are static and identical in terms of initial energy and communication capacity. This assumption may not hold in practice, where node movement, hardware variation, or environmental factors can influence network performance. Extending the protocol to support mobile and heterogeneous sensor nodes would enhance its practical applicability.

Finally, the current configuration of weights in the fitness function is determined through simulation rather than through an adaptive real time process. Although this study identified effective weight combinations for different base station placements, a real time adaptation based on current network conditions such as remaining energy, node distribution, or data traffic could further enhance performance and reliability.

6. Conclusions

This paper presented PUMA-GRID, a new clustering and routing protocol for wireless sensor networks that combines the Puma Optimization Algorithm with a grid-based A* inspired multi-hop routing method. The proposed framework was designed to address two main challenges in WSNs: extending network lifetime and ensuring balanced energy consumption among sensor nodes. By using the adaptive exploration and exploitation balance of the Puma Optimizer, PUMA-GRID achieved more effective cluster head selection compared to traditional and peer protocols. At the same time, the grid-based routing strategy reduced long distance transmissions by selecting intermediate relays in an intelligent manner, which lowered communication overhead and limited the hotspot problem.

Extensive simulations with the base station placed both inside and outside the monitored field demonstrated the strength of PUMA-GRID across different performance metrics. The protocol consistently delayed the rounds of first, half, and last node death, showing improved stability and longer lifetime. It also increased packet delivery, maintained more live nodes, preserved residual energy more efficiently, and reduced the number of control packets compared to LEACH and AEO based protocols. In addition, the Coverage Fairness Index analysis showed that PUMA-GRID ensured more uniform spatial coverage, which is essential for real world applications such as environmental monitoring and disaster detection. The study of weight combinations confirmed that the balance between intra cluster distance, distance to the base station, and residual energy must be adapted to deployment conditions for the best outcome.

Although the results are promising, more work is required to bring the protocol closer to practical use. Future directions include extending PUMA-GRID to mobile sensor networks where mobility of nodes and the base station introduce further challenges in cluster stability and routing. Another important step is to integrate adaptive methods, such as learning based models, that can adjust fitness function weights automatically as the network changes. Further improvements may also be achieved by cross layer optimization that considers routing, medium access scheduling, and duty cycling together to reduce energy use.

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Abbreviations

The following abbreviations are used in this manuscript:

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AEO	Atomic Energy Optimization
AEO-GRID	AEO with Grid based Routing
AEO-SH	AEO Single Hop
AEOWSNC	Atomic Energy Optimization for Wireless Sensor Network Clustering
AVOACS	African Vulture Optimization Algorithm based Clustering Scheme
BDA	Binary Dragonfly Algorithm
BS	Base Station
CFI	Coverage Fairness Index
CH	Cluster Head

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CMD	Communication Mode Decider
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
EEM-LEACH-ABC	Energy Efficient Multi hop LEACH with Artificial Bee Colony
FND	First Node Dead
GA	Genetic Algorithm
GPS	Global Positioning System
GWO	Grey Wolf Optimizer
HND	Half Node Dead
KPSOFL	K-means + Particle Swarm Optimization + Fuzzy Logic
LEACH	Low Energy Adaptive Clustering Hierarchy
LND	Last Node Dead
NOMA	Non-Orthogonal Multiple-Access
PO	Puma Optimizer
PSO	Particle Swarm Optimization
PUMA-GRID	Puma Optimizer with Grid based Routing
PUMA-SH	Puma Optimizer Single Hop
RSSI	Received Signal Strength Indication
SHO-CH	Spotted Hyena Optimizer for Cluster Head selection
TDMA	Time Division Multiple Access
TDoA	Time Difference of Arrival
ToA	Time of Arrival
WSN	Wireless Sensor Network

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