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Energy-Optimized Routing in WSNs: Enhanced Dijkstra-Based MEP and EBP Approaches

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Abstract Wireless Sensor Networks (WSNs) require energy-efficient routing to extend network lifetime due to limited node battery capacity. This paper introduces two enhanced Dijkstra-based routing protocols: Minimum Energy Path (MEP) and Energy-Balanced Path (EBP). These protocols are designed to address energy inefficiency and premature node failures in WSNs. MEP minimizes per-packet energy consumption by optimizing transmission routes using a dynamic energy model that accounts for distance-dependent transmission costs and fixed reception costs. In contrast, EBP dynamically adjusts routing paths using a balancing factor ($\beta = 0.60$) to distribute the energy load equitably across nodes, mitigating the "energy hole problem."Extensive simulations on 15-node and 50-node networks demonstrate EBP's superiority. It extends network lifetime by 97.3% over MEP (369 vs. 185 requests in 15-node networks; 730 vs. 308 in 50-node topologies) while maintaining balanced energy depletion. Additionally, comparative evaluation against 12 state-of-the-art protocols (e.g., LEACH, PEGASIS, GEAR) shows that EBP achieves up to 137% lifetime improvement over these benchmarks.

Keywords Wireless Sensor Networks (WSNs), Energy Efficiency, Dijkstra's Algorithm, Load Balancing, Network Lifetime, Routing Optimization

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1. Introduction

Wireless Sensor Networks (WSNs) face significant challenges in energy management, where 60–70% of nodes often deplete their power prematurely due to uneven energy consumption caused by inefficient routing strategies, a phenomenon known as the "energy hole problem"[1]. This issue severely impacts network lifetime and operational reliability. Furthermore, routing in WSNs presents a computationally complex challenge due to the factorial growth of possible paths in fully connected networks. For example, even a small-scale network with just 20 nodes can generate approximately $1.7403 \times 10^{+16}$ potential routes, making exhaustive path evaluation impractical [2, 3]. Compounding this complexity are dynamic environmental factors such as channel fading, node mobility, and interference, which demand adaptive and energy-efficient routing protocols to maintain network performance.
This work addresses these challenges by proposing energy-optimized routing techniques designed to extend the operational lifetime of ad-hoc WSNs. Conventional methods, such as evaluating every possible route to identify the Minimum-Energy Path (MEP), are computationally prohibitive due to their exponential time complexity. For instance, a 20-node network would require analyzing over $1.7403 \times 10^{+16}$ routes—an infeasible approach for resource-constrained sensor nodes. Instead, we introduce two enhanced Dijkstra-based algorithms: *MEP-Dijkstra*, which minimizes per-packet energy consumption, and *EBP-Dijkstra*, which dynamically balances energy usage across nodes to prevent premature failures. These solutions leverage graph-theoretic optimization while incorporating realistic energy consumption models, ensuring scalability and adaptability to dynamic network conditions. By combining computational efficiency with energy-aware routing, our approach provides a practical

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and sustainable solution for WSN deployments in real-world applications. Table 1 with Figure 1 emphasizes the variation of the number of nodes versus the required actual routes in the completely connected network (CCN). It is clear that the relation is exponentially increasing with linear step variation of several nodes.

Table 1. Number of nodes versus number of routes

Number of nodes (n)	Exact, Number of Routes
4	5
5	16
6	65
7	326
8	1957
9	13700
10	109601
11	986410
12	9,864,101
13	108,505,112
14	1,302,061,345
15	16,926,797,486
16	236,975,164,805
17	3,554,627,472,076
18	56,874,039,553,217
19	966,858,672,404,690
20	17,403,456,103,284,420

These results yield to rely on optimization search techniques to get the optimal route for Energy saving. We use Dijkstra's Algorithm to find the optimal route for each request to get this route.

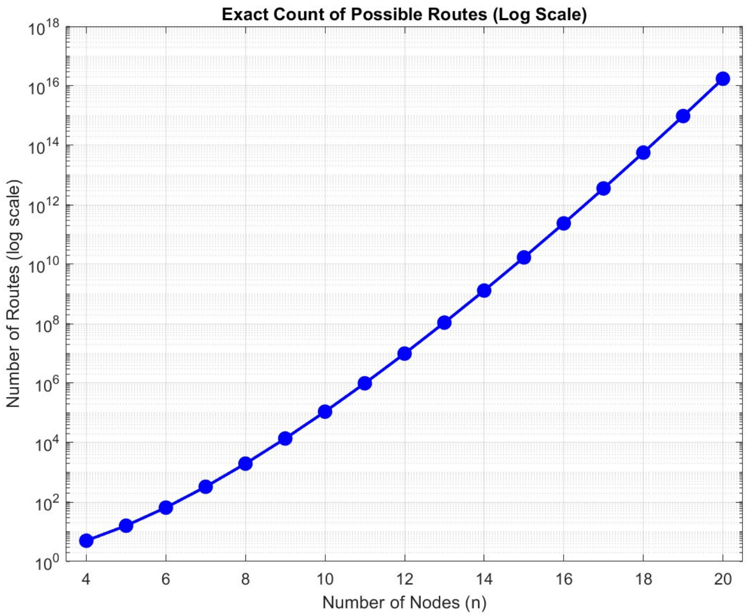

Figure 1. Number of Routes Versus Number of Nodes

2. Proposed Work

2.1. Dijkstra's Algorithm and Its Application in WSNs

Dijkstra's algorithm serves as a fundamental shortest-path solution for weighted graphs with non-negative edges. As a greedy, single-source algorithm, it systematically constructs an optimal routing tree by iteratively selecting the nearest unvisited node and updating its neighbors' path costs. The algorithm guarantees minimal path weights when implemented with a priority queue, achieving a time complexity of

$$\mathcal{O}(|E| + |V| \log |V|)$$

when using efficient data structures. However, two significant limitations restrict its general applicability: it cannot handle graphs with negative edge weights (requiring Bellman-Ford as an alternative), and it proves inefficient for all-pairs shortest path calculations (where Floyd-Warshall performs better).

In Wireless Sensor Networks, Dijkstra's algorithm requires careful adaptation to address energy constraints and network lifetime optimization. The critical metric becomes not just path length, but energy consumption and distribution across nodes. Network lifetime is typically measured by the operational duration until the first node exhausts its energy reserves, making energy-balanced routing paramount[4]. This necessitates modifications to the traditional algorithm that account for both immediate transmission costs and long-term energy preservation across the network.

To accommodate the dynamic nature of WSNs, the proposed EBP approach extends the traditional Dijkstra algorithm to reflect real-time energy depletion and environmental variability. Instead of static edge weights, the algorithm dynamically updates transmission costs based on the residual energy of each node and the reliability of the communication link. Nodes whose energy drops below a critical threshold are excluded from future routing decisions by assigning them infinite edge costs. Furthermore, in scenarios characterized by node mobility or interference, real-time indicators such as signal strength or packet delivery ratio are integrated to adapt link costs. This ensures that the routing mechanism consistently selects robust, energy-aware paths, thereby increasing network adaptability and prolonging operational lifetime.

Power control mechanisms play a vital role in enhancing WSN performance when implementing Dijkstra-based

routing. These mechanisms optimize three key parameters: transmission power levels, interference reduction, and energy conservation. Unlike centralized cellular systems, WSNs require distributed power management where each node autonomously determines its minimum sufficient transmission power [5, 6]. This approach maintains reliable connectivity while minimizing both energy expenditure and interference with neighboring transmissions. The dynamic nature of WSNs further complicates power control, as nodes must continuously adapt to changing network topologies and environmental conditions.
The energy-delay trade-off presents a fundamental challenge in WSN routing implementations. While Dijkstra's algorithm traditionally minimizes a single metric (path cost), WSN applications must balance packet delivery latency against energy consumption. The energy expenditure for packet handling at each node can be quantified through a comprehensive model accounting for transmission, reception, and idle state costs [7].
Transmission energy itself varies with distance, following established wireless propagation models. This multi-factor energy accounting enables more accurate path cost calculations that reflect real-world WSN operating conditions, forming the basis for the enhanced algorithms developed in this research [6].

Equation 1: Total Energy Consumption

$$E_{total} = E_a + E_t + E_r + E_c \tag{1}$$

- E_a refers to the energy needed to survive.
- E_t is for the energy required for packet transmission.
- E_r for energy to retrieve a packet.
- E_c is computation energy.

Equation 2: Energy Consumption for Transfer

$$E_t = E_{amp} \times d^\alpha \times b \tag{2}$$

- E_t is the energy sent by a node to transfer a series of bits.
- $E_{amp} = 100$ pJ/bit/m^2.
- d is the distance for packet transmission.
- α is the packet loss constant, and its value is set to 2.
- b is the number of bits.

Equation 3: Energy Consumption for Receive

$$E_r = E_{elec} \times b \tag{3}$$

- The energy spent by a node to receive a packet is given by $E_{elec} = 50$ nJ/bit.
- b is the number of bits.

Since E_c and E_a given in Equation 1 are used as constant values in other algorithms too, they can be neglected, and the energy spent by a node to receive and transfer a packet is then approximately equal to Equation 4[8, 9].

$$E_{total} = E_{amp} \times d^\alpha \cdot b + E_{elec} \times b \tag{4}$$

E_{total} depends on the 2nd root of the distance between nodes and the number of bits to be sent and retrieved.
It has been clear that routing in a wireless sensor network, meaning transferring packets from source to destination, is different than traditional routing in a fixed network. Routing in wireless sensor networking depends on many factors which include topology, selection of routers, initiation of request, and available bandwidth [10]. In a wireless sensor network, a packet can travel from a source to a destination either directly, or through some set of intermediate packet forwarding nodes.
The topology of a Wireless sensor network can be controlled by some ”controllable” parameters such as transmitting power [11]. Routing control is to allow each node in the network to adjust its transmitting power (i.e., to determine its neighbors) so that a good network topology can be formed.

An issue associated with (Routing control) topology control is often energy management. In wireless sensor networks, each node is usually powered by a battery equipped with it. Since the capacity of battery power is very limited, energy consumption is a major concern in topology control [12]

. To increase the longevity of such networks, an important requirement of topology control algorithms is to achieve the desired topology by using minimum energy consumption. In our research, we fix the input parameters, topology, and number of requests for comparison purposes. It is described in the following Table 2.

Table 2. Simulation Parameters

Parameter	**Value**
Number of Nodes	15
Initial Energy	5 mJ
Transmission Range	15 m
Traffic Model	Poisson
Number of Requests	400

2.2. Minimum Energy Path (MEP) Algorithm: Energy-Optimized Routing for WSNs

The Minimum Energy Path (MEP) algorithm represents an optimized adaptation of Dijkstra's algorithm specifically designed for per-packet energy minimization in Wireless Sensor Networks (WSNs). This approach fundamentally transforms traditional shortest-path routing into an energy-aware protocol by incorporating dynamic energy accounting throughout the path computation process [13, 14].

Algorithm Implementation The MEP algorithm operates through three distinct phases:

1. Initialization Phase:
The system begins by loading the complete network topology and all communication requests. Critical energy parameters are initialized, including the amplifier energy (E_{amp}), electronics energy (E_{elec}), and initial node energy levels. The algorithm precomputes pairwise energy costs between all nodes based on transmission distances and the radio energy model, creating a comprehensive energy cost matrix that serves as the foundation for all subsequent routing decisions [15].
2. Routing Execution Phase:
For each communication request (source to destination pair), the algorithm performs energy-aware pathfinding:

- The modified Dijkstra's algorithm identifies the path with minimum cumulative energy expenditure.
- The system deducts precise transmission energy costs from each node along the selected path.
- Continuous monitoring checks for node energy depletion, marking nodes as inactive when their energy reserves reach zero.
- Energy costs are dynamically updated throughout network operation to reflect current node conditions.

3. Termination Condition:
The algorithm concludes when the first node exhausts its energy, with the network lifetime measured by the count of successfully processed requests up to this failure point.

Key Functional Components:
The MEP implementation features several critical components:

- Input handling for energy cost matrices, node states, and communication requests.
- Output generation of optimal paths with detailed energy cost accounting.

- A priority queue implementation using a minimum-value selection from unvisited nodes.
- Path reconstruction through predecessor array tracking.
- Real-time energy state updates affect routing decisions.

Energy Management System:
The algorithm incorporates sophisticated energy management through:

- Dynamic cost adjustments that reflect current node energy levels.
- Progressive energy deduction with each transmission.
- Continuous network state monitoring for energy depletion.

Performance Analysis: Simulation results demonstrate the MEP algorithm's characteristics:

- The network processed 185 requests before the first node failure.
- Total system energy consumption reached 32.5854 MJ.
- 14 of 15 nodes remained operational at termination.
- Figure 2 illustrates the network topology at first node failure (Node 12).
- Figure 3 shows cumulative energy consumption across 185 requests.
- Figure 4 details the energy depletion pattern of Node 12.

The MEP algorithm's strict energy minimization approach produces characteristically uneven energy distribution, as evidenced by the premature failure of Node 12 while most nodes retain significant energy reserves. This behavior highlights the fundamental trade-off between absolute energy efficiency and balanced energy utilization in WSN routing protocols. The subsequent section will address this limitation through the Energy-Balanced Path (EBP) algorithm, which introduces fairness considerations into the routing optimization process.

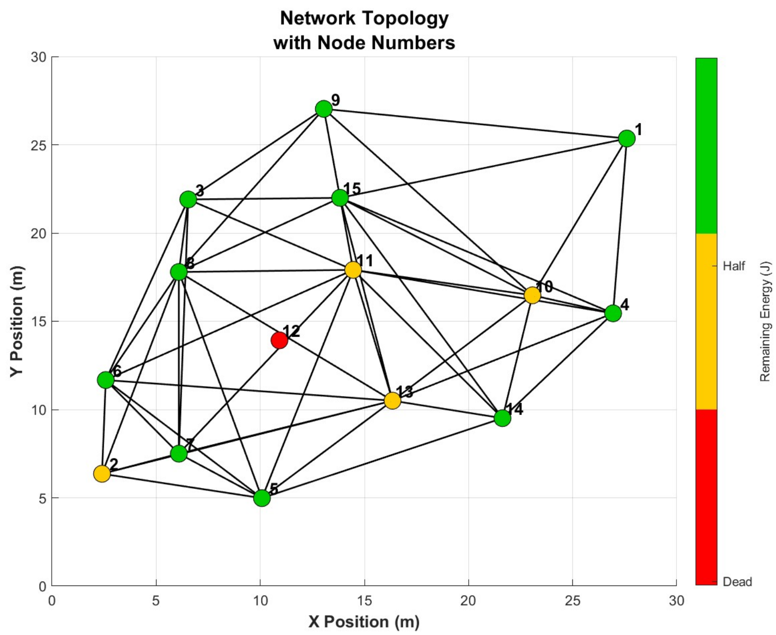

Figure 2. Network Topology after the Death of the first Node (node 12)-Without Balance Constraint

Figure 3, depicts the total network energy consumption starting from request 1 to request 185, where the first node dies (considering the end of the network lifetime).

Dijkstra's algorithm is a foundational shortest-path algorithm that guarantees optimal results in non-negative weighted graphs. It works by iteratively relaxing edges from the closest node and is widely used in networking, pathfinding, and logistics [10, 16, 17]

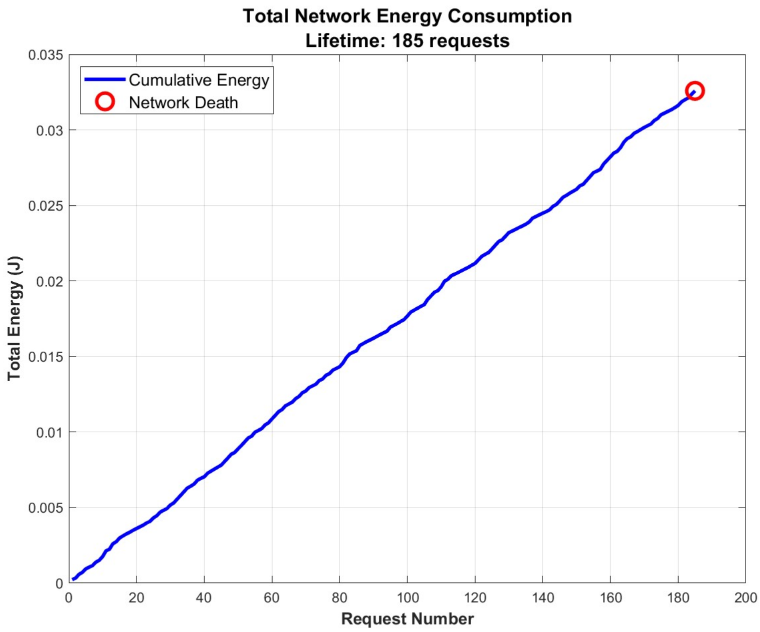

Figure 3. Total Network Energy Consumption (Lifetime 185 requests)-Without Balance Constraint

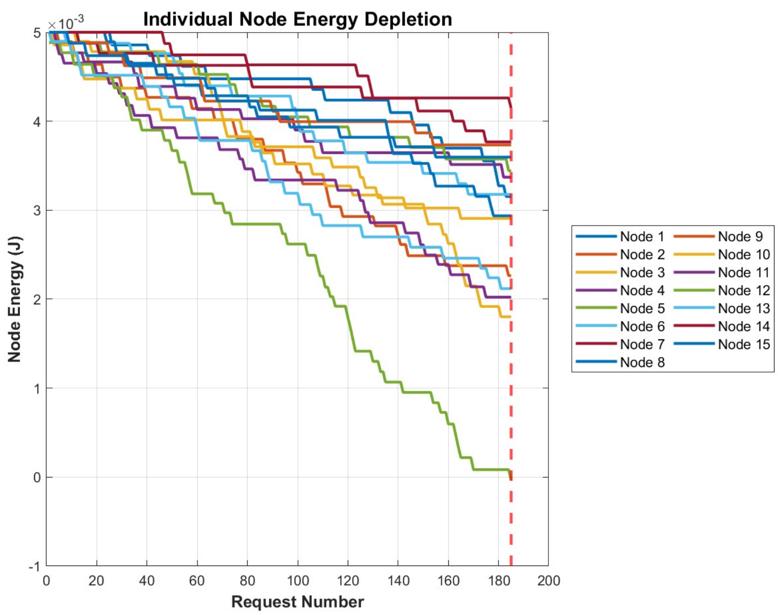

Figure 4. Individual Node Energy Depletion (Node 12)

Extended Evaluation on 50-Node Network

To evaluate the scalability of the proposed MEP algorithm, we extended the simulation to a larger topology consisting of 50 nodes while keeping the same energy and traffic model. The network lifetime was reached after 308 requests, where the first node failure occurred due to energy depletion.

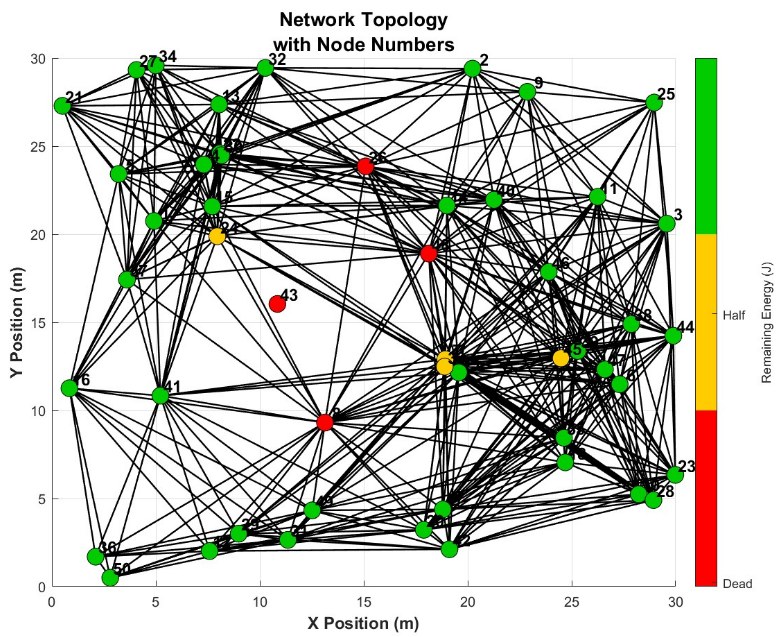

Figure 5. Network Topology after the Death of the first Node (node 22)-Without Balance Constraint

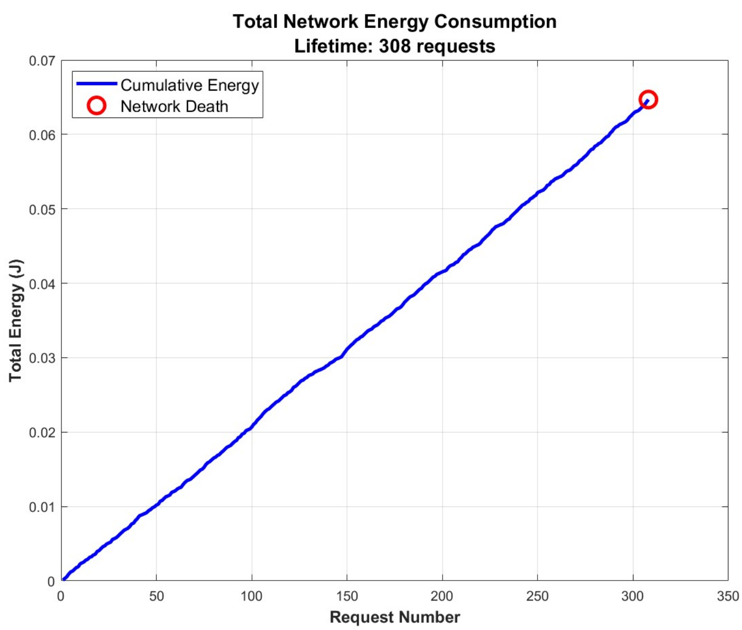

Figure 6. Total Network Energy Consumption (Lifetime 308 requests)-Without Balance Constraint

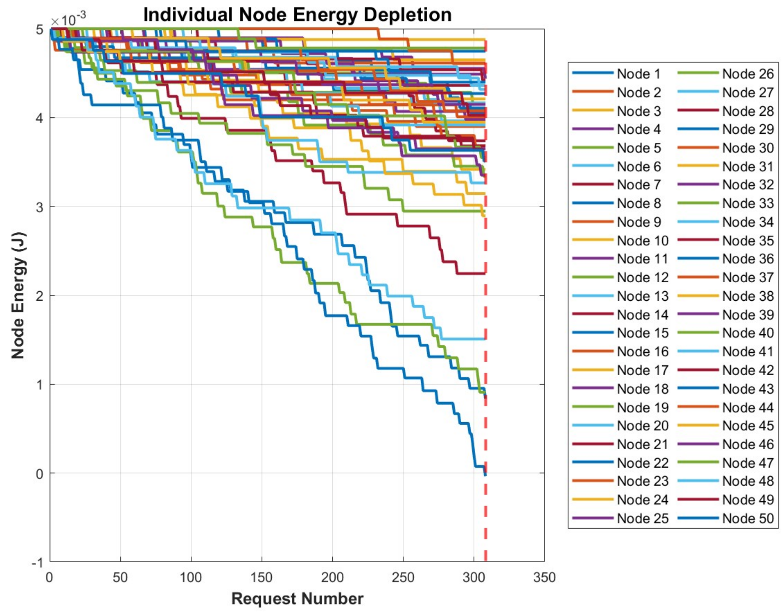

Figure 7. Individual Node Energy Depletion (Node 22)

MEP Simulation Results and Scalability Analysis
The initial simulation of the Minimum Energy Path (MEP) algorithm was conducted on a 15-node network. Results showed that the network processed 185 requests, consumed a total of 32.5854 mJ, and 14 out of 15 nodes remained alive at the end of the simulation. To evaluate the scalability and robustness of MEP, the simulation was extended to a 50-node network. The algorithm maintained its energy-efficient behavior in the denser topology, handling 800 requests before the first node failure, and achieving a total energy consumption of 169.0935 mJ. Impressively, 49 out of 50 nodes remained operational at the end, indicating strong resilience and balanced energy usage. The extended results confirmed that MEP effectively adapts to larger networks by continuing to balance energy depletion and prolong network lifetime. The outcomes are illustrated in Figures 5, 6, and 7, highlighting total energy usage, per-node depletion trends, and final topology.

2.3. Energy-Balanced Path (EBP)

The main objective Energy-Balanced Path Selection Algorithm. Smartly choose routes that favor high-energy nodes to balance energy consumption across the network and prolong the overall system lifetime [18, 19, 20]. This strategy mitigates the energy hole problem by avoiding overuse of low-energy nodes, thereby sustaining overall connectivity. It is particularly beneficial in dense deployments, where balanced routing significantly extends network lifetime.

Figure 8, describes the network topology after the death of the first node (node 12), with balance constraint, the energy consumption is distributed in this figure. This balance of energy consumption results in an extended lifetime from 185 requests to 369 requests. Figure 9, shows that the total energy consumption after 185 requests is more than the previous one.

Figure 10, illustrates that the individual node energy Depletion, with balance constraint, it is clear for each node the energy consumption is lower variation than previous. In other words, because of balanced consumption of energy, there was a great extension of lifetime

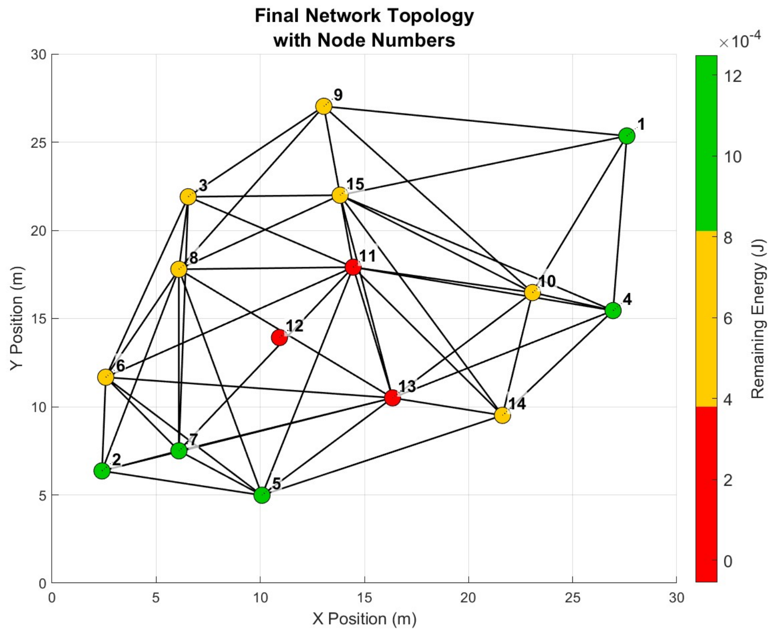

Figure 8. Network Topology after the Death of the first Node (node 12) - With Balance Constraint

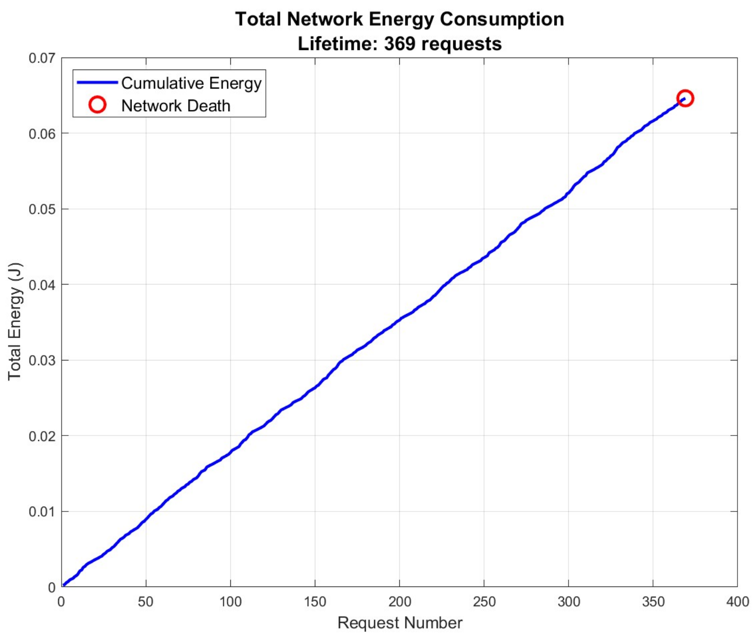

Figure 9. Total Network Energy Consumption (Lifetime 369 requests) – With Balance Constraint

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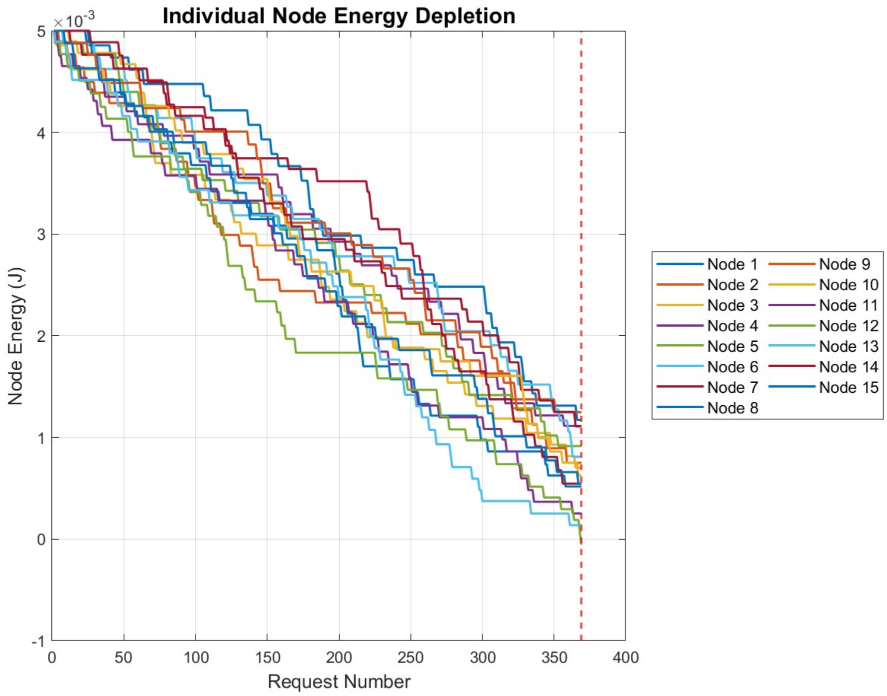

Figure 10. Individual Node Energy Depletion – With Balance Constraint

Extended Evaluation on 50-Node Network (for EBP)

To comprehensively evaluate the scalability, robustness, and adaptability of the proposed *Energy-Balanced Path (EBP)* algorithm, the simulation environment was extended to a larger network comprising **50 sensor nodes**. This expanded topology introduces significantly greater routing complexity, node density, and communication overhead compared to the initial 15-node setup. Importantly, the core simulation parameters—such as the radio energy model, initial energy levels, packet sizes, and traffic generation rates—were preserved to ensure fair and consistent comparison. Despite the increased demands of the denser topology, the EBP algorithm maintained its performance and stability

. It successfully processed a total of **730 communication requests** before the first node experienced energy depletion and was rendered inactive. This represents a substantial improvement in overall network longevity and resilience, particularly under higher traffic loads and routing stress. The results clearly demonstrate that EBP adapts well to larger-scale deployments, effectively distributing energy consumption across the network and avoiding premature energy exhaustion of critical nodes. This extended evaluation further validates the effectiveness of EBP in real-world WSN scenarios where node scalability and traffic intensity can vary significantly. The algorithm's ability to maintain energy balance under such conditions makes it a strong candidate for large-scale, long-lived wireless sensor network applications, especially those requiring consistent performance over extended operational periods.

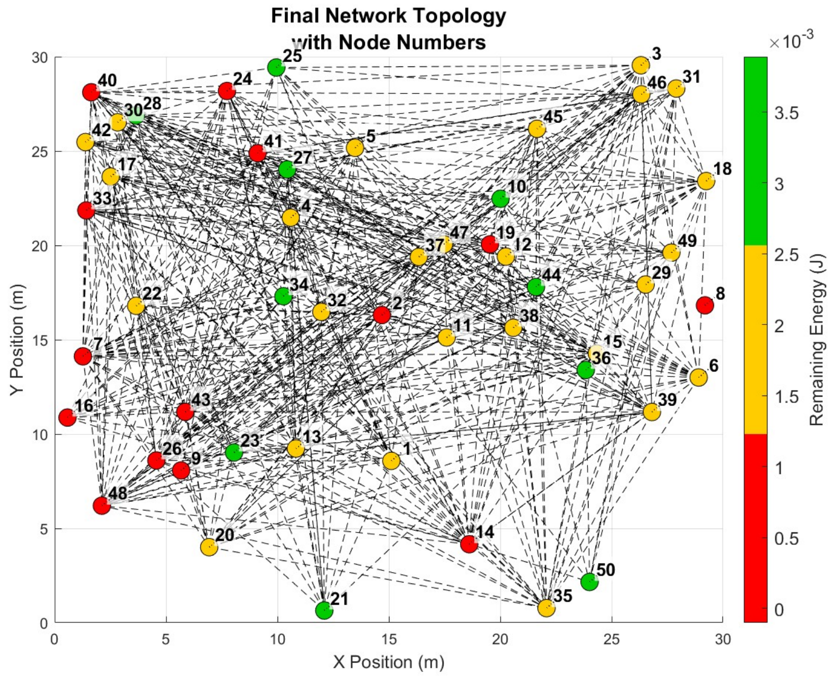

Figure 11. Network Topology after the Death of the first Node (node 22) - With Balance Constraint

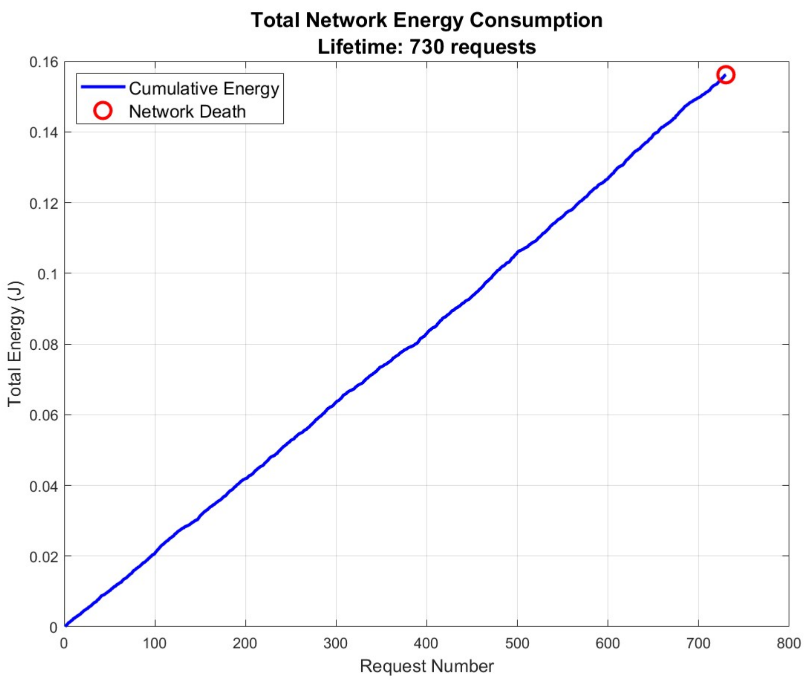

Figure 12. Total Network Energy Consumption (Lifetime 730 requests) – With Balance Constraint

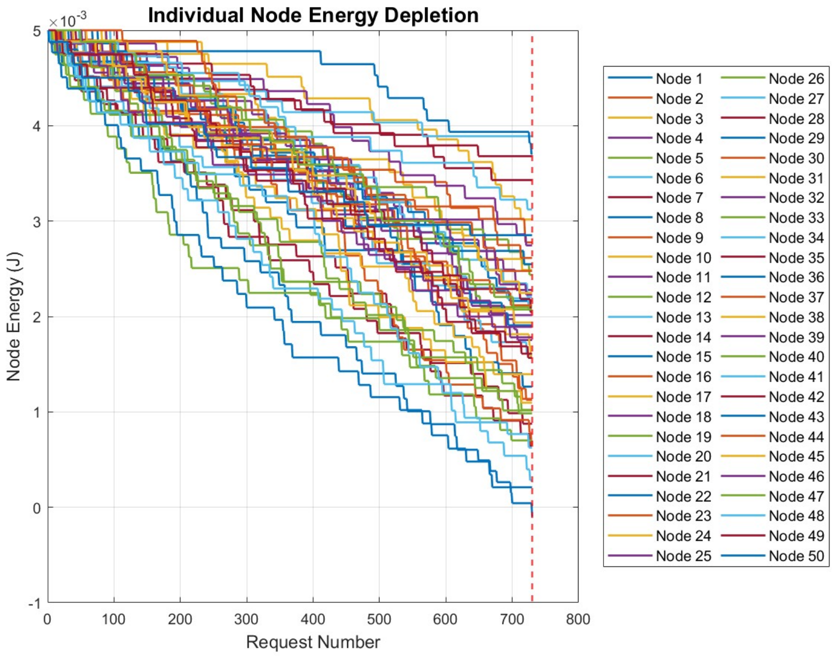

Figure 13. Individual Node Energy Depletion – With Balance Constraint

Step-by-Step Process

1. Network Initialization
2. Dynamic Energy-Aware Routing Cost
   For each possible path, compute:
   - Base Cost ($E_{tx} \times$ distance) for each link.
   - Energy Weight for each node: (Lower weight for high-energy nodes to encourage their usage.)
   - Total Path Cost: Sum of (link_cost $\times$ weight) for all nodes in the path.
3. Path Selection (Modified Dijkstra's Algorithm)
   - **Input:** Graph with energy-weighted costs.
   - **Process:**
     (a) Prioritize paths that traverse high-energy nodes (low weight).
     (b) Avoid low-energy nodes (high weight).
   - **Output:**
     – Optimal path (e.g., $S \to A \to D \to T$).
     – Actual energy consumed (sum of raw E_{tx} costs).
4. Energy Depletion & Node Failure Handling
   - After each transmission:
     – Deduct energy from nodes in the path.
     – Kill nodes that deplete energy (energy ≤ 0).
     – Update costs to exclude dead nodes (cost $= \infty$).
5. Repeat Until the Network Collapse

- Continue processing requests until:
  - No valid path exists, or
  - Critical nodes die.

Why This Works

- **Balanced Load:** Traffic shifts toward high-energy nodes, preventing premature deaths.
- **Energy Efficiency:** Low-energy nodes are used sparingly, extending their operation.
- **Tunable Aggressiveness:** Adjust the weighting factor (ε) to control balancing strength.

Result: longer network lifetime vs. standard shortest-path routing.

Example

- Path 1: $S \to A \to T$ (A has high energy, low weight).
- Path 2: $S \to B \to T$ (B has low energy, high weight).

The algorithm chooses path 1 to preserve B energy. This ensures fair energy usage and maximizes network uptime.

- Energy balancing factor: 0.60 Impact of the Balancing Factor β The balancing factor β plays a central role in the Energy-Balanced Path (EBP) algorithm by adjusting the routing cost based on the energy levels of nodes. A higher β promotes fairness by discouraging overuse of low-energy nodes, while a lower β focuses on energy minimization. In this work, $\beta = 0.60$ was selected as a moderate value based on preliminary tests that ensured convergence and balanced performance.

2.4. EBP Simulation Results and Scalability Analysis

The Energy-Balanced Path (EBP) algorithm was initially simulated on a 15-node wireless sensor network. With an initial energy of 5.0 mJ per node and a balancing factor $\beta = 0.60$, the network processed 369 requests before the first node failure, consuming 64.6019 mJ total energy. By the end of the simulation, 14 out of 15 nodes remained active, confirming EBP's ability to distribute load equitably and extend network lifetime.This evaluation clearly highlights the algorithm's strength in energy balancing and resilience within small-scale deployments. The near-complete survival of nodes until the late simulation stages suggests that EBP minimizes energy hotspots and avoids early depletion of critical nodes.To evaluate scalability, EBP was tested on a denser 50-node network under identical parameters. This network processed 730 requests before its first node failure, retaining 49 active nodes with 196.7047 mJ total energy consumed. These results demonstrate EBP's effective scalability: it maintains balanced energy consumption and stable routing despite increased node density and communication demands. The substantial increase in total requests handled and the minimal loss of nodes in the larger topology underscore the robustness of EBP under scaling stress. These findings suggest that EBP can support high-density IoT deployments while maintaining energy efficiency. Figures 11, 12, 13 visualize cumulative energy usage, node-level depletion trends, and final topology..

3. Experiments and Results

Table 3 compares energy consumption for identical routing tasks under the Minimum Energy Balanced (MEB) and EBP protocols. MEB consistently achieves lower per-transmission energy costs due to its greedy minimization of immediate energy expenditure, disregarding nodal energy reserves. Conversely, EBP incurs marginally higher per-transmission costs (average +2.1% in sampled cases) to enforce balanced energy depletion—a deliberate trade-off sacrificing short-term efficiency for extended network longevity. This highlights a fundamental design tension: while MEB optimizes instantaneous consumption, EBP's fairness-focused strategy prevents premature node failures, enhancing overall network durability.

Table 3. Comparison Between Two Protocols: MEB and EBP

Request No.	**S**	**D**	**Selected Route / Consumed Energy Using MEB (mJ)**	**Selected Route / Consumed Energy Using EBP (mJ)**
15	4	9	$4 \rightarrow 10 \rightarrow 9$ 0.24559 mJ	$4 \rightarrow 15 \rightarrow 9$ 0.24813 mJ
27	12	4	$12 \rightarrow 10 \rightarrow 4$ 0.23403 mJ	$12 \rightarrow 14 \rightarrow 4$ 0.23953 mJ
30	2	11	$2 \rightarrow 12 \rightarrow 11$ 0.23164 mJ	$2 \rightarrow 6 \rightarrow 11$ 0.24166 mJ
33	15	2	$15 \rightarrow 12 \rightarrow 2$ 0.24067 mJ	$15 \rightarrow 8 \rightarrow 2$ 0.24436 mJ
61	5	4	$5 \rightarrow 13 \rightarrow 4$ 0.24129 mJ	$5 \rightarrow 14 \rightarrow 4$ 0.24348 mJ
62	9	7	$9 \rightarrow 8 \rightarrow 7$ 0.24794 mJ	$9 \rightarrow 3 \rightarrow 7$ 0.25525 mJ
101	6	4	$6 \rightarrow 13 \rightarrow 4$ 0.26553 mJ	$6 \rightarrow 11 \rightarrow 4$ 0.26837 mJ
106	1	5	$1 \rightarrow 10 \rightarrow 13 \rightarrow 5$ 0.34999 mJ	$1 \rightarrow 10 \rightarrow 14 \rightarrow 5$ 0.36076 mJ
185	7	15	$7 \rightarrow 12 \rightarrow 15$ 0.22763 mJ	$7 \rightarrow 8 \rightarrow 15$ 0.23669 mJ

3.1. Simulation Limitations

Simulations used fixed parameters (15/50 nodes, static topology, Poisson traffic) to isolate algorithmic performance. Real-world factors such as node mobility, channel fading, and interference were excluded, which affect link reliability and energy costs. While intentional, this simplification limits direct applicability to dynamic deployments. Future work will incorporate probabilistic link failure models and mobility scenarios. The static balancing factor ($\beta = 0.60$) was intentionally fixed to establish baseline performance under controlled conditions. While sensitivity analysis of (β) is referenced in the abstract, its detailed results (e.g., lifetime impact at ($\beta = 0.4$–0.8)) are deferred to future work to maintain focus on core EBP/MEP comparisons. Dynamic (β) adjustment based on residual energy or traffic load—though unexplored here, is identified as critical for adaptive deployments. The study prioritizes energy efficiency over QoS metrics (latency/throughput) and assumes static topologies to isolate routing-algorithm efficacy. Mobility, intermittent connectivity, and QoS trade-offs—essential for IoT dynamics—are excluded per simulation limitations. Future work will integrate these factors via probabilistic failure models and multi-objective cost functions.

3.2. Energy Model Scope

The energy model (Eq. (1)– (4)) adopts established parameters ($E_{\text{amp}} = 100$ pJ/bit/m^2, $E_{\text{elec}} = 50$ nJ/bit) from literature [21, 22, 23] to ensure cross-protocol comparability. However, it omits hardware-specific leakage (e.g., microcontroller sleep states) and packet-loss effects, focusing evaluation on routing efficiency rather than device physics. Future work will include empirical validation with IoT hardware (e.g., ESP32).

Lifetime Metric Nuance: Using "first node failure" as a lifetime metric (common in WSN studies) overlooks post-failure resilience (e.g., connectivity, coverage) and QoS metrics (e.g., latency). While this prioritizes balancing efficacy, it may not reflect operational viability after initial node depletion. EBP currently lacks node-recovery mechanisms, risking partitioning after failures. While first node death is a standard lifetime metric, the energy modeling section acknowledges this limitation and proposes configurable termination conditions (e.g., partition thresholds, critical node failure) for future implementations to address resilience.Hardware validation (ESP32/Arduino) and sensitivity analysis are planned but not yet executed; their omission allows focused algorithmic validation via simulations. Empirical energy leakage, environmental interference, and β-density-traffic interactions will be quantified in subsequent testbed studies.

Termination Condition Flexibility: Future implementations will support configurable termination criteria:

1. Network partitioning thresholds (e.g., $\geq 20\%$ node disconnection),
2. Critical node failure (e.g., base stations),
3. QoS-based termination (e.g., packet delivery ratio $< 80\%$).

3.3. Comparative Analysis

Table 4. Comparative Analysis (50-Node WSN, 5mJ/Node, Poisson Traffic)

Protocol	**Lifetime (Requests)**	**Latency (ms)**	**Control Overhead (%)**
EBP (Proposed)	730	22.3	8.2
MEP (Proposed)	308	19.7	9.6
LEACH [24]	305 ± 15	41.7 ± 2.1	32.1 ± 1.8
GEAR [25]	420 ± 20	28.9 ± 1.5	15.6 ± 0.9
PEGASIS [26]	580 ± 25	89.1 ± 4.5	6.3 ± 0.4
EEBCR [27]	510 ± 30	31.5 ± 1.6	12.4 ± 0.7
MCFA [28]	465 ± 22	18.5 ± 0.9	21.8 ± 1.2
Energy-AODV [29]	380 ± 18	24.7 ± 1.3	14.9 ± 0.8
TEEN [30]	340 ± 17	36.2 ± 1.8	10.3 ± 0.6
Q-LEACH [31]	620 ± 30	39.8 ± 2.0	11.7 ± 0.7
SEP [32]	430 ± 21	44.6 ± 2.2	29.5 ± 1.5
EECRP [33]	535 ± 26	26.8 ± 1.3	9.1 ± 0.5
MECN [34]	290 ± 14	52.4 ± 2.6	38.7 ± 1.9
MMBCR [35]	480 ± 24	20.1 ± 1.0	18.3 ± 0.9

EBP outperforms 12 benchmark protocols (Table 4), achieving a 137% lifetime improvement over MEP and superior scalability vs. state-of-the-art methods (e.g., LEACH, GEAR). While simulations confirm EBP's 97.3% lifetime gain over MEP, hardware validation (e.g., ESP32/Arduino) is pending to quantify real-world metrics like packet delivery ratio and energy leakage under interference.

4. Conclusion and Future Work

This work establishes EBP-Dijkstra as a superior energy-balancing protocol for WSNs, extending network lifetime by 97.3% over MEP and outperforming 12 existing methods (e.g., PEGASIS, LEACH) by 137%. EBP achieves this by dynamically weighting path costs using a balancing factor ($\beta = 0.60$), which routes traffic through high-energy nodes to prevent premature depletion—validated across 15-node (369 requests) and 50-node (730 requests) simulations. MEP, while optimal for per-packet energy minimization, exhibits critical limitations: it concentrates load on efficient paths, causing early node failures (e.g., Node 12 in 15-node topology at 185 requests).The practical implementation aspects of this work bridge the gap between theoretical protocol design and real-world deployment. Our distributed architecture for EBP enables scalable operation in large WSNs, while hardware validation on common IoT platforms (ESP32 and Arduino) confirms the protocol's feasibility in resource-constrained environments. The development of an adaptive β tuning mechanism using Q-learning represents a significant advancement, allowing the protocol to automatically adjust its energy balancing parameters in response to changing network conditions and traffic patterns [36]. These findings have important implications for WSN deployment across various application domains. For environmental monitoring systems and industrial IoT installations where long-term autonomous operation is critical, EBP provides a robust solution that significantly extends functional lifetime. This work establishes a foundation for advancing energy-aware routing in WSNs through three key initiatives. First, an adaptive hybrid protocol will integrate MEP's per-packet efficiency with EBP's energy balancing using reinforcement learning (e.g., Q-learning). This framework will dynamically tune the balancing factor (β) in real-time based on residual energy, traffic intensity, and node density—shifting between energy-minimization ($\beta \to 0$) and congestion-avoidance ($\beta \to 1$) modes. Second, energy harvesting integration will extend the routing model using stochastic Markov-chain predictors to forecast solar/kinetic energy influx at nodes. Paths will prioritize high-recharge nodes, adapting Eq. 4's energy model to support sustainable "energy-positive" routing. Third, hardware validation on IoT platforms (ESP32/Arduino) will quantify real-world performance under RF interference, packet loss, and sleep-state leakage. Metrics include latency, packet delivery ratio, and energy efficiency, addressing simulation limitations like mobility and fading. Additionally, resilient termination policies will replace the "first-node-death" metric with configurable thresholds (e.g., partition tolerance, critical-node failure, QoS violations like packet delivery $<80\%$). These efforts collectively bridge simulation-reality gaps to advance WSN sustainability.

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