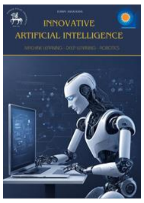

INNOVATIVE ARTIFICIAL INTELLIGENCE

RESEARCH ARTICLE

Energy-Efficient Error Control Approach for Optimal Pathfinding Using the Floyd Algorithm in Wireless Sensor Networks

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Abstract

Wireless sensor networks (WSNs), a vital component of the Internet of Things (IoT), are distributed and self-organizing systems comprising tiny, low-cost devices with limited processing power, memory, communication capabilities and energy resources. A persistent challenge in WSNs is the unreliability of wireless communication channels, which often results in data packet loss. To tackle this issue, error control strategies are essential for improving data transmission efficiency. This paper introduces a novel approach that integrates the Floyd algorith, a classical shortest-pathfinding method, to design an error control scheme specifically for WSNs in IoT applications. The proposed method effectively mitigates environmental interferences while optimizing energy consumption, enhancing both communication reliability and network efficiency. Simulation results demonstrate the method's capability to select optimal paths from source nodes to sink nodes, significantly improving error control, reducing node energy consumption, extending network lifetime and enhancing overall reliability.

Keywords: *Wireless sensor network, Energy efficiency, Error control, Optimal pathfinding, Floyd algorithm, Network lifetime.*

1. Introduction

The growing demand for advanced network technologies and sensor systems has spurred the development of Wireless Sensor Networks (WSNs). These networks consist of small, battery-powered sensor nodes equipped with radio frequency transceivers that communicate wirelessly and collaborate to perform specific tasks. Typically, sensor nodes collect environmental data, such as temperature, humidity or motion and transmit it to external networks through designated nodes called sinks [1]. To enhance the autonomy of individual nodes and extend the network's operational lifetime, various energy-saving techniques are employed. These include placing nodes in sleep mode to conserve energy during inactive periods, minimizing communication power consumption through efficient data transmission protocols and implementing multi-hop data transmission, where intermediate nodes relay data, reducing the distance and energy required for transmission to the sink [2]. By optimizing energy usage, these strategies help ensure the long-term sustainability and efficiency of WSNs.

WSNs have garnered significant attention in recent years, leading to numerous studies addressing challenges such as Medium Access Control (MAC), network topology, routing protocols and error control strategies. A major focus of research in this field is energy conservation, aimed at extending the lifetimes of sensor nodes and the overall network. The loss of a single node can disrupt network functionality, making it unavailable. Given the limited battery life of each sensor node, minimizing power consumption in sensors and processors is essential for ensuring the successful and reliable operation of the network. Recent advancements have further enhanced the adaptability of WSNs by enabling optimized power usage, routing decisions, and error control strategies. Consequently, power and energy efficiency remain critical considerations, with the optimal design of WSNs prioritizing minimal power usage to maintain reliable communication [3].

Another challenge in wireless sensor network technologies is the unreliability of the wireless communication channel, which can lead to packet loss. To address this issue, various error control strategies have been developed and successfully implemented. Error control methods, which include error detection and correction, enable the reliable transfer of data over communication channels that are often affected by various types of noise. As a result, errors can occur during data transmission. Recent research has focused on minimizing energy consumption in wireless sensors while ensuring reliable communication. Coding techniques are among the existing methods for error control, balancing reliability with energy efficiency. While some methods that correct errors reduce energy consumption by minimizing the number of data packet transmissions, the energy required for decoding often increases. These trade-offs highlight the challenges related to energy deficiency in error control coding [4].

In this paper, we propose a novel method that eliminates the need for coding, decoding and additional control operations, while considering the network structure to achieve optimal data packet transfer, reduced energy consumption, high communication reliability and overall efficiency. The core structure of the wireless sensor network is modeled as a graph, where the cluster heads are represented as vertices and the wireless channels between them, based on their radio ranges, are represented as edges. In our proposed method, the Floyd algorithm is used to determine the optimal path for data packet transmission from the cluster heads to

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the destination node (sink). The optimal path is defined as the one where the sum of the nodes' physical distance and the error rate, influenced by environmental noise, is minimized and the residual energy of the nodes along the path is maximized. Additionally, advanced techniques can be integrated into the process to dynamically adjust routing decisions based on real-time environmental conditions and network performance, further optimizing the path selection and energy efficiency.

The paper is organized as follows: Section 2 provides an overview of existing methods in error control and optimized pathfinding strategies for wireless sensor networks. Section 3 introduces the Floyd algorithm, while Section 4 presents the proposed algorithm for finding the shortest path using the Floyd algorithm in wireless sensor networks. Section 5 discusses the corresponding simulation results and Section 6 concludes the paper.

2. Related Works

Errors in WSNs often result from the corruption of transmitted bits at the receiver and error control methods focus on the detection and correction of these bits. In WSNs, data transmission through nodes is vulnerable to errors caused by external phenomena such as noise and other environmental factors. While numerous studies have focused on error control techniques in wireless networks, particularly in cellular networks, these methods are not directly applicable to WSNs. This is primarily due to the unique challenges of WSNs, such as limited energy resources and low sensor hardware complexity, which require energy-efficient error control strategies and prevent the deployment of high-complexity codes. Consequently, efficient error control strategies are essential to reduce the Bit Error Rate (BER). One such approach is the Adaptive Error Control (AEC) strategy, which has been proposed to improve error control by validating data packets and enhancing intra-network communications in WSNs [5].

Recently, there has been growing attention to energy consumption analysis in wireless networks, particularly in relation to error control techniques. Error control mechanisms are essential for ensuring reliable communication in WSNs and they can generally be categorized into three main approaches: Automatic Repeat Request (ARQ) [6], Forward Error Correction (FEC) [7] and Hybrid Automatic Repeat Request (HARQ) [8]. ARQ-based error control relies on retransmitting lost data packets to achieve recovery. In contrast, FEC adds redundancy to the transmitted packet, allowing the receiver to reconstruct the original data even if some bits are received with errors. HARQ schemes combine the advantages of both ARQ and FEC, increasing error resilience by incrementally enhancing the packet's error correction capability through retransmissions. While each approach offers its benefits, they all have a direct impact on energy consumption in WSNs, as they either increase the amount of data transmitted or require additional processing for error recovery.

Another significant challenge in WSNs is routing. Routing protocols in WSNs are generally classified into two main types: (1) cluster-based routing and (2) flat routing protocols. In cluster-based routing, elected cluster-heads are responsible for discovering and maintaining routing information, while in flat routing, all nodes in the network participate in route discovery and maintenance [9]. A typical energy-efficient routing protocol can be described in three phases: (1) Interest propagation: When a sink is interested in obtaining specific information, such as data on a phenomenon or object, it floods its interest throughout the network. Each node then stores the minimum routing distance to the sink, referred to as the node's routing cost, which also correlates with the energy consumption of the optimal path between that node and the sink. (2) Data forwarding: If the observations from certain sensor nodes match the interest propagated, those nodes forward data packets containing the required information to the sink using a specified routing scheme. (3) Route maintenance: To ensure path continuity, the sink periodically initiates localized flooding in the network, keeping all paths active.

In this section, we provide an overview of some existing methods addressing routing issues and finding the shortest path among sensor nodes. In the study of Ramos et al. [10], the authors propose the Minimum Cost Forwarding (MCF) approach for routing in sensor networks. The MCF method identifies the shortest paths from all sensor nodes to the base station without requiring explicit routing tables at each node. However, routing all data along the shortest path could deplete the energy of upstream nodes, potentially causing coverage loss in certain regions of the network. To address this issue, our method limits the amount of energy each node can expend per round. In the study of Jain et al. [11], the authors introduce an energy-efficient routing protocol that balances delay and energy concerns. Inspired by the Ant Net protocol [12], this algorithm uses ant pheromone concepts to create two prioritized queues for differentiated traffic. However, this approach may be infeasible for current sensor nodes due to the substantial memory needed to store both queues. The problem is further compounded in highly populated sensor networks, as the routing table size at each node is dependent on the number of neighbors.

In the study of Kaur et al. [13], the authors examine distinct ant-based algorithms for WSNs, with a particular focus on developing an initial pheromone distribution that is effective during system start-up. Similarly, in the study of Zhou et al. [14] presents an ant colony algorithm designed for Steiner Trees, which has potential applications in routing problems. However, this approach does not account for the specific requirements of wireless sensor networks, nor does it address the critical aspect of energy management, which is vital for WSN performance. Furthermore, the ant-based algorithms discussed in the study of Sun et al. [15] assume that end-to-end communication between sensor nodes is a requirement of WSN applications and base their design on this premise. However, in most WSN scenarios, communication typically occurs in a hop-by-hop or single-hop manner, where data is transmitted from the source node (sensor node) to a sink node responsible for aggregating sensor data from the network. The sink node often has significantly different characteristics compared to regular sensor nodes, such as higher energy reserves, greater memory and enhanced processing capabilities. These differences, which are crucial for effective algorithm design, are overlooked in the referenced algorithms.

In the study of Zhang et al. [16], a cluster-based routing protocol is utilized within clusters, assuming that cluster heads have less stringent energy constraints and possess precise knowledge of the sensor nodes' locations within their respective clusters. The cluster heads determine the optimal transmission range for each node and utilize a shortest-path-based scheme to establish routing paths. Re-routing is considered only when a node's energy level falls below a predefined threshold. Notably, the approach proposed in this paper does not require the base station to have knowledge of the sensor nodes' locations and aims to achieve balanced energy dissipation across all sensor nodes. To support this objective, the Floyd algorithm [17] is identified as a promising solution, as it efficiently finds the shortest path and is a highly applicable method in wireless sensor networks. The subsequent sections of this paper explore various research efforts that have employed the Floyd algorithm in similar network contexts. While recent studies have driven significant advancements in the field, earlier foundational works also played a crucial role in shaping key concepts and methodologies for wireless sensor networks. These contributions, particularly those utilizing the Floyd algorithm, explored areas such as node placement optimization, energy-efficient communication and graph-based network modeling. The following paragraphs highlight some of these influential works, which continue to provide valuable insights for contemporary research.

In the study of Shang et al. [18], the authors present a centralized algorithm, referred to as the multi-dimensional evaluation method, for determining the positions of sensor nodes in a wireless sensor network. The algorithm is divided into three main steps. First, the Floyd algorithm is applied to compute the shortest paths between sensor nodes, resulting in the construction of a distance matrix. Second, the relative positions of the nodes are estimated based on this distance matrix. Finally, the algorithm minimizes the sum of squared errors between the estimated and actual positions of the nodes to accurately determine their true locations. Similarly, in the study of Hawick et al. [19], a method is introduced to define and analyze a graph corresponding to a wireless sensor network, focusing on the optimal placement of mobile sensors. This method leverages the Floyd, Eardly and Floyd-Fulkerson algorithms. Simulation results of this approach demonstrate significant improvements in network coverage, fault tolerance and overall network lifetime.

In the study of Chen et al. [20], the authors introduced a method for data processing within a wireless sensor network called energy efficiency rate controlling. This method determines the placement of representative nodes and the data transmission path based on the overall network topology. By applying the Floyd algorithm and considering the energy consumption of nodes along the path, the approach achieves optimal results for low-density networks by approximating distances. Similarly, in the study of Bischoff et al. [21], the authors proposed a novel method for determining node placement in occasional wireless sensor networks. This method supports search operations for node boundaries and their distances, employing graph structures for network modeling and the Floyd algorithm to calculate appropriate distances between nodes. In the study of Commander et al. [22], the authors developed a model to enhance agent node communication in occasional wireless sensor networks. By utilizing a new heuristic function alongside the Floyd algorithm, the model maximizes potential communication within the network. Simulation results demonstrate the efficiency of this approach in real-world networks.

In the study of Poornima et al. [23], an energy-efficient routing system for Wireless Body Area Networks (WBANs) is proposed, combining levy flight and frilled lizard optimization with the momentum sparrow search for optimal cluster head selection. The approach enhances network lifespan, reduces energy consumption and improves packet delivery in healthcare monitoring applications. In the study of Saxena et al. [24], a hybrid metaheuristic approach combining Whale Optimization and Lion Optimization (WL-optimization) is proposed for cluster-based routing in wireless sensor networks. The method improves route stability and prevents early convergence to local optima, optimizing parameters like energy, distance, traffic rate and throughput and demonstrating better performance compared to other metaheuristic algorithms. In the study of Maximus et al. [25], a hybrid fuzzy logic and barnacles mating optimization (FL-BMO) approach is proposed for efficient cluster head selection in WSNs, enhancing energy efficiency and network lifetime. Additionally, a sunflower optimization routing technique improves routing efficiency and throughput in this network.

In the study of Verma et al. [26], a Mutation-grounded Multi-Layer Perceptron (MUMLP) is used for secure and energy-efficient optimal routing in Wireless Sensor Networks (WSNs), with data encryption handled by an Improved Elliptical Curve Cryptography (IECC) mechanism. The Boltzmann Selection Probability-centric Gravitational Search Algorithm (BSP-GSA) is utilized for optimal cluster head selection, while Block Chain (BC)-enabled authentication ensures secure user access to data, contributing to the extended network lifetime from the perspective of energy consumption by nodes. In the study of Dinakaran et al. [27], an energy-aware routing (EAR) model is proposed to enhance network lifetime in ad hoc wireless networks by considering security and energy efficiency. The Hybrid Dark Forest-based Gazelle Optimization Algorithm (HDFGOA) is introduced to optimize routing by minimizing energy consumption and interference while maximizing route quality and congestion control. Experimental results demonstrate the effectiveness of the proposed method compared to conventional algorithms.

The main contributions of the current paper, which provide a clearer distinction between our approach and existing methods, are as follows:

1. Novel integration of Floyd algorithm for error control in WSNs: This paper presents the first-ever integration of the Floyd algorithm, a classical shortest-pathfinding method, into a wireless sensor network error control scheme for IoT applications. The use of this algorithm for optimizing path selection and mitigating communication errors in WSNs represents a novel approach.

2. Improvement of communication reliability and network efficiency: The proposed method effectively mitigates environmental interferences, optimizing both communication reliability and network efficiency. This is achieved by selecting optimal paths from source nodes to sink nodes, ensuring forceful data transmission in the presence of noise and interference.

3. Energy-efficient error control: By optimizing the selection of communication paths and minimizing unnecessary transmissions, the method contributes to energy-efficient operation of WSNs. The energy consumption of sensor nodes is reduced, which extends the network lifetime and improves overall performance.

4. Simulation validation of performance improvements: Simulation results demonstrate the method's effectiveness in improving error control scheme. These results validate the proposed approach as a promising solution for enhancing the reliability and longevity of WSNs.

5. Network configuration analysis based on key factors: The paper provides an analysis of three distinct configurations of the proposed method. Each configuration evaluates different combinations of parameters, such as error rate, remaining energy and distance, to assess their impact on network reliability and energy efficiency. This analysis provides deeper visions into the relative importance of the mentioned factors in real-world scenarios.

6. Comprehensive modeling assumptions for practical application: The proposed approach is grounded in practical modeling assumptions, including the use of a clustering mechanism, random node distribution, static sensor nodes and fixed base station location. These assumptions ensure that the method is applicable to real-world WSNs in IoT environments and offers practical solutions into the challenges of energy-efficient error control.

7. Scalability and versatility in WSNs for IoT: The proposed method is designed to be scalable, handling networks with varying numbers of nodes and dimensions. Its versatility makes it further applicable to diverse IoT-based WSN configurations, developing its potential for widespread use in various domains.

3. Materials and Methods

3.1. Floyd Algorithm

Suppose *G(V, E)* is a directed graph with *n* vertices. In this graph, *V* represents the set of vertices and *E* represents the set of edges. The graph is a weighted graph, where each edge is assigned a positive weight, which may correspond to various factors such as communication value, distance between two vertices or other parameters. A set of edges connects pairs of vertices in the graph. The length of a simple path (a path that does not revisit any vertex) in a weighted directed graph is the sum of the weights of the edges along that path. The Floyd algorithm is commonly used to solve the shortest path problem in such graphs. This problem is an optimization problem, meaning there are multiple possible solutions, with the optimal solution being the one that minimizes (or maximizes, depending on the problem type) the objective value. In the case of the shortest path, the goal is to find the path with the minimum weight among all possible paths between the vertices [28].

Due to the existence of multiple shortest paths between vertices, the mentioned method seeks to identify all possible paths. A simple approach to solving this problem would involve determining the length of all paths from a particular vertex to every other vertex, but the time complexity of this algorithm is worse than exponential. This is a common issue in optimization problems, where many algorithms suffer from exponential time complexity or worse. In such graphs, the Floyd algorithm, which uses dynamic programming, can efficiently determine the shortest path with minimal cost between all pairs of vertices. The time complexity of this algorithm is significantly better than that of the brute-force approach. Additionally, by making a small modification—described in the next section—the shortest path between vertices can be determined more precisely. The steps of the Floyd algorithm can be outlined as follows.

A weighted graph consisting of *n* vertices can be represented using a two-dimensional array called the adjacency matrix *(W)*. In the first step, the adjacency matrix is created, which determines the weights of direct communication between pairs of vertices. This matrix represents the communication values for all node pairs in the graph, considering only direct edges between two vertices (i.e., *D(0) = W*). In the second step, the algorithm calculates the sum of weights of all paths passing through the first vertex, selecting the shortest paths among them. Each path created in this step has a maximum of three vertices (*D(1)*). In the third step, the algorithm computes the sum of weights of all paths that pass through both the first and second vertices, again selecting the shortest paths. Each path in this step has a maximum of four vertices (*D(2)*). This process continues, with each subsequent step considering paths that pass through one additional vertex. In the *n*th step, the algorithm calculates the sum of weights for all paths starting from the source vertex and ending at the destination vertex, passing through all the vertices of the graph, with the shortest path chosen at each step (*D(n) = D*).

To solve the shortest path problem, we can derive the values of *D* from the adjacency matrix *W*. This can be achieved by constructing an *n+1* matrix *D(k)*, where *D(k)[i][j]* represents the length of the shortest path from vertex v_i to vertex v_j , using only the vertices in the set {v_1, v_2, ..., v_k} as intermediate vertices. Specifically, *D(n)[i][j]* is the length of the shortest path from v_i to v_j that may pass through any of the other vertices, while *D(0)[i][j]* represents the shortest path from v_i to v_j that does not pass through any other vertices. In essence, *D(0)* corresponds to the initial weight matrix *W* and *D(n)* corresponds to the final shortest path matrix *D*.

The algorithm can be outlined as follows:

- Compute the optimal cost matrix for the graph's vertices (*D* matrix).
- Initialize the *D* matrix to match the adjacency matrix *W*.
- After the first step, the matrix *D(1)* shows the shortest paths between pairs of vertices, allowing paths to pass through the first vertex. This is represented by the Eq. 1:

$$D\ (1)\ [i]\ [j]\ =\ min\,\{D\ (0)\ [i]\ [1]\ +\ D\ (0)\ [1]\ [j], D\ (0)\ [i]\ [j]\} \tag{1}$$

- After the second step, matrix *D(2)* contains the shortest path values between vertex pairs, with paths allowed to pass through the first and second vertices. This is represented by Eq. 2:

$$D\ (2)\ [i]\ [j]\ =\ min\,\{D\ (1)\ [i]\ [2]\ +\ D\ (0)\ [2]\ [j], D\ (1)\ [i]\ [j]\} \tag{2}$$

- Additionally, matrix *D(k)* at the end of the *k*th step is computed using Eq. 3:

$$D\ (k)\ [i]\ [j]\ =\ min\,\{D\ (k-1)\ [i]\ [k]\ +\ D\ (k-1)\ [k]\ [j], D\ (k-1)\ [i]\ [j]\} \tag{3}$$

- Finally, matrix *D(n)* represents the optimal values of all shortest paths between vertex pairs in the graph, providing the final solution to the shortest path problem.

Furthermore, the optimal path matrix *P* for the graph's vertices can also be determined. In this matrix, *P[i][j]* holds a value of zero if there is no intermediate vertex between v_i and v_j. If there is at least one intermediate vertex in the shortest path from v_i to v_j, *P[i][j]* will store the greatest index value of the intermediate vertex along that path. Floyd can be implemented to compute both the *D* and *P* matrices, as shown in Algorithm 1.

Algorithm 1. Floyd Algorithm

```
Input:
   n → number of vertices
   W[n][n] → weight matrix

Output:
   D[n][n] → shortest path distance matrix
   P[n][n] → path matrix

1. Initialize P[i][j] = 0 for all i, j  // Set the path matrix to 0
2. Set D[i][j] = W[i][j] for all i, j  // Set the distance matrix equal to the weight matrix

3. for k = 1 to n do  // Iterate over each intermediate vertex
     for i = 1 to n do  // Iterate over each source vertex
        for j = 1 to n do  // Iterate over each destination vertex
           if D[i][k] + D[k][j] < D[i][j] then  // Check if a shorter path exists
              P[i][j] ← k  // Update path matrix to store intermediate vertex
              D[i][j] ← D[i][k] + D[k][j]  // Update distance matrix with the shortest path
           end if
        end for
     end for
 end for

4. Procedure FindPath(s, d, P):
    if P[s][d] ≠ 0 then  // Check if an intermediate vertex exists in the path
       Call FindPath(s, P[s][d], P)  // Recursively find the path from s to the intermediate vertex
       Print "V", P[s][d]  // Print the intermediate vertex
       Call FindPath(P[s][d], d, P)  // Recursively find the path from the intermediate vertex to d
    end if
    End
```

The computational complexity of the proposed approach is analyzed in terms of both time and space. The time complexity of the Floyd algorithm is $O(n^3)$, where n represents the number of vertices or sensor nodes. Regarding space complexity, the algorithm requires $O(n^2)$ space to store the distance matrix (D) and the path matrix (P), where n is the number of vertices. This analysis demonstrates that the proposed method efficiently balances computational cost with the need for accurate and reliable error control in wireless sensor networks.

A sample weighted graph is presented in Figure 1. For instance, if we want to determine the optimal path and its associated cost from vertex v_2 to vertex v_5, we can use the proposed Floyd algorithm. By considering the minimum computing cost, we refer to the value in the second row and fifth column of matrix *D*, which is 5, indicating the cost of the shortest path between v_2 and v_5. Additionally, the optimal path from v_2 to v_5 can be derived from the final matrix *P*. Therefore, the optimal path for moving from v2 to v5, with a cost of 5, is v2 → v4 → v5. The corresponding matrices illustrating the iterative process are presented in Figure 2. The recursive process of determining this path is depicted in Figure 3, which shows the optimal path in the form of a tree structure.

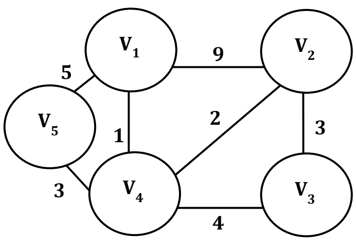


Figure 1. A sample weighted graph.

$$W = D^0 = \begin{bmatrix} 0 & 9 & \infty & 1 & 5 \\ 9 & 0 & 3 & 2 & \infty \\ \infty & 3 & 0 & 4 & \infty \\ 1 & 2 & 4 & 0 & 3 \\ 5 & \infty & \infty & 3 & 0 \end{bmatrix} \quad P = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$D^1 = \begin{bmatrix} 0 & 9 & \infty & 1 & 5 \\ 9 & 0 & 3 & 2 & 14 \\ \infty & 3 & 0 & 4 & \infty \\ 1 & 2 & 4 & 0 & 3 \\ 5 & 14 & \infty & 3 & 0 \end{bmatrix} \quad P = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$D^2 = \begin{bmatrix} 0 & 9 & 12 & 1 & 5 \\ 9 & 0 & 3 & 2 & 14 \\ 12 & 3 & 0 & 4 & \infty \\ 1 & 2 & 4 & 0 & 3 \\ 5 & 14 & \infty & 3 & 0 \end{bmatrix} \quad P = \begin{bmatrix} 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$D^3 = \begin{bmatrix} 0 & 9 & 12 & 1 & 5 \\ 9 & 0 & 3 & 2 & 14 \\ 12 & 3 & 0 & 4 & \infty \\ 1 & 2 & 4 & 0 & 3 \\ 5 & 14 & \infty & 3 & 0 \end{bmatrix} \quad P = \begin{bmatrix} 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$D^4 = \begin{bmatrix} 0 & 3 & 5 & 1 & 4 \\ 3 & 0 & 3 & 2 & 5 \\ 5 & 3 & 0 & 4 & 7 \\ 1 & 2 & 4 & 0 & 3 \\ 4 & 5 & 7 & 3 & 0 \end{bmatrix} \qquad P = \begin{bmatrix} 0 & 4 & 4 & 0 & 4 \\ 4 & 0 & 0 & 0 & 4 \\ 4 & 0 & 0 & 0 & 4 \\ 0 & 0 & 0 & 0 & 0 \\ 4 & 4 & 4 & 0 & 0 \end{bmatrix}$$

$$D = D^5 = \begin{bmatrix} 0 & 3 & 5 & 1 & 4 \\ 3 & 0 & 3 & 2 & 5 \\ 5 & 3 & 0 & 4 & 7 \\ 1 & 2 & 4 & 0 & 3 \\ 4 & 5 & 7 & 3 & 0 \end{bmatrix} \qquad P = \begin{bmatrix} 0 & 4 & 4 & 0 & 4 \\ 4 & 0 & 0 & 0 & 4 \\ 4 & 0 & 0 & 0 & 4 \\ 0 & 0 & 0 & 0 & 0 \\ 4 & 4 & 4 & 0 & 0 \end{bmatrix}$$

Figure 2. Iterative computation of distance (D) and predecessor (P) matrices.

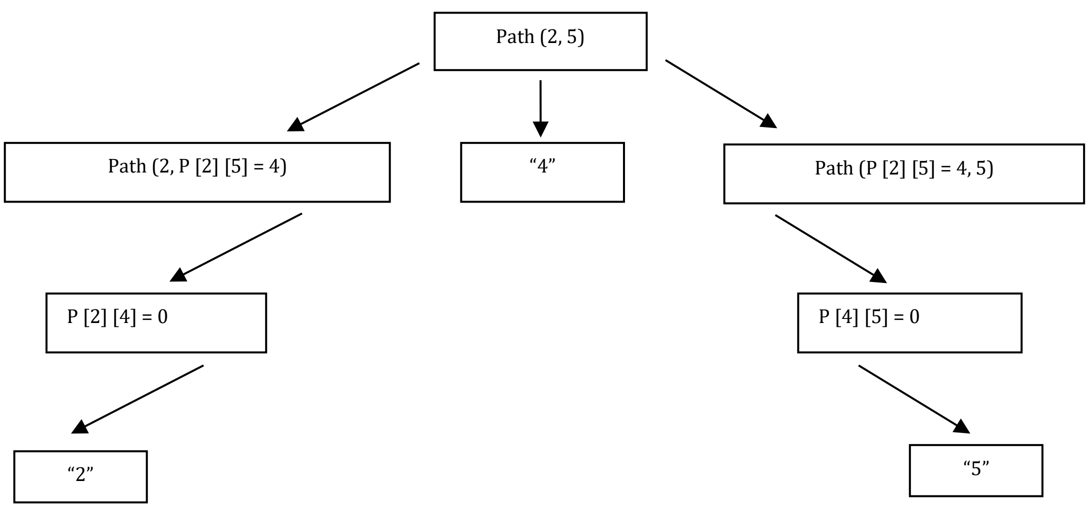


Figure 3. Optimal path of search tree from v_2 and v_5.

3.2. Proposed Approach

In graph theory, finding the shortest path involves determining a path between two vertices where the sum of its edge weights is minimized and this problem can be approached in three ways: single-source shortest path, which finds the shortest paths from a single vertex to all others; single-destination shortest path, which determines the shortest paths from all vertices to a single vertex; and all-pairs shortest path, which computes the shortest paths between every pair of vertices in the graph. Among these, the all-pairs shortest path approach is the most efficient for scenarios requiring a comprehensive analysis of the graph. Our proposed method is built upon this approach, incorporating factors such as node residual energy, error rate and distance, making it particularly applicable to WSNs. The inherent graph topology of WSNs, due to the wireless and broadcasting nature of communication, enables nodes to interact with others within their radio range. Data in WSNs is typically transferred from multiple nodes to a single sink node, necessitating efficient algorithms such as spanning tree or graph-based methods for tasks like data aggregation and object tracking. Consequently, graph-theoretic algorithms, including the proposed method, are highly effective for optimizing operations in WSNs.

The network model assumed in this paper is event-driven, operating through a clustering mechanism. In this setup, wireless sensor nodes are static and randomly distributed within a typical environment, with each node belonging to a network cluster based on its identifier number as ID. These clusters are organized and managed by cluster heads, which are the members with the highest identifier number within each cluster. The role of the cluster head is to aggregate data from the sensor nodes within its cluster and forward it toward the base station. The data transmission from the sensor nodes to the base station occurs through a multi-hop communication process facilitated by the cluster heads, using the newly proposed method. As data packets are transmitted among cluster heads, various factors must be considered to ensure optimal network performance. These factors include the presence of errors in wireless communication channels, the distances between cluster heads and energy consumption levels. To enhance the network's efficiency, these parameters are carefully integrated into the design, ensuring that the network can handle data traffic while minimizing energy use and ensuring reliable communication across the system.

In wireless sensor networks, the limited radio range of sensors restricts each sensor to transmitting data only to a few neighboring sensors. Meanwhile, there are numerous possible paths for each cluster head to send data to the base station, but identifying the most optimal path is the primary focus of this paper. Since data transmission consumes energy and sensor nodes gradually deplete their energy reserves over time, this eventually leads to node failures and the expiration of the network's operational lifetime. Therefore, transmitting data to the destination with minimal energy consumption while maximizing sensor lifespan is critical for enhancing the network's longevity. By employing an optimal method for data routing, the network's reliability and durability can be significantly improved. This is a key concern in the field of wireless sensor networks, where power consumption and energy efficiency are central to many scientific research efforts aiming to extend network lifetimes and improve overall performance.

The unique characteristics of wireless sensor networks, combined with environmental noise, make error occurrence in wireless channels from nodes to the base station both probable and unavoidable. To address this challenge, employing an error control technique that prioritizes energy efficiency is the most effective approach. Rather than consuming significant energy for error correction, a more efficient strategy involves reducing the probability of errors by determining an optimal path for transmitting sensing data to the base station. Additionally, selecting shorter routes with fewer hops between cluster heads enhances the efficiency of data transmission. This is because shorter paths reduce both the distance-dependent error rate in wireless channels and the energy consumption of nodes, thereby contributing to improved network performance and longevity.

Building upon the existing knowledge in this field, if we develop a method where energy consumption, error rate and distance are simultaneously minimized, we can achieve an optimal energy-efficient error control approach that ensures the least passing distance among cluster heads. As discussed in the previous section, the Floyd algorithm offers an efficient solution for determining the shortest path among the vertices of a weighted graph and is particularly applicable to wireless sensor networks. In this section, we extend the application of this algorithm to identify the optimal path within the network. The problem is modeled based on the following assumptions:

- The network operates using a clustering mechanism and functions on an event-driven basis.
- Sensor nodes are distributed randomly across a predefined environmental space.
- All wireless sensor nodes are static.
- The physical locations of the network's cluster heads are known and accessible.
- The position of the base station is fixed and serves as the final destination for data collected by the cluster head nodes.
- All sensor nodes are of the same type, possess identical radio ranges and can communicate with other nodes within their respective ranges.
- All sensor nodes start with the same initial energy, which depletes over time as data is transmitted and received.

In this context, the wireless sensor network is represented as a weighted graph. Here, the cluster head nodes act as the graph's vertices, while the wireless communication channels between cluster heads—determined by their radio ranges—serve as the graph's edges. The base station, positioned as a fixed vertex within the graph, functions as the final destination for all cluster heads. This structure is depicted in Figure 4, providing a clear visualization of the network's representation as a weighted graph.

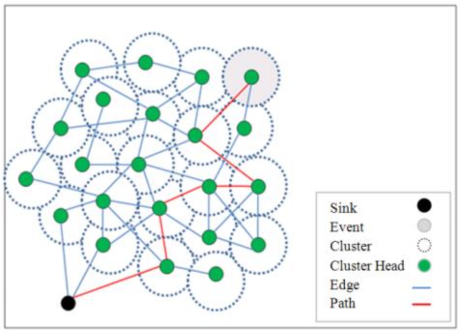


Figure 4. Corresponding graph with clustering wireless sensor network.

In the proposed method, the Floyd algorithm is employed to ensure that cluster head data packets are delivered to the sink through the most optimal path. This path is determined based on the minimization of the total distance between cluster heads, the minimization of error rate influenced by environmental noise and the maximization of the remaining energy of the cluster heads. The integration of these diverse factors into a single optimization framework is achieved through the use of an appropriate fitness function.

Given that the parameters involved in determining the optimal path—such as distance, error rate and remaining energy—operate within different numerical domains, it is not feasible to directly combine them without normalization. To address this, each parameter is mapped to a normalized domain [0, 1] to enable meaningful combination and comparison. This normalized aggregation of parameters is referred to as the weighted fitness function.

This function incorporates weights for each parameter, where Ci represents the effective coefficient of the *i*th parameter, Pi denotes the normalized value of the *i*th parameter and K signifies the total number of parameters, which is three in this method. The formulation of this fitness function is mathematically represented in Eq. 4. This approach ensures a balanced and fair contribution of each parameter toward determining the most optimal path in the network.

$$W_F = \sum_{i=1}^{k} C_i \times P_i \tag{4}$$

The proposed method considers three key parameters to evaluate the optimal path:

1. P_1 parameter (distance): This parameter represents the individual distance between cluster heads. It is modeled using a two-dimensional matrix called Dis_{ij}, where the element at the *i*th row and *j*th column denotes the distance between a pair of cluster heads v_i and v_j. This matrix is crucial in capturing the spatial relationships between cluster heads within the network.
2. P_2 parameter (remaining energy): This parameter accounts for the remaining energy of the cluster heads, ensuring that the path selection favors nodes with higher energy levels to enhance network longevity. A one-dimensional matrix R_Eng_j is used to model P_2, where the *j*th element indicates the remaining energy of the intermediate cluster head v_j.
3. P_3 parameter (error rate): The error parameter models the effects of environmental noise, which is critical due to the high noise susceptibility of wireless sensor networks. To simulate noise realistically, specific functions such as the Gaussian relationship are employed to distribute error values reasonably. The Gaussian function maps the generated values to a defined range, and the resulting numbers are stored in a one-dimensional matrix called Err_Rate_{ij}. Here, the *j*th element represents the error rate between a pair of cluster heads v_i and v_j.

These parameters are integrated into the fitness function to calculate the most optimal path, ensuring the minimization of distance and error rate while maximizing the remaining energy of the cluster heads. This comprehensive approach addresses critical aspects of network performance, including efficiency, reliability and energy conservation.

4. Simulation

Building on the previously described parameters P_1, P_2 and P_3, the proposed method calculates the weights of graph edges corresponding to the wireless sensor network using Eq. 5 and Eq. 6.

$$weight_{ij} = \alpha Dis_{ij} + \beta(1 - R\_Eng_j) + \delta Err\_Rate_{ij} \tag{5}$$

$$\begin{cases} Err\_Rate_{ij} = F(g(x)) \\ g(x) = \dfrac{1}{\sqrt{2\pi\sigma^2}} e^{-(\frac{x-\mu}{\sigma})^2} \end{cases} \tag{6}$$

$$\alpha, \beta, \delta \in [0, +\infty]$$

These equations integrate the distance matrix (Dis_{ij}), the remaining energy matrix (R_Eng_j) and the error rate matrix (Err_Rate_{ij}) into a unified weight formula. The effective coefficients α, β and δ control the relative influence of these parameters:

- α governs the impact of the distance matrix (Dis_{ij}), emphasizing the spatial separation between cluster heads.

- β affects the contribution of the remaining energy matrix (R_Eng_j), prioritizing energy-efficient paths.
- δ adjusts the influence of the error rate matrix (Err_Rate_{ij}), addressing noise and reliability.

The combined weight function ensures a balanced trade-off between distance minimization, energy conservation and error reduction. To enable dynamic adjustments based on network requirements, the effective coefficients α, β and δ can be tuned to the mentioned range. This flexibility allows continuous manipulation of the edge weights and optimal path selection, ensuring adaptability to varying conditions and priorities within the wireless sensor network. Such a weighted graph structure, with adjustable parameters, enables the proposed method to determine paths that optimize key performance metrics, enhancing both the reliability and efficiency of the network.

We utilized MATLAB R2022b software for implementing the proposed method and evaluating its effectiveness in wireless sensor networks. The experiments were designed to analyze the reliability and energy efficiency of the network under different parameter combinations. Specifically, we explored three scenarios: (1) considering only the error rate, (2) combining the error rate with remaining energy and (3) integrating all three parameters, including error rate, remaining energy and distance. These scenarios aimed to assess the robustness of the proposed method in identifying the optimal path under various environmental and network conditions. The initial assumptions used in our implementation are summarized in Table 1, providing the baseline configuration for the wireless sensor network simulations. These include details on the number of cluster head nodes, initial energy, network dimensions, error rate, radio range and energy consumption per data transmission. By setting these parameters, we ensured consistency across experiments and focused on the impact of the fitness function on network reliability and energy efficiency.

Table 1. Initial assumptions for the proposed method implementation.

Parameter	Value	Description
Number of cluster head nodes	75	Total number of cluster heads used in the simulation
Initial energy	3J	The starting energy level for each cluster head node
Environment dimensions	100m × 100m	The simulated area where the nodes are randomly distributed
Error rate	0.2	Probability of communication errors in wireless channels
Radio range	20m	Maximum distance a cluster head node can communicate directly with another node
Energy per transferring data	0.001J	Energy consumed by each cluster head for transmitting a single data packet

Before delving into the detailed results, we explore three distinct configurations of the proposed method to analyze the impact of various factors on the network's performance. Each configuration focuses on a different combination of parameters—error rate, remaining energy and distance—allowing us to assess the relative importance of each factor. The following subsections describe the different scenarios, their corresponding mathematical formulations and the resulting performance outputs. These configurations aim to provide a deeper understanding of how each factor influences the network's reliability and energy efficiency under varying conditions:

- Fitting the error rate: In this case, according to Eq. 7, the effective coefficients of the energy factor (β) and distance factor (α) are assumed to be zero. The output from this configuration is shown in Figures 5 to 7 in the (a) sections.

$$weight_{ij} = \delta Err\_Rate_{ij} \tag{7}$$

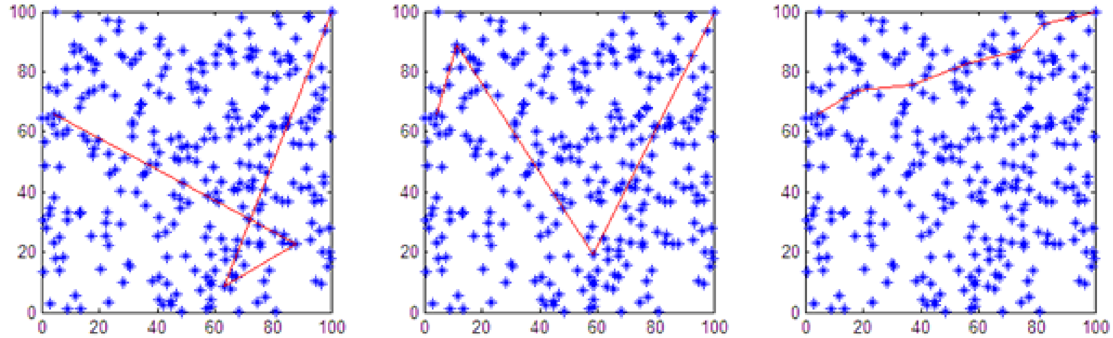
- Fitting the error rate and remaining energy: Here, according to Eq. 8, the effective coefficient of the distance factor (α) is assumed to be zero. The output from this configuration is shown in Figures 5 to 7 in the (b) sections.

$$weight_{ij} = \beta(1 - R\_Eng_j) + \delta Err\_Rate_{ij} \tag{8}$$

- Fitting the error rate, remaining energy and distance: In this case, according to Eq. 9, the effective coefficients of all factors are assumed to be non-zero. The output from this configuration is shown in Figures 5 to 7 in the (c) sections.

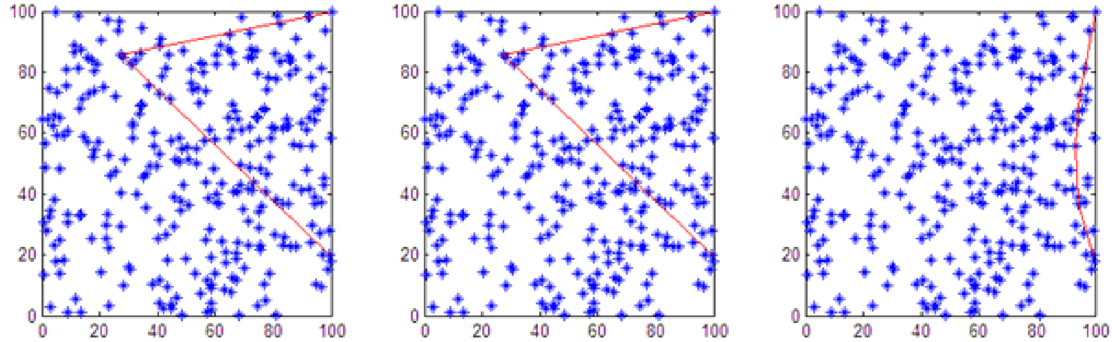
$$weight_{ij} = \alpha Dis_{ij} + \beta(1 - R\_Eng_j) + \delta Err\_Rate_{ij} \tag{9}$$

It is important to note that the node numbers referenced throughout the paper specifically correspond to the cluster head nodes. The sink is positioned in the upper-right corner of the defined network environment. In this setup, events are assumed to occur randomly, with the nearest cluster head node detecting the event. Once detected, the event is transmitted to the sink along the optimal path, which is determined using the Floyd algorithm as outlined in the proposed method. The routing paths of the cluster head nodes for three distinct events are shown in Figures 5 to 7, each representing a different fitting configuration.



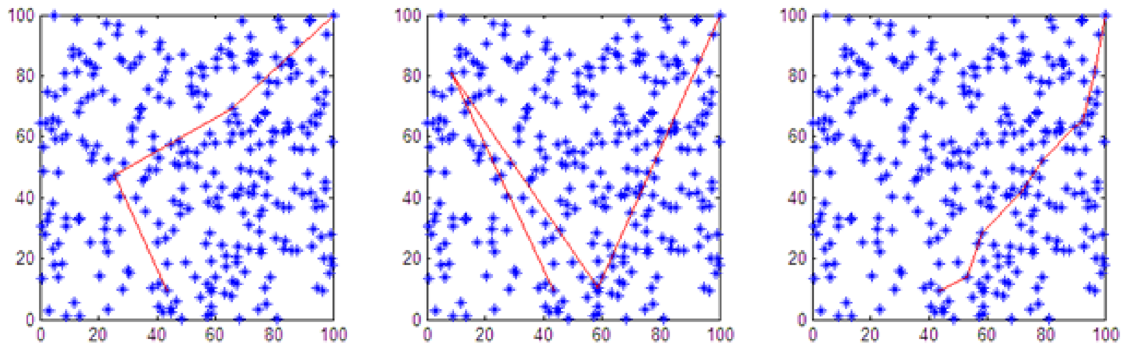
(a) (b) (c)

Figure 5. Routing operation for random event 1 detection (a) Routing based on the error parameter, b) Routing based on error and energy parameters, c) Routing based on error, energy and distance parameters (optimal path)).



(a) (b) (c)

Figure 6. Routing operation for random event 2 detection (a) Routing based on the error parameter, b) Routing based on error and energy parameters, c) Routing based on error, energy and distance parameters (optimal path)).



(a) (b) (c)

Figure 7. Routing operation for random event 3 detection (a) Routing based on the error parameter, b) Routing based on error and energy parameters, c) Routing based on error, energy and distance parameters (optimal path)).

For a more explanation, figures 5, 6 and 7 collectively demonstrate three modes of routing operation in the context of event detection. In (a) sections, the routing is based solely on the error parameter, illustrating how events are transmitted through cluster heads from the event's occurrence to the sink, guided by error minimization. In (b) section, the routing considers both error and energy parameters, optimizing the energy usage while maintaining reliability. Finally, in (c) section, the routing incorporates error, energy and distance parameters, resulting in the most optimal configuration by balancing all three factors. These simulations represent varying iterations of routing operations under three criteria: (1) error parameter only, (2) error and energy parameters and (3) error, energy and distance parameters. The results highlight the adaptability of the proposed method in addressing diverse network conditions, with the optimal path achieved in the (c) configuration, ensuring both reliability and energy efficiency for event detection and data transmission.

5. Results and Dicussion

Figure 8 illustrates the simulation results of nodes' average remaining energy over 1200 random events in a wireless sensor network, aiming to evaluate the network lifetime based on different parameter combinations. The horizontal axis represents the number of event rounds, while the vertical axis shows the average remaining energy of the nodes. The green plot corresponds to the proposed method, which incorporates three parameters: 1) error, 2) energy and error and 3) distance, energy and error, demonstrating superior energy efficiency compared to the other methods. The blue plot considers two parameters—1) error and 2) energy and error—and exhibits moderate performance. In contrast, the red plot represents the least efficient case, accounting for only one parameter: error. These results emphasize the benefits of considering multiple parameters, particularly the inclusion of distance alongside energy and error, in enhancing network energy efficiency and prolonging its lifetime.

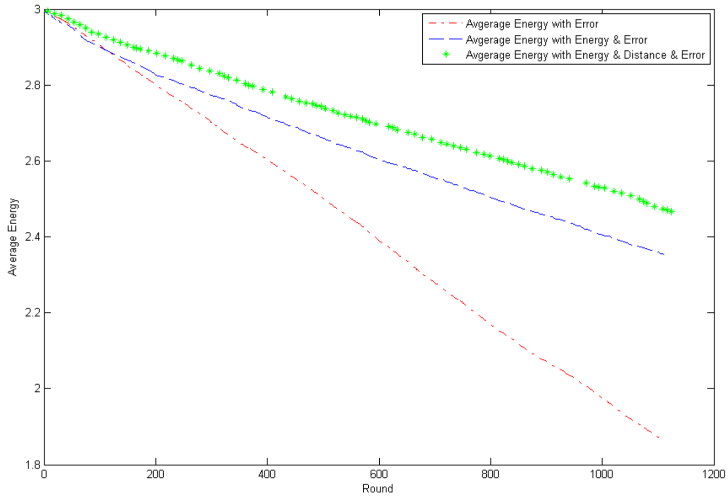


Figure 8. Average remaining energy of nodes under different parameter combinations.

Figure 9 illustrates the node dying steps across three different methods, with the horizontal axis representing the number of nodes and the vertical axis showing the iteration steps at which nodes die. The blue curve corresponds to the proposed method, which incorporates three factors, namely distance, energy and error parameters. This approach achieves the best performance, with nodes surviving for significantly more steps. For example, after 4000 iterations, 20 nodes remain active in the network using this method. The green curve represents a method that considers energy and error parameters, showing moderate performance, while the red curve, which accounts only for the error parameter, results in the fastest node depletion. This comparison highlights the advantage of integrating multiple factors, as demonstrated by the superior results of the blue curve, in ensuring energy-efficient and error-resilient network performance.

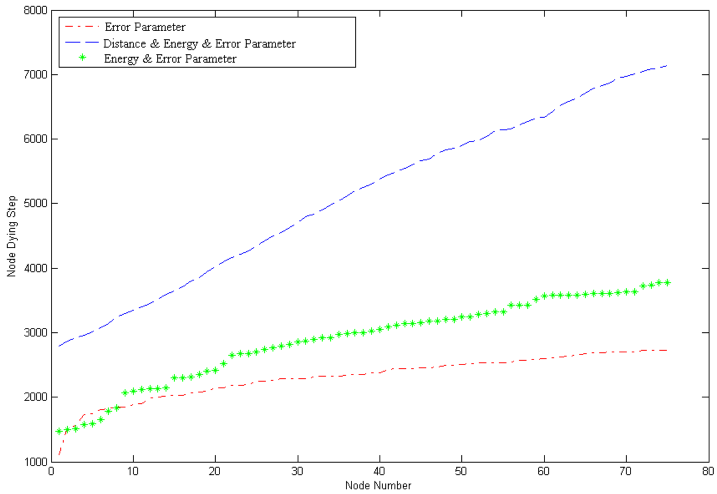


Figure 9. Node dying steps for methods with varying parameters.

6. Conclusions and Future Works

This paper introduces a novel error control approach for WSNs in IoT applications by integrating the Floyd algorithm for optimal pathfinding. The method addresses the challenges of unreliable communication channels in WSNs, mitigating environmental interferences and optimizing energy consumption. Simulation results in MATLAB R2022b show that the approach, which combines distance, energy and error factors, significantly enhances energy efficiency, network reliability and lifetime compared to other methods. By selecting optimal paths from source nodes to sink nodes, the proposed method reduces energy consumption and prolongs node survival, showcasing its potential to improve WSN performance in IoT environments. This paper introduces a novel error control approach for WSNs in IoT applications by integrating the Floyd algorithm for optimal pathfinding with advanced optimization techniques.

Future research will focus on scaling the approach for larger IoT networks and refining the error control mechanisms for even greater performance. While the proposed method is fundamentally based on mathematical principles, future studies may investigate its integration into artificial intelligence-driven techniques to enhance optimization and adaptability. For instance, reinforcement learning could be utilized to dynamically optimize pathfinding and error correction based on network conditions and traffic patterns. Additionally, exploring alternative pathfinding algorithms, such as A or Dijkstra's algorithm, could offer comparative advantages in specific network scenarios. Furthermore, leveraging the unique features of IoT networks, such as edge computing and data fusion at the sensor level, could provide more scalable solutions. These directions will contribute to the development of more intelligent and resilient WSNs for a wide range of IoT applications in different scenarios.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval.

This article has no conflicts of interest with any individual or institution.

Author Contribution Statement

Bita Ghasemkhani contributed to the conceptualization, experimental design, data collection, conducting analyses, literature review and drafting of the manuscript. Professor Shahram Babaie provided supervision, critical review and guidance throughout the research process.

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