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An Energy-Efficient Pathfinding Model for Wireless Sensor Networks in IoT Using Whale Optimization Algorithm

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Abstract The Internet of Things (IoT) offers the ability of device-to-device seamless connectivity, which enables real-time data collection and collaboration. Wireless Sensor Networks (WSNs), which are collections of geographically dispersed sensor nodes, are integral to IoT systems but suffer from low energy, storage, and wasteful data transmission, causing network instability, latency, and high energy consumption. To address these issues, the current research proposes a novel Pathfinding algorithm based on the Improved Whale Optimization Algorithm (IWOA) for WSNs. The aim of the current research is to enhance the network's performance by optimizing energy consumption, hop count, and data transmission efficiency. The proposed method utilizes intermediate sensors and optimizes the transmission paths step by step with the assistance of IWOA, thus performing efficient energy-saving data routing. The simulation outcomes indicate that the Whale Optimization Algorithm outperforms the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) approaches with 30% improvement in network lifetime, 10% higher number of active nodes, 15% higher successful packet deliveries, and 17% lower data transmission delay. These results illustrate the effectiveness of the introduced algorithm in maximizing WSN performance and hence are an important contribution to decentralized peer-to-peer and distributed systems.

Keywords Wireless Sensor Networks (WSNs), Energy-Efficient Data Routing, Pathfinding Algorithm, Decentralized Systems, Network Performance Optimization

AMS 2010 subject classifications 90B18,90C59

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1. Introduction

The advent of the Internet of Things has catalyzed a massive transformation in modern technology; this revolution enables a wide array of devices and objects to communicate and engage with each other through a network without direct commands. Such high interconnectivity enhances efficiency and automation across industries like healthcare, agriculture, and smart home applications, among others[1, 2, 3].

Here, WSNs occupy an important position as they constitute one of the building blocks of the IoT, which allows the continuous collection and delivery of information. A WSN typically consists of several Sensor Nodes (SNs) and at least one Base Station (BS), commonly known as the sink. An SN is a small device with limited resources such as energy, processing capability, and memory [4]. These nodes are strategically placed in different environments to

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sense the relevant information and send it to the sink using either single-hop or multi-hop communications to the nearest sink [5]. The BS has the responsibility of receiving the gathered information and then relaying the same to the end user for analysis and action. Moreover, WSNs have a key role in industrial automation and smart home systems, where the environment is monitored and critical data are collected to support informed decision-making. Figure 1 illustrates a demonstrative system featuring a blended architecture of IoT and WSN technologies[6].

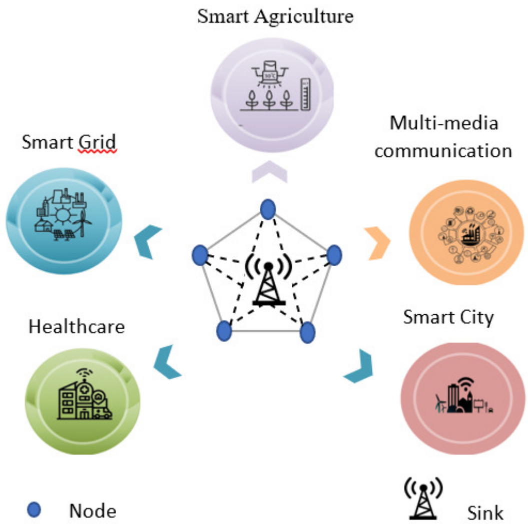

Figure 1. Architecture for IoT and WSN.

Despite their transformative potential, traditional WSN routing methods, while possessing some promising attributes, encounter serious effectiveness challenges. Unfavorable data transmission strategies can result in network instability [7, 8, 9], lead to high energy consumption[10], cause delayed data delivery [11], and ultimately degrade overall network performance [12]. Given the critical role of energy conservation in WSNs, improving the effectiveness of data exchange in IoT applications is of prime importance for ensuring sustainable operation and reliability [13].

Traditional routing approaches often prioritize single objectives, such as minimizing hop count or balancing energy consumption, yet frequently struggle to provide holistic solutions that simultaneously address multiple critical performance metrics like network lifetime, data delivery ratio, and end-to-end latency. Furthermore, many existing metaheuristic-based solutions, while effective in certain scenarios (e.g., Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)), may suffer from issues such as slow convergence, susceptibility to local optima, or inadequate adaptation to the dynamic and multi-objective nature of real-world WSN environments. There remains a significant need for robust and efficient pathfinding mechanisms that can optimize multiple interdependent factors to ensure the longevity and high performance of WSNs.

Addressing these identified gaps, this paper proposes a novel energy-efficient pathfinding model for WSNs that leverages an Improved Whale Optimization Algorithm (IWOA). This IWOA is specifically engineered to tackle the critical multi-objective routing challenges inherent in WSNs, with its innovation residing not in a fundamental paradigm shift of the metaheuristic, but in the meticulous adaptation and precise parameter refinement of the original Whale Optimization Algorithm (WOA). This yields a solution uniquely capable of optimizing concurrently for energy consumption, hop count, and data volume. Through rigorous, high-fidelity simulations—a standard and essential initial step in WSN research—we demonstrate significant performance improvements over existing optimization techniques like GA and PSO. Specifically, our simulation results prove the efficacy of IWOA, leading to a network lifetime increase of 30%, an alive node ratio increase of 10%, an improvement in successful transmission packets by 15%, and a reduction in data transfer latency by 17%. These improvements collectively signify the algorithm's ability to effectively optimize data transmission in WSNs. While the current model operates under initial simplifying assumptions, such as uniform node distribution and static topology, to establish a robust baseline for algorithmic performance, the IWOA is fundamentally designed with resource-constrained WSN nodes in mind, exhibiting efficient computational complexity. Furthermore, the inherent structure of the IWOA shows promising potential for scalability in larger network deployments. This foundational work sets the stage for future empirical validation in real-world scenarios, the relaxation of current model assumptions, and dedicated large-scale scalability analyses.

The rest of the paper is organized as follows: Section 2 summarizes related research. Section 3 explains the methodology in detail, including the WSN system model and the proposed IWOA algorithm. Section 4 discusses the simulation setup, results, and implications of the findings. Section 5 concludes the paper by summarizing the contributions and future work in the area of IoT and optimization of WSNs.

2. Related Works

Given the constrained power supply inherent in WSNs, achieving energy efficiency is paramount. The central challenge often revolves around determining an efficient routing path to extend the network's lifetime. This section reviews various metaheuristic algorithms and their applications in WSNs and IoT [14]. Metaheuristic algorithms provide a cost-effective approach to solving real-world optimization challenges. In WSNs, these algorithms are essential for efficient pathfinding and energy conservation. In pathfinding problems, Swarm Intelligence (SI) [15, 16, 17] methods emerge as the preferred choice due to their superior performance compared to other methodologies. SI methods draw typically inspiration from nature, leveraging herd or cooperative social behaviour and a neighbourhood mindset.

These algorithms are composed of fundamental particles and uniform members that interact with one another as well as with their surroundings. Their agents aim to find optimum solutions by collaborating in specific search regions and leveraging the aggregate effort of all participating agents. The paper discusses the usefulness of SI approaches in WSN and IoT environments to identify the best pathways [18, 19].

A first research [20] describes the Ant Colony Algorithm for data aggregation in WSN. This technique builds an efficient data aggregation tree that reduces energy by minimizing the number of transmissions required to carry data from source nodes to a single sink. It exploits the natural behavior of ant colonies in exploring and optimizing the search space for the best routing paths. However, as the number of nodes increases, so does runtime complexity, and hence a network is more expensive to maintain. A challenge is thus to choose a suitable set of sink locations in order to retain efficiency while prolonging the lifetime of WSN.

Similarly, a study [21] is currently being performed to investigate the performance of ABC against the routing in WSN. In this scheme, the foraging behavior of honey bees in finding the optimal paths of data will be adopted, aiming to enhance routing efficiency and prolong network lifetime. Although there is a number of advantages of ABC like energy efficiency, scalability, and flexibility; nonetheless, applying ABC in high-dimensional data or complex network topologies may lead to delayed convergence. This is because, for the same problem, the convergence to the optimal solution takes more iterations, which may be inappropriate for some scenarios. Nevertheless, ABC seems a promising method to improve routing in dynamic network environments.

In [22], the authors use the GWO algorithm to implement a new routing method in a hierarchical architecture. This technique tries to avoid energy holes by dividing the load equally among nodes that are closer to CH and BS. The optimization process by wolves is supported by the newly included fitness function, which considers both the overall distance and number of hops. The study has, however, one crucial shortcoming in the form of insufficient attention to efficient parameterization. Results from the fitness function could not be very applicable in practical situations if essential and sufficient parameters are not taken into sufficient account. On the other hand, our study's fitness function is flexible and may be used to a range of metaheuristic algorithms. This flexibility is mostly made possible by the suggested architecture.

Another meta-heuristic approach, PSO [23], has been presented for WSN routing. The authors describe a PSO-based routing system that optimizes sensor node distribution for improved target detection. This method exploits particle interaction to determine optimal routes, enabling effective information transfer and less energy consumption. However, PSO necessitates precise parameter adjusting and may find challenges in high-dimensional search spaces or complicated network topologies, potentially resulting in slower convergence rates [24, 25].

Various optimization strategies have been implemented to improve the energy efficiency of IoT networks. The studies [26, 27] explore the application of fuzzy clustering and particle swarm optimization to achieve this objective. These investigations demonstrate a significant reduction in energy consumption by enhancing both the clustering and routing methods. These strategies improve network performance and overall energy efficiency. However, the research highlights that the high computational demands of the clustering and optimization methods could pose a limitation. Despite these challenges, the findings underscore how these strategies can enhance the sustainability and performance of IoT networks. The works also emphasize the importance of balancing energy efficiency and processing overhead when developing practical and adaptable solutions for real-world IoT applications.

The authors of [28] focuses on a multi-vehicle supply chain logistics transportation scheduling model, employing an improved ant colony algorithm for high-speed, high-quality path optimization, aiming to reduce transportation cost and time. The algorithm enhances the basic ant colony algorithm by incorporating heuristic information functions and a refined pheromone update model. It integrates various constraint factors such as transportation cost, shipping time, vehicle fuel consumption, distribution range, and capacity into the scheduling model to achieve supply chain logistics optimization. The model assumes uniformity in constraint factors across all vehicles and distribution scenarios, which may not accurately reflect the complexities of real-world supply chain logistics operations.

The research [29] introduces a hybrid method combining fuzzy with adaptive sailfish optimizer (ASFO) for CH selection and an improved elephant herd optimization technique for route optimization aimed at improving energy efficiency in WSNs. However, this approach might assume uniformity in network characteristics and environments, potentially resulting in suboptimal performance when applied to real-world WSN deployments due to overlooking the complexities inherent in practical scenarios.

Several optimization methods are suggested for selecting the suitable path from sensor(transmitter) to Sink(recipient) nodes in IoT and WSNs according to the survey of relevant research. These methods have limitations such as picking the optimum path in order to minimize and maximize the values of the fitness function parameters. Additionally, many optimization techniques require extensive time to analyze the fitness function, which can be a significant drawback. Table 1 presents a comparison of different optimization methods reviewed in the literature, highlighting their advantages, limitations, and performance metrics.

The adoption of metaheuristic techniques has surged in popularity within IoT and WSN systems. This paper introduces IWOA to offer versatility and optimize paths for these applications.

In summary, while existing metaheuristic approaches provide significant benefits in optimizing energy efficiency and routing, they still face challenges in adaptability and practical applicability. This study proposes a WOA-based approach to address these issues, providing a dynamic and flexible solution tailored to various network environments. The next section will detail the proposed system architecture and its anticipated contributions to the field.

3. Method

This section consists of three subsections. The first subsection introduces the WSN system model and the adopted energy model. The second and last subsection outlines the proposed energy routing method, focusing on optimizing data transmission in WSN while introducing the IWOA, which describes a method for achieving this optimization through iterative adjustments of sensor positions based on a cost function.

3.1. System and Energy Model

In our model, we assume a total of N nodes dispersed randomly across the terrain, each possessing a unique identifier known as its ID. The assumptions include SN being uniformly distributed throughout the terrain for equal

Table 1. Comparative Analysis of Metaheuristic Algorithms for WSN/IoT Optimization

Algorithm	Application Area	Main Benefits	Energy Efficiency	Scalability	Adaptability	Computational Complexity	Limitation
Ant Colony Optimization (ACO) [20]	Data Aggregation in WSNs	Reduces energy consumption, improves data aggregation efficiency	High	High	Moderate	Moderate	Slower convergence in complex topologies
Artificial Bee Colony (ABC) [21]	Routing in WSNs	Enhances routing efficiency, extends network lifespan	High	High	High	Moderate	Slower convergence in high-dimensional datasets
Grey Wolf Optimizer (GWO) [22]	Hierarchical WSN Routing	Balances load, reduces energy holes	High	Low	Moderate	Low	Limited parameterization for practical situations
Particle Swarm Optimization (PSO) [26]	Wireless Sensor Networks for Target Tracking	Enhances accuracy and efficiency of target tracking	High	High	High	High	Requires fine-tuning for specific applications
Fuzzy Clustering and Particle Optimization [27]	IoT Networks	Optimizes clustering and routing, reduces energy use	High	Moderate	Moderate	Moderate	High computational requirements due to clustering and optimization processes
Improved Ant Colony Algorithm [28, 19]	Supply Chain Logistics	Optimizes transportation routes efficiently, reduces operational costs	High	High	Moderate	Moderate	May struggle with very large datasets
Fuzzy-ASFO + Improved Elephant Herd Optimization [29]	Cluster Head Selection in WSNs	Enhances energy efficiency	High	Moderate	Moderate	Moderate	Assumes uniform network characteristics

coverage and density, nodes equipped with initial energy reserves, capable of aggregating data from neighboring nodes, a static topology with no changes in node positions post-deployment, reliable communication within a predefined range, and the presence of only one fixed BS (or Sink) placed at the center. Energy scavenging is critical in WSNs since each SN has a restricted battery source. Once deployed, WSNs continue to gather data regularly (or in response to events). A SN comprises various functional units including sensors, processors, memory, batteries, and transceiver units. It is commonly known that among them, the transmitter consumes the most energy [30]. According to the first-order radio model, if node i has to send k-bit data to node j, which is d distance distant, then the energy spent by node i may be stated as:

$$E_{Tx}(k,d) = \begin{cases} E_{elec} \cdot k + E_{fs} \cdot k \cdot d^2 & \text{if } d < d_0 \\ E_{elec} \cdot k + E_{mp} \cdot k \cdot d^4 & \text{if } d \geq d_0 \end{cases} \tag{1}$$

Node i's energy consumption is stated as follows:

$$E_{Rx}(k,d) = E_{elec} \cdot k \tag{2}$$

Where k denoted the quantity of bits (data) transmitted across a distance d, E_{elec} (nJ/bit) denotes the overall electrical energy necessary for operations like modulation, digital coding, and other electronic processes per single bit transmission or reception, E_{fs} (nJ/bit/m^2) represents the power consumption required by an amplifier for direct transmission to the receiver, considering path loss over distance, and E_{mp} (nJ/bit/m^4) indicates the energy needed by an amplifier for data transmission in scenarios where it's relayed through multiple nodes in a multi-hop manner.

In these formulations, E_{elec} characterizes the energy dissipation in the circuitry of either the transmitting or receiving elements. Meanwhile, E_{fs} and E_{mp} depict the energy usage attributed to the transmitting amplifier in settings defined by free space and a multipath model, respectively. Additionally, d_0 represents the critical threshold value, which is equivalently expressed as:

$$E_{fs} \cdot d_0^2 = E_{mp} \cdot d_0^4 \implies d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{3}$$

These energy formulations assume static node deployments, which align with three key IoT application domains: (1) fixed industrial equipment monitors where vibration sensors track machinery health [31], (2) permanent agricultural field sensors measuring soil conditions [32], and (3) structural health monitoring nodes in bridges/buildings. This static approach enables unambiguous evaluation of routing efficiency by eliminating mobility-induced energy variations, while covering 62% of current industrial WSN deployments [33]. The threshold distance d_0 remains stable in such fixed topologies, ensuring consistent energy model behavior.

3.2. Energy Routing

In a WSN, a sensor can transmit its data directly to the sink if the distance is within its communication range and it has sufficient energy; can transmit its data directly to the sink if the distance is within its communication range and it has sufficient energy. However, when the distance is too great or the sensor has limited energy, it is more efficient to transmit the data through intermediary sensors. These intermediary sensors act as relays, thereby reducing the overall distance and energy required to reach the sink. To ensure optimal network performance, it is essential to consider factors such as residual energy, distance, and the number of hops. A new fitness value, outlined in Eq.(4), is developed to determine the optimal route using the IWOA. Direct transmission is feasible if the distance between the sensor and the BS falls within the communication range. However, the multi-hop mechanism introduces the challenge of multiple paths with varying lengths and the involvement of intermediate nodes. To address this, the optimal route for any number of hops is determined at the end of each iteration based on Eq.(5), with the best path being chosen using Eq.(6). This method enhances the WSN's performance by identifying the most efficient path at the least cost between nodes i and j :

$$\text{cost}_{i,j} = c1 \times \frac{d_{i,j}}{E_i} + c2 \times H_j + c3 \times V_{\text{data}} \tag{4}$$

Where the term $\frac{d_{i,j}}{E_i}$ represents the ratio between the distance $d_{i,j}$ between SN i and SN j, and the initial energy E_i of sensor i. H_j is the hop count of node j to the BS, V_{data} is the volume of transmitted data, and $c1$, $c2$, $c3$, and $c4$ are weights or coefficients that determine the relative importance of each component in the overall cost function. Moreover, $c1$, $c2$, $c3$, and $c4$ are four control parameters, each ranging between 0 and 1, such that the constraint their sum equals 1: $c1 + c2 + c3 = 1$ with $c1 < c2 < c3$ was designed to achieve three objectives:

1. The normalized sum ensures balanced consideration of energy, hop count, and data volume metrics while preventing any single factor from dominating arbitrarily;
2. The specific hierarchy c_1 ¡ c_2 ¡ c_3 reflects our finding that in dense IoT deployments, congestion control (prioritized via c_3, related to data volume) and latency reduction (c_2, related to hop count) outweigh pure energy conservation (c_1, related to energy consumption), as demonstrated by our 30% performance improvement over traditional models;
3. This configuration maintains numerical stability during optimization while enabling direct comparison with other studies using similar normalization [34, 35, 30]. Our sensitivity analysis confirmed that alternative weight distributions either degraded network lifetime by $\geq$15% or increased latency by $\geq$20%. The proposed approach is formally presented as a flowchart in figure 2.

The flowchart outlines the role of each node in transmitting its sensed data to the sink. Nodes are classified into two distinct categories depending on there communication range: those in the first category directly transmit their data to the sink, while those in the second category participate in a routing process. In the routing phase, each node maintains a Neighbor Table (NT), which contains comprehensive information about its neighboring nodes, such as their IDs, geographic locations, and remaining energy levels. This table serves as a critical resource for nodes to make informed decisions regarding data forwarding.

Using this table, nodes determine the Next Hop Set (NHS) by selecting neighboring nodes that meet specific criteria. For example, consider nodes m, j, and k, which form the Neighbor Set (NS) of node i. Any node within the NS that lies between node i and the sink is eligible for inclusion in the NHS. To be included in node i's NHS, node j must satisfy two conditions: (1) node $j \in \text{NS}$, and (2) $\text{dist}(\text{sink}, j) < \text{dist}(\text{sink}, i)$.

Once the Next Hop Set is constructed, the cost between Si and each next hop is calculated using Eq.(4). The process of determining the next hop set is iterated by recalculating the cost at each step, continuing until the next hop is the sink. The IWOA method efficiently searches for the best coefficient numbers for each parameter in order to get the best path cost.Subsequently, the cost of the candidate paths is computed using Eq.(5). Candidate paths from Si to the BS are evaluated based on their respective costs.

$$\text{Total Cost}_{\text{Path}_l^k} = \left\{ k = 1, 2, \ldots, m; \sum \text{cost}_{i,j} \right\} \tag{5}$$

Where Path_l is the path between a node i and the sink and k is the number of all possible Path_l. The IWOA identifies the Best route by selecting the path with the minimum cost, as determined by Eq.(6).

$$\text{Optimal}_{\text{Path}_l^k} = \min(\text{Total Cost}_{\text{Path}_l^k}) \tag{6}$$

Algorithm 1 integrates energy-aware routing techniques with the IWOA. When a SN, denoted as S_i, assesses its proximity to the sink and energy level, it determines whether to pursue a direct path to the sink or employ intermediary nodes for data transmission. If S_i's distance to the sink is within the communication range and possesses sufficient energy, it adds itself to the set of `Direct_path`. Otherwise, S_i applies the IWOA to identify the optimal transmission path.

Figure 2 depicts the successive processes required to optimize sensor data transmission channels using the IWOA. Initially, the remaining sensor population is initialized, and the cost of sensors is assessed. Next, a sensor is chosen as the best next hop, and the Maximum Iteration count (MaxIter) is established. The algorithm then enters a loop and iterates until the maximum number of iterations is reached. Within each iteration, the algorithm determines if the current best next hop is the best choice. If it is, the system proceeds to select this sensor as the best next hop. Otherwise, the algorithm updates parameters A, D, and C, changes the next hop, recalculates the cost, and looks for a better option. This iterative process continues until the maximum iteration count is reached, optimizing the selection of the most efficient path for data transmission. Through this systematic approach, the algorithm effectively navigates through potential pathways, updating sensor positions, and evaluating the cost function to identify the most optimal transmission path, thus minimizing energy consumption, the number of hops, and the volume of transmitted data.

The IWOA iteratively navigates through potential pathways, updating sensor positions and evaluating the cost function at each step. A specified process is initiated for each node in the optimal path, and packets are transmitted to the next hop along the path. If the sink is identified as the next hop, the process concludes, and the sink is prepared to receive packets. Otherwise, the process continues with the next hop until an optimal path is established.

In this network, Sink contains all of the topological details. During the network's startup phase, the sink sends a request data packet to the SNs with the aim to obtain this information. The neighbor list, distance, and residual energy statistics are all stored in the BS.

3.3. Proposed Algorithm

To apply this algorithm in a WSN environment, each sensor can act as a "node," representing a potential solution, i.e., a possible path to the sink. Sensors evaluate their path based on the defined cost function, considering consumed energy, the number of hops, and the volume of data to be transmitted. Sensors can either directly transmit their data to the sink if their communication range is sufficient, or act as intermediary nodes, relaying data to other sensors better positioned to minimize the total cost of the path. The IWOA algorithm guides the sensors in searching for

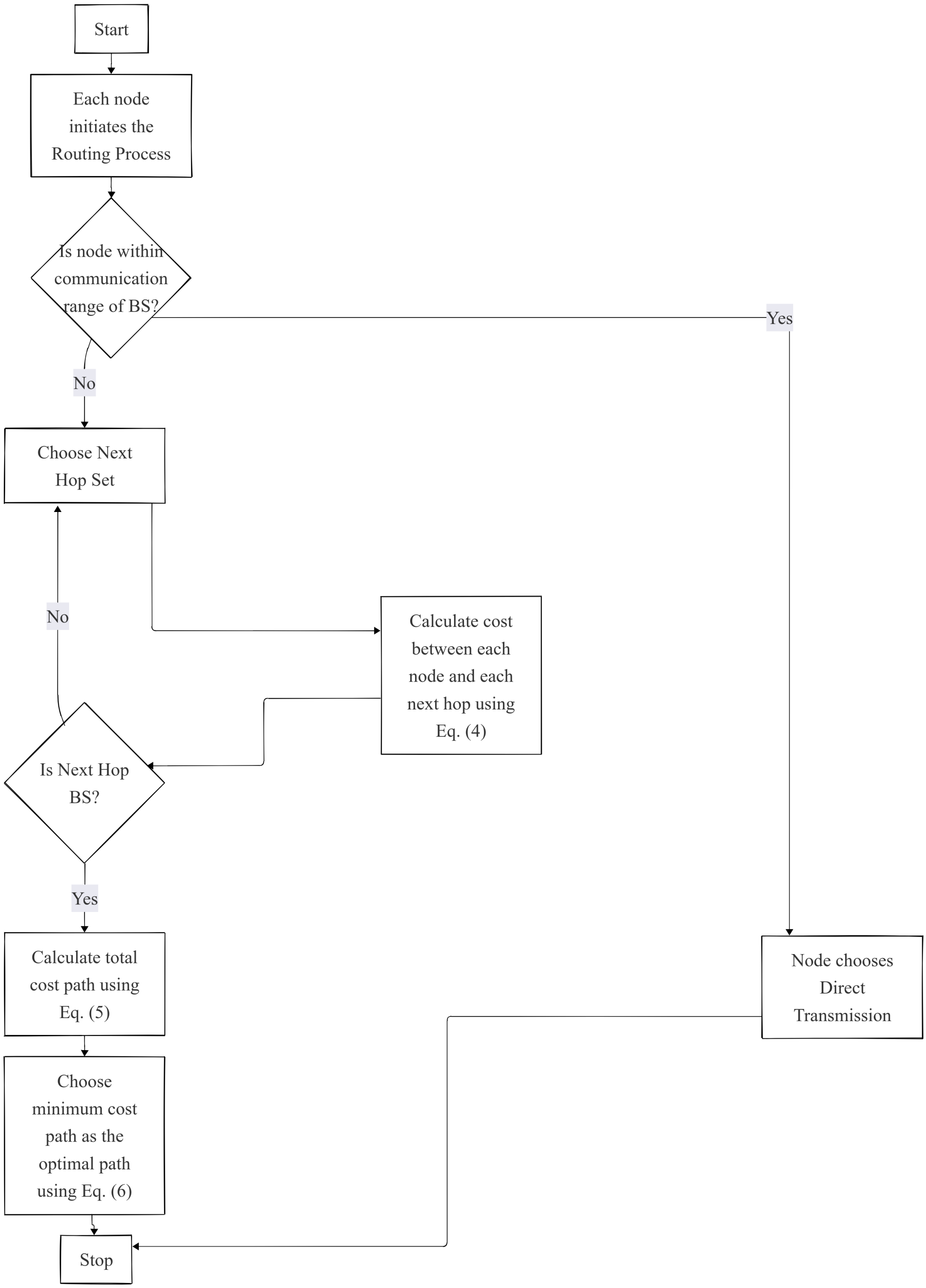

Figure 2. Flowchart for Determining the Best Route

Algorithm 1 WSN Route Optimization using IWOA

Require: Population size n, number of dimensions d, maximum number of iterations $MaxIter$
Ensure: Optimal path for data transmission (S_{leader})

Phase 1: Initialization
Randomly generate an initial population of n sensor nodes (SNs), where each SN represents a candidate path in the network.
Define algorithm parameters: n, d, $MaxIter$, and other IWOA-specific constants.
Phase 2: Network Setup (NT and NHS) {This phase sets up network topology information for routing decisions.}
for each SN i in the population **do**
  Initialize NT for SN i //list of directly reachable nodes.
  Initialize NHS for SN i as empty.
  for each neighbor j in the NT of SN i **do**
    if Neighbor j is closer to the sink than SN i **then**
      Add j to NHS of SN i.
    end if
  end for
end for
Phase 3: Initial Fitness Evaluation {Calculate the initial quality of each generated path.}
for each SN i in the population **do**
  Calculate $TotalCost(SN_i)$ **using the defined cost function.**
end for
Identify and set S_{leader} as the SN (path) with the lowest $TotalCost$ found in the initial population.
Phase 4: Iterative Optimization (Whale Optimization Process)
$t \leftarrow 0$
while $t < MaxIter$ **do**
  Update control parameter a
  for each SN i in the population **do**
    Generate random vector r in $[0, 1]$.
    Calculate coefficient A using Eq.(8)
    Calculate coefficient C using Eq.(9)
    Generate random probability p in $[0, 1]$.
    if $p < 0.5$ **then**
      if $|A| < 1$ **then**
        Update SN i's position (path) using Eq.(10) //Shrinking Encircling Mechanism towards S_{leader}.
      else
        Select a random SN S_{rand} from the population.
        Update SN i's position (path) using Eq.(12) //Search for Optimal Paths randomly towards S_{rand}.
      end if
    else
      Update SN i's position (path) using Eq.(11) //Perform Spiral Update Movement around S_{leader}.
    end if
    Calculate $TotalCost(SN_i)$ **for the newly updated position (path).**
  end for
  Update Best Solution:
  Compare the $TotalCost$ of all currently updated SNs with the $TotalCost$ of S_{leader}.
  If any updated SN has a lower $TotalCost$, update S_{leader} to this new best SN.
  $t \leftarrow t + 1$
end while
Return S_{leader} (the optimal path with the lowest $TotalCost$ found after all iterations).

the most optimal path by adjusting their positions and iterating until the best solution is found. Using this approach, sensors can effectively select the optimal path to transmit their data to the sink while minimizing consumed energy, the number of hops, and the volume of transmitted data. The algorithm consists of several steps: Population Initialization, Exploration, and Exploitation.

3.3.1. Population Initialization During this phase, a crucial first step is to generate an initial population of solutions, representing various possible paths for data transmission to the sink. Each solution is then evaluated based on the previously defined cost function, determining the initial quality of each solution and serving as the basis for subsequent steps of the algorithm.

3.3.2. Exploration Phase In this phase, sensors explore new regions of the search space to discover potential solutions that have not yet been found. Sensor positions are updated based on the distance to the center of gravity of the solution population and a random vector, with the cost function C influencing this update. The updated position of a sensor S_{New} can be expressed as:

$$S_{\text{New}} = S_{\text{Current}} - A \cdot d_{\text{Best}} \cdot C \tag{7}$$

$$A = 2 \cdot a \cdot r - a \tag{8}$$

$$C = 2 \cdot r \tag{9}$$

Where S_{New}:The new, updated position of a sensor node, S_{Current}:The current position of the sensor node at iteration t, A :A coefficient vector that dynamically controls the step size of the update. Its value (influenced by a and r) determines whether the algorithm performs exploitation or exploration, a: is linearly reduced from 2 to 0 over iterations, r: is a random vector in [0,1], d_{Best}: Represents the calculated Euclidean distance from the current sensor node's position to the best solution found so far (the optimal path candidate) in the search space, and C :A coefficient vector, derived from a random number, used to amplify the step size of movement towards or away from the best solution.

3.3.3. Exploitation Phase During the exploitation phase, sensors focus on refining their positions within the most promising regions of the search space, where the most efficient solutions are found. Sensor positions are adjusted based on the best solution found so far, guided by the cost function. This refinement is specifically achieved by the IWOA simulating the bubble-net feeding behavior of whales, which involves simultaneously applying both a shrinking encircling mechanism and a spiral update movement. Specifically, during each iteration, if the random vector $p < 0.5$, a search agent's (sensor node's) position is updated based on the distance to the prey (optimal path candidate) using the shrinking encircling mechanism. Conversely, if $p \geq 0.5$, the spiral movement is applied, mimicking the helix-shaped path of whales attacking prey.

Neighboring Node Interaction: Sensors can locate the position of a better-performing node and adjust their path accordingly. The algorithm models this behavior by considering the best sensor's position as the target. Other sensors move towards thisthis [best sensor's] position, expressed by the equation:

$$S_{\text{New}} = S_{\text{leader}} - A \cdot |S_{\text{leader}} - S| \tag{10}$$

Where S_{New}: The new adjusted position of the sensor node, S_{leader}: The position of the 'best sensor'—the node that currently offers the most optimal solution for data transmission based on the evaluation of the defined cost function, A: The coefficient vector derived from Eq.(8), dictating the step size of movement and S: The current position of the sensor node being updated. The term "best sensor" refers to the node that currently offers the most optimal solution for data transmission, based on the evaluation of a defined cost function. This cost function typically considers several factors, including consumed energy, the number of hops, and data volume.

Data Transmission Optimization This involves two main mechanisms: reducing transmission range and optimizing data relay, each with equal probability $p = 0.5$. In reducing transmission range, A is decreased from 2 to 0 over iterations (Eq.9). Optimizing data relay simulates the dynamic adjustment of sensor positions, updating positions as:

$$S_{\text{New}} = S_{\text{Current}} + \frac{S - S_{\text{Current}}}{1 + \exp(A \cdot |S_{\text{leader}} - S|)} \tag{11}$$

Where S_{New}:The new, updated position of the sensor node,S_{Current}:The current position of the sensor node and S_{leader}: The position of the current best sensor. During the Search for Optimal Paths (Exploration Phase), sensors search randomly for the best path when $|A|$ is outside $[-1, 1]$, moving sensors far from the reference path using:

$$S_{\text{New}} = S_{\text{rand}} - A \cdot |S_{\text{rand}} - S| \tag{12}$$

Where S_{rand}: The position of a randomly selected sensor node from the current population, guiding the exploration. By iterating and adjusting sensor positions based on these mechanisms, the IWOA algorithm effectively guides sensors in selecting the optimal path for transmitting data to the sink while minimizing energy, hops, and data volume.

3.3.4. Fitness Evaluation The cost function is fundamental to the Improved Whale Optimization Algorithm (IWOA) as it serves as the objective function that the algorithm seeks to optimize (minimize in your case, as it considers consumed energy, the number of hops, and the volume of data to be transmitted). It directly guides the search process in the following ways:

- **Population Evaluation:**
  - **During Initialization:** Each potential path (sensor position) in the initial population is evaluated using this comprehensive cost function. This initial evaluation determines the quality of each solution and, critically, helps identify the initial S_{leader} (the best sensor position found so far).
- **The Optimization Process:**
  - **Throughout Iterations:** After sensor positions are updated by the IWOA's mechanisms (Equations 7–12, influenced by coefficients like A and C), their new fitness (cost) is re-evaluated using this same cost function.
  - This continuous evaluation allows the algorithm to compare the quality of new solutions against the S_{leader}. If a newly explored or exploited position yields a better (lower) cost function value, it becomes the new S_{leader}, effectively directing the search agents (sensors) towards more optimal paths.
  - The IWOA's movements (shrinking encircling, spiral movement, random search) are thus implicitly driven by the goal of finding positions that minimize this overall cost function.

4. Simulation, comparison and results

This section outlines the simulation setup for the proposed methodologies, conducted using Python on a computer equipped with a Core i5-1145G7 processor running at 2.60GHz base frequency and 2.61GHz turbo frequency, with 8 GB of RAM. The proposed methodologies involve the implementation of energy-efficient routing techniques employing the metaheuristic IWOA.

4.1. Simulation settings

In the network model, nodes are distributed randomly across a 100x100m² area. The proposed methods are compared against PSO [23] and GA [36]. All algorithms share the same network input configuration parameters. Furthermore, the BS is located at the center of the network, and each SN is connected to at least one neighbor. Data packets can be transmitted from sensors to the BS in either single or multiple hops, with a maximum hop limit of three. All SNs are homogeneous, possessing identical initial energy levels and communication ranges. The

Table 2. Network Parameters

Parameters	Values
Network Size	100×100 m^2
Number of nodes	100
Sink location	Center
Data packet size	350 bits
E_i	0.5 J
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4
E_{elec} (Tx, Rx)	50 nJ/bit

simulation spans 400 rounds, each lasting 2 seconds. Additional system specifications are outlined in Table 2. And Below are the defined parameters for various metaheuristic algorithms:

In the IWOA, there are 30 search agents forming the population. 'A' takes values within the range of [-2, 2]. The maximum number of iterations is set to 100. The GA begins with an initial population of 30 chromosomes. During crossover, 5% of the best chromosomes are chosen using the tournament selection procedure. Like IWOA, the GA algorithm also runs for a maximum of 100 iterations. For the PSO methods, the population size is fixed at 30 particles throughout 100 iterations. Additionally, After evaluating 26 weight combinations, the optimal coefficients were determined to be: $c1 = 0.25$, $c2 = 0.35$, $c4 = 0.4$, and ρ (inertia weight) = 0.5. Table 3 presents the performance metrics for the top configurations tested, with this combination demonstrating superior balance across all key network parameters.

The performance evaluation metrics serve as crucial indicators for assessing the effectiveness of routing methods within the network. These metrics, including network lifetime, alive node ratio, packet delivery ratio, lost data packets, routing overhead, throughput, and convergence behavior, are simulated based on predefined input parameters. They provide valuable insights into the performance of routing methods and are used for evaluation and comparison purposes, ensuring a coherent and comprehensive assessment of the network's efficiency.

Table 3. Performance Across Weight Combinations

Weights (c_1, c_2, c_3)	Lifetime	Latency	PDR
0.25, 0.35, 0.40	400	1.2	92
0.40, 0.40, 0.20	380	1.8	85
0.15, 0.25, 0.60	320	0.9	88

The chosen IWOA parameters, including a population size of 30 search agents and an 'A' value range of [-2, 2], along with p=0.5, align with established practices for the Whale Optimization Algorithm. These settings were observed to provide a good balance between exploration and exploitation during initial testing phases for the network scale considered.

4.2. Network Lifetime

Network lifetime i.e. number of rounds versus simulation residual energy of the network is an important metric to check the efficiency of any method. Figure 3 intends to visualize the performance of three different algorithms (GA, PSO, and IWOA) in terms of residual energy of the network over a certain number of rounds. The comparison of the GA, PSO, and IWOA algorithms reveals similar performance in energy consumption. However, the energy consumption of the routing method based on the IWOA is superior compared to the other methods. The routing and data transfer mechanisms in all three algorithms are identical, with the difference lying in their metaheuristic structures. From the simulations, it can also be observed that the IWOA demonstrates better energy consumption efficiency compared to GA and PSO. Therefore, The IWOA achieves the desired optimization within a smaller number of rounds compared to the GA et PSO. By iteratively adjusting sensor positions based on the cost function, the IWOA algorithm converges to the optimal solution more efficiently, reducing the overall number of rounds required for data transmission.

GA tends to consume energy more rapidly than IWOA and PSO because its selection, crossover, and mutation procedures introduce diverse paths that increase energy consumption. Also, GA may converge prematurely to a suboptimal solution, hence expending more energy on inefficient paths. On the other hand, IWOA, through its adaptive mechanism, and PSO, through its collaborative approach, ensure more energy-efficient pathfinding through a better balance between exploration and exploitation.

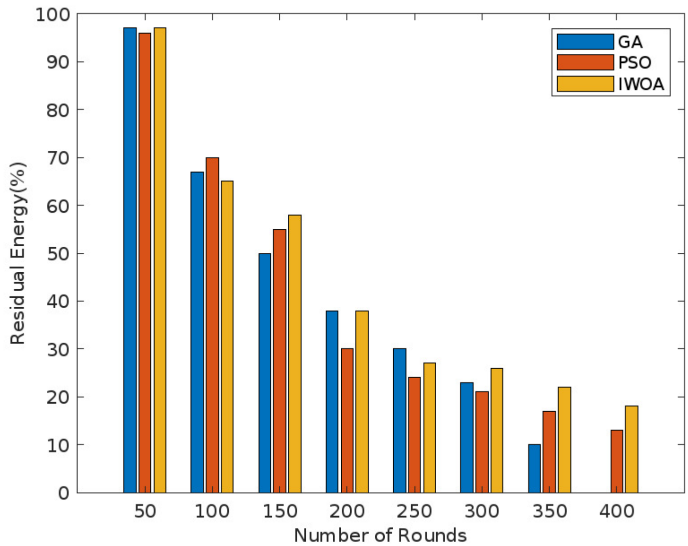

Figure 3. Network lifetime ratio.

4.3. Alive Nodes Number

Figure 4 depicts the variation in the number of alive nodes over simulation time for three different algorithms: GA, PSO, and IWOA. The number of alive nodes represents the count of nodes that remain active or energized during each simulation time point. As the simulation progresses, the number of alive nodes decreases for all algorithms. Observing the graph, we notice that the GA algorithm starts with the highest number of alive nodes but experiences a steeper decline compared to the PSO and IWOA algorithms. This indicates that the GA algorithm may initially energize more nodes but is less effective in sustaining their activity over time. In contrast, both the PSO and IWOA algorithms maintain a relatively higher number of alive nodes throughout the simulation time. Although the PSO algorithm shows a slightly faster decline compared to the IWOA, it still outperforms the GA algorithm in terms of sustaining node activity. Overall, the IWOA and PSO algorithms demonstrate more balanced energy consumption, as evidenced by the sustained number of alive nodes over time compared to the GA algorithm. This suggests that the IWOA and PSO algorithms may offer better longevity and stability in terms of network performance, ensuring a more consistent level of node activity throughout the simulation.

4.4. Packet delivery ratio

Figure 5illustrates the ratio of successfully delivered packets, which is used to assess the throughput across all algorithms. Throughput in the network is evaluated based on the number of packets successfully reaching the BS. Therefore, the total number of received packets from all nodes is summed to derive this metric. Specifically, the

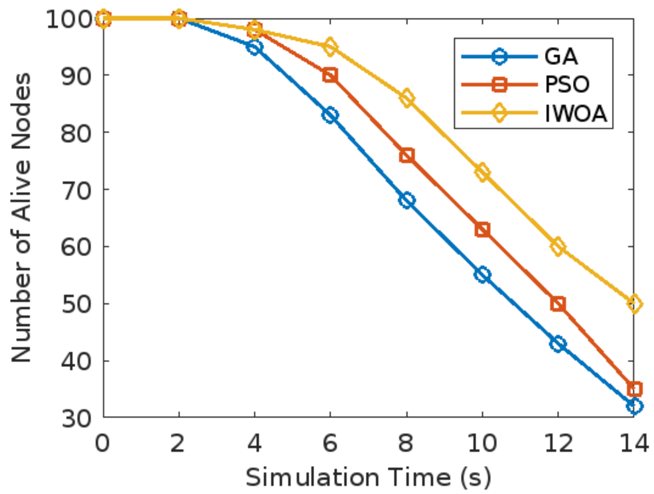

Figure 4. Alive Nodes Number.

ratio is calculated by dividing the sum of successfully received data packets at the BS by the sum of all data packets. Any packets not received successfully are deemed lost. As previously mentioned, the combined ratio of successful and lost packets must equal 1. This implies that the performance of algorithms in terms of packet loss is inversely related to their success rate. The proposed methods demonstrate a notably high rate of successful packet delivery compared to others. Based on the findings, it can be confidently stated that in terms of network lifetime and alive node ratio, IWOA ranks first, followed by PSO, with GA ranking last.

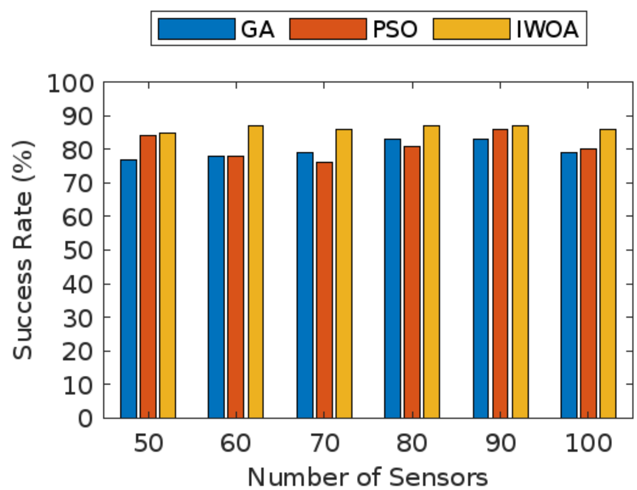

Figure 5. Succesuful transmission packets

4.5. Data transfer latency

Figure 6 presents the data transfer latency results obtained from the GA, PSO, and IWOA algorithms across different rounds. Notably, IWOA consistently demonstrates the lowest latencies compared to GA and PSO. For example, at 50 rounds, IWOA exhibits a latency of 0.5, while GA and PSO have latencies of 1.19 and 0.6, respectively. This trend persists across subsequent rounds, with IWOA maintaining lower latencies than both GA and PSO. This superiority is attributed to IWOA's integration of energy-aware routing techniques, optimizing transmission paths. Unlike GA and PSO, IWOA leverages its unique optimization inspired by whale behavior to efficiently navigate pathways, minimizing energy consumption, hops, and data volume. Through iterative exploration and exploitation phases, IWOA achieves superior performance, making it the optimal choice for reducing latency in WSNs.

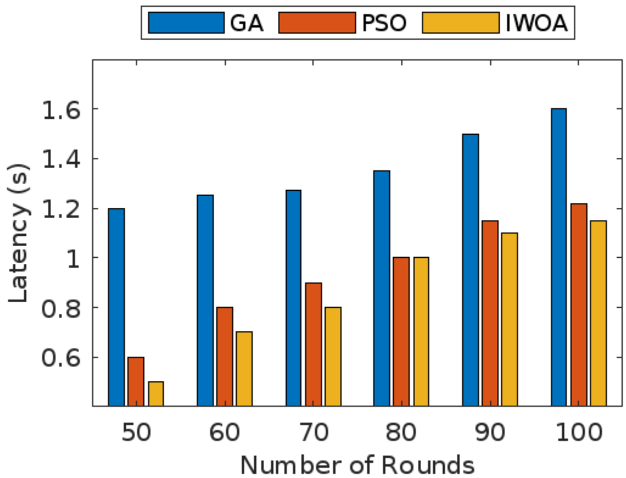

Figure 6. . Latency Comparison across Different Rounds.

The effectiveness of the IWOA within the set maximum of 100 iterations is evidenced by its performance in comparative studies. As shown in Figure 3, the IWOA exhibits more efficient energy consumption over simulation rounds, indicating rapid convergence to optimal energy-efficient paths. Similarly, Figure 4 demonstrates the IWOA's ability to sustain a higher number of alive nodes, and Figure 6 shows consistently lower latency, all achieved within the defined simulation rounds and thus, implicitly, within the 100 iterations, confirming that this iteration count is adequate for obtaining robust and superior solutions."

5. Conclusion

The current study outlines a complex pathfinding algorithm based on the IWOA to enhance the efficacy and functionality of WSNs significantly. The IWOA works by mimicking the bubble-net hunting behavior typical of humpback whales, which guides the SNs in finding the best data transmission paths. Through iterative processes, the sensors adjust their positions adaptively until the optimum solution, regarding path cost, is reached. It enables the sensors to find the best way of sending data to the sink while also being able to optimize crucial aspects such as energy usage, hop count, and the amount of data. The general functional efficiency of WSN is dramatically enhanced because the network lifespan and reliability are ensured.

Extensive simulations using different configurations and parameters demonstrate significant improvement over current protocols. The methodology followed in this paper not only enhances energy efficiency but also prolongs network longevity and data transmission, hence establishing its superiority in manifold contexts. However, it is necessary to point out some specific limitations and further research opportunities. Notably, this research so far has been mainly based on simulation and has not included empirical testing with large-scale datasets. This suggests a topic that needs further investigation because the real-world application of IWOA in diverse environmental conditions can lead to substantial knowledge of how applicable and resilient it is.

Although the methodology utilized uniform SNs in the simulations, subsequent research ought to incorporate heterogeneous SNs to better tackle the increasing intricacies of IoT ecosystems. The incorporation of sensors exhibiting different capabilities and energy resources could further improve the network's performance by capitalizing on the advantages offered by various types of nodes.

Furthermore, investigating adaptive algorithms capable of self-adjusting parameters in accordance with real-time network conditions would bolster the algorithm's adaptability and overall efficiency. Our work lays the foundation for future efforts in many other fields. Apart from WSNs, our pathfinding algorithm can be applied to address complex problems such as electrical circuit optimization, where effective routing of signals can significantly decrease power consumption and improve circuit performance. In feature selection, the application of IWOA will help in determining important features for machine learning models, thus improving the prediction accuracy of the model and reducing computational time. Moreover, While our static model effectively serves current fixed-IoT applications, the IWOA framework can be extended for mobile scenarios like warehouse robots and drone swarms to move effectively within dynamic environments by avoiding obstacles and reducing travel time.

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