HYBRID WHALE-ANT OPTIMIZATION ALGORITHM (WAOA) FOR ENERGY-EFFICIENT ROUTING IN WIRELESS SENSOR NETWORKS

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ABSTRACT :
Wireless Sensor Networks (WSNs) play a crucial role in gathering data from inaccessible areas. However, the limited energy capacity of sensor nodes makes energy-efficient routing a key challenge for ensuring the effective operation of WSNs. Clustering and routing are two essential processes to tackle this issue: clustering helps organize sensor nodes into groups to reduce energy consumption and extend the network's lifetime, while routing focuses on identifying optimal paths to transmit data from source nodes to destination nodes. However, energy-efficient routing is known to be an NP-hard problem, requiring a delicate balance between energy conservation and overall network performance. This paper introduces a Hybrid Whale-Ant Optimization Algorithm (WAOA) for energy-efficient routing in WSNs. WAOA leverages the Whale Optimization Algorithm (WOA) to identify the most suitable cluster heads in the search space, while Ant Colony Optimization (ACO) determines the best path from source sensors to the cluster head within its designated area.
Linear programming is employed to model optimization tasks for selecting cluster heads and identifying the most efficient route. Performance evaluation reveals that the proposed WAOA outperforms MOORP, MMABC, and AZEBR, enhancing the network lifetime by 5.78%, 16.11%, and 18.52%, respectively.
Keywords: Wireless Sensor Networks, Whale Optimization Algorithm, Ant Colony Optimization, Energy-Efficient Routing

INTRODUCTION :
Wireless Sensor Networks (WSNs) have become increasingly vital across various domains, such as industrial automation, environmental monitoring, precision agriculture, and healthcare. These applications rely on efficient and reliable data transfer from a large number of distributed sensor nodes (SN) to the Cluster Head (CH). However, operational challenges arise due to the limited power supply of these compact, battery-operated sensors and fluctuating environmental conditions [1]. Prolonging the lifespan of WSNs is a critical issue that must be addressed to meet the growing demand for their applications. In many cases, recharging sensor batteries is either impractical or difficult. Therefore, optimizing energy usage becomes essential to extend the network's lifespan [2]. Several optimization strategies have been suggested to achieve energy-efficient routing in WSNs [3], [4], [5].
In larger WSNs, direct communication is often impractical because of the limited energy capacity of the sensors. As a result, distant sensors employ multi-hop communication techniques to transmit their data to the CH [6]. Sensors located near the CH act as intermediaries, forwarding data from other sensors positioned farther away. However, these intermediary nodes deplete their energy faster due to the additional data transmission load, leading to premature energy exhaustion. Consequently, multi-hop

communication introduces challenges such as bottlenecks, energy holes, and uneven energy consumption across the network [7], [8], [9].

THE IMPACT OF CLUSTER HEAD POSITIONING ON WSN PERFORMANCE:

The placement of Cluster Heads (CHs) within the network plays a crucial role in determining energy consumption and the network's overall lifespan. This consideration was central to the proposed WOA simulation analysis, where we evaluated scenarios with the Base Station (BS) positioned both near and far from the network. We also examined both homogeneous and heterogeneous environments to gain a better understanding of energy consumption. Proper CH deployment minimizes packet retransmissions, ensuring reliable data delivery to the CHs [10]. This configuration improves several aspects of network performance, such as balancing energy usage among sensors, lowering energy consumption, minimizing network delays, extending the network lifespan, enhancing scalability, and increasing resilience by enabling data transmission to multiple CHs regardless of connectivity issues. However, increasing the number of CHs adds to the network's overall cost, making it essential to determine the optimal number of CHs for maximizing lifespan while keeping expenses manageable. Once the appropriate number of CHs is determined, the next challenge is identifying the most energy-efficient locations for these CHs [11], [12].

CH placement has a significant influence on the longevity of network operations. However, clustering and routing in WSNs are recognized as NP-hard (Non-deterministic Polynomial-time hard) problems [13]. The complexity of these problems increases with the network's topology, making it difficult to find exact solutions, especially in large-scale WSNs. These clustering and routing tasks represent typical combinatorial optimization challenges with exponentially expanding search spaces, where traditional optimization methods are often ineffective. In recent years, metaheuristic algorithms have gained popularity for addressing energy-efficient routing and clustering problems within reasonable computational times [14], [15]. One approach, known as the Metaheuristic Optimization for Optimal Routing and Clustering Problem (MOORP) [16], uses a combination of the dragonfly algorithm and a decision-making process to optimize CH selection. Each node quickly establishes a route to efficiently manage newly generated data, providing multiple optimal paths to reduce network overhead. This method aims to prevent void nodes and paths; however, nodes that do not participate in routing are excluded from the protocol. Another study introduced a Quality of Service (QoS)-based routing protocol, called MMABC, which employs the Markov model [17]. In this approach, sensors are randomly distributed across the network, and the Low-Energy Adaptive Clustering Hierarchy (LEACH) method is used to select CHs. The MMABC algorithm starts working from the second round, with the Markov model choosing CHs based on energy consumption and location. The Artificial Bee Colony (ABC) algorithm then assesses whether these CHs are suitable. However, this protocol uses fixed weight parameters for energy management, which may require adjustments to adapt to changing network conditions and requirements.

The Associative Zone-Based Energy Balanced Routing (AZEBR) protocol presented in [18] uses neighboring regions to determine optimal routes, minimizing message exchange rates. It aims to maximize the efficiency of multi-hop packet forwarding to CHs, resulting in better energy utilization and lower delays.

The AZEBR framework combines a gradient-based network structure with on-demand multi-hop, multi-path routing to identify the most energy-efficient routes, reducing energy consumption at the sensor nodes.Recently, nature-inspired optimization algorithms like Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), and Particle Swarm Optimization (PSO) have become popular due to their effectiveness in solving complex, dynamic problems [19], [20], [21]. However, the success of these methods depends on the specific problem and the characteristics of the search space. To our knowledge, no prior research has simultaneously used WOA for clustering and ACO for routing, with a focus on energy balancing and addressing the energy hole issue in WSNs. This proposed approach leverages these algorithms to optimize both clustering and routing, ensuring more efficient network operation.

WAOA: A HYBRID ALGORITHM FOR ENERGY-EFFICIENT CLUSTERING AND ROUTING IN WSNS :

The WAOA algorithm leverages the effectiveness of nature-inspired metaheuristic algorithms to address the aforementioned challenges in WSNs. In this research, we propose a hybrid algorithm, WAOA, to improve energy-efficient clustering and routing. This approach combines the strengths of the Whale Optimization Algorithm (WOA) and Ant Colony Optimization (ACO), enabling the discovery of high-quality solutions in the dynamic and complex environments typical of WSNs.
The performance of WAOA is evaluated across various WSN topologies, under both homogeneous and heterogeneous conditions. Simulation results demonstrate the algorithm's efficiency through reduced energy consumption and extended network lifespan. The core contribution is the hybridization of WOA and ACO to enhance clustering and optimize routing in WSNs. WOA is employed for CH selection, as it effectively balances the exploration of the search space with the exploitation of promising solutions.
ACO identifies the optimal path between CHs and the BS by utilizing pheromone trails and probabilistic decision-making to ensure efficient routing. We further analyze routing overhead and packet drop rates in two scenarios (BS placed centrally and at a fixed distance) and across both homogeneous and heterogeneous environments to pinpoint inefficiencies, minimize data loss, and maximize network lifetime.
This paper is organized as follows: Section 2 reviews relevant literature on clustering and routing. Section 3 details the proposed WAOA algorithm. Section 4 presents the results and analysis. Section 5 concludes the paper and outlines potential future research directions.

RELATED WORK:

This section provides a detailed review of prior research on clustering and routing in WSNs, organized into three primary categories: Non-metaheuristic, Metaheuristic, and Hybrid Metaheuristic approaches.

Non-Metaheuristic Approaches

Non-metaheuristic methods rely on traditional, deterministic algorithms and simpler heuristics. Greedy algorithms, which make decisions based on local optimum solutions. Cluster-based protocols, such as the Low-Energy Adaptive Clustering Hierarchy (LEACH), which follow predefined rules for clustering and routing. Distance-based methods, like direct transmission, which prioritize communication based on proximity metrics.In contrast to these methods, metaheuristic algorithms employ more sophisticated, high-level strategies to solve complex problems.
Guanghui Ha et al. [22] introduced an innovative method that utilizes advanced weighting schemes and optimized parameters to enhance clustering and routing protocols in WSNs. Their approach ensures balanced cluster formation and dynamically adjusts protocol parameters to respond to changing network conditions. The primary objective of their work is to reduce energy depletion and extend the network's lifespan. A comparative analysis with similar methods reveals... (Remaining content continues as per the original structure).

ESTABLISHED PROTOCOLS AND RECENT ADVANCES IN WSN ROUTING AND CLUSTERING :

Protocols like LEACH and HEED (Hybrid Energy-Efficient Distributed Clustering) have been widely used for improving energy efficiency and network performance. However, comparative analyses with newer methods highlight significant enhancements in both energy optimization and network longevity.S. Nagadivya et al. [23] proposed a protocol with two distinct phases.

In the first phase, the forward node set is selected using a fuzzy logic-based predictive model, prioritizing minimal transactions, low residual energy (RE) usage, and high link quality. The second phase, known as candidate coordination, identifies the most efficient relay node based on RE and distance, which then forwards data to the sink node. M. Moshref et al. [24] introduced the Enhanced Non-Dominated Sorting Genetic Routing Algorithm (ENSGRA) to improve Quality of Service (QoS) in WSNs. Their approach incorporates clustering and scheduling techniques for efficient routing. Initially, CHs are selected through Non-Dominated Sorting Genetic (NSGA-III) with multi-parent crossover (MPX).

Reference points are adjusted to enhance non-dominated Pareto Front solutions. The algorithm evaluates fitness using a multi-objective function based on network coverage, energy consumption, and active sensors. Clustering ensures path reliability, while node connectivity is maintained within specified radius limits. Simulation results demonstrate that ENSGRA offers a promising solution for optimizing routing and enhancing QoS in WSNs. ChuanXu et al. [25] proposed a Region-Based Source Routing Protocol (RSRP) to improve energy utilization and extend network lifespan. The protocol balances energy consumption across different regions and dynamically adjusts routing paths based on real-time energy levels and network conditions.

Comparative analysis with traditional protocols, such as AODV (Ad hoc On-Demand Distance Vector) and LEACH, shows notable improvements in energy efficiency, data delivery rates, and network longevity. This study provides valuable insights into overcoming energy constraints while enhancing network performance.

Metaheuristic-Based Approaches :

N. Kumar et al. [26] explored the challenges posed by the rapid expansion of IoT, necessitating reconfigurable WSNs. Software-Defined Networking (SDN) offers a solution by enabling automatic reconfiguration and dynamic selection of control nodes for task assignment and routing.

The NP-hard problem of selecting control nodes, considering residual energy and transmission distance, is tackled using the Fork and Join Adaptive Particle Swarm Optimization (FJAPSO) algorithm. This green routing approach extends the network’s lifespan by optimizing the number and placement of control nodes. FJAPSO outperforms traditional algorithms in enhancing energy efficiency and cluster management.

Z. Wang et al. [27] proposed two algorithms—CGTABC-1 and CGTABC-2—based on an improved artificial bee colony optimization technique. These algorithms aim to optimize clustering and CH selection in WSNs. CGTABC-1 employs both employed and onlooker bees to search for optimal nectar sources and iteratively updates them within the search scope. The algorithm uses a greedy strategy to calculate fitness values and retain superior nectar sources. Similarly, CGTABC-2 follows the same mechanism to select the most effective CHs by continuously updating nectar sources and evaluating their fitness. Both algorithms emphasize improving energy efficiency and network performance.

T. Kaur et al. [28] developed a Multi-Objective ACO-Based QoS-Aware Cross-Layer Routing (MACO-QCR) protocol to address the challenges of QoS-aware routing in WSNs. This approach integrates ACO with a cross-layer design, considering multiple QoS metrics—such as energy efficiency, data delivery ratio, and end-to-end delay—for performance optimization. MACO-QCR aims to tackle the complexities of QoS-aware routing while improving network performance across multiple parameters.

METAHEURISTIC HYBRIDIZATION-BASED APPROACHES:

Shaha Al-Otaibi et al. [33] developed an optimized, dynamic cluster-based routing method by hybridizing Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO).

1. Cluster Formation: PSO is employed to form clusters within designated regions, creating a minimum spanning tree to enhance energy efficiency and fairness.
2. Optimal Route Selection for the Mobile Sink (MS): The best route for the MS to collect data from CHs and return to the Base Station (BS) is selected by constructing a boundary of Rendezvous Points (RPs).
3. MS-Based Intelligent Data Routing: The MS follows the optimal path, broadcasting data upload messages to CHs and assigning time frames for data uploads based on their responses.

This method ensures efficient data gathering and reduces energy consumption while prolonging network lifespan.

X. Xue et al. [34] introduced an efficient cluster formation and CH selection method by integrating the k-medoids algorithm with an Improved Artificial Bee Colony (IABC) approach. This hybrid strategy facilitates rapid computations, making it suitable for managing complex networks. The k-medoids algorithm identifies clusters, while IABC optimizes CH selection by balancing exploration and exploitation.

ADDITIONAL METAHEURISTIC HYBRID APPROACHES :

R. Chaudhry et al. [29] proposed a Multi-Objective Harris Hawks Optimization (MOHHO) algorithm to improve energy efficiency in software-defined WSNs (SDWSNs). MOHHO balances multiple objectives by optimizing the placement of control nodes (CNs), ensuring equitable load distribution, reduced delays, and extended battery life. Given that CNs often have limited and non-rechargeable batteries, energy efficiency is a critical concern in SDWSNs.

V. Agarwal et al. [30] suggested a Mobile Sink (MS)-based intelligent routing scheme comprising three phases:

1. Cluster Formation: The network is divided into regions, and PSO is employed to form clusters with minimal long-distance connections, reducing energy usage.
2. Optimal Path Planning: RPs are identified along the MS's route, and unused RPs are linked through renumbering.
3. MS Data Routing: The MS broadcasts data upload messages and waits for responses from CHs within a specific threshold. Time frames are allocated based on responses, and the MS moves to the next RP if no reply is received.

THIS SCHEME ENHANCES DATA COLLECTION, ENERGY EFFICIENCY, AND NETWORK LONGEVITY:

1. Setup Phase: The Multi-Objective Grey Wolf Optimization (MOGWO) technique determines the optimal positions for RPs and forms clusters based on various performance metrics.
2. Intelligent Data Gathering Phase: An optimal path is created for the MS to visit RPs and gather data from the SNs. Rotating RPs ensures balanced energy consumption and prolongs network lifespan.

Seyyedabbasi et al. [32] focused on optimizing routing paths using fitness functions. Their approach selects the least-cost path for each hop and determines the best overall route among all possible hop counts. They also introduced Incremental Grey Wolf Optimization (I-GWO) and Expanded GWO (Ex-GWO) to enhance routing by prioritizing essential SN characteristics, ensuring energy-efficient routing. These methods address the complexities of pathfinding in WSNs and IoT environments, where distributed intelligence plays a crucial role in solving NP-hard problems.

ADDITIONAL METAHEURISTIC HYBRID APPROACHES:

The authors also proposed a hybrid Cross-Layer-Based Harris Hawks Optimization (CL-HHO) algorithm for the routing process. CL-HHO offers the benefit of rapid search capability, providing fast responses and quick convergence during routing operations. The results demonstrate that CL-HHO significantly improves the overall Quality of Service (QoS) in WSNs. By integrating efficient clustering and routing methods, network efficiency and responsiveness are enhanced, making this approach a promising advancement in WSN management and optimization. Kooshari et al. [35] developed a data collection optimization strategy for WSNs by combining the Water Strider Algorithm (WSA) for CH selection and Ant Colony Optimization (ACO) for routing. The WSA generates potential CH candidates randomly and evaluates them using an objective function, while ACO identifies the optimal routing paths based on pheromone levels.

The hybridization of these algorithms ensures effective identification of suitable CHs and efficient routing paths for data collection. A Mobile Sink (MS) then gathers data from nodes along the optimized route and transmits it to the Base Station (BS). This approach demonstrates improved performance in data transmission and energy efficiency, making it a promising solution for WSN optimization.

R. Mishra et al. [36] investigated methods to improve energy utilization and extend the lifespan of WSNs. Their proposed method integrates the Butterfly Optimization Algorithm (BOA) and Particle Swarm Optimization (PSO) for CH selection and routing. BOA determines the optimal number of CHs among densely populated nodes by considering factors such as remaining power, distance, node degree, and centrality. The distance between CHs and the BS is also taken into account during CH formation. ACO is employed for route selection, optimizing the path between CHs and the BS.

To evaluate the method's performance, key metrics such as stability period, the number of active nodes, and total power consumption are analyzed. This nature-inspired approach demonstrates notable improvements in energy management and network longevity, enhancing both power efficiency and overall performance in WSNs.

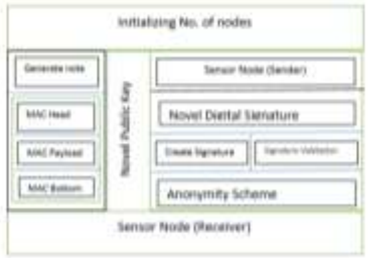
COMPARATIVE ANALYSIS AND ADVANTAGES OF THE PROPOSED WAOA:

As highlighted in Table [1], the proposed Whale-Ant Optimization Algorithm (WAOA) introduces a more refined solution for energy-efficient routing in Wireless Sensor Networks (WSNs). Unlike many existing protocols that conduct simulations in either homogeneous or heterogeneous environments with the Base Station (BS) located either centrally or in a corner area, WAOA evaluates performance across both environments. For each scenario, we assess energy consumption patterns with two different BS positions—one in the center and another at a remote location. This dual evaluation offers a more comprehensive understanding of energy depletion among Sensor Nodes (SNs).

Furthermore, altering the BS location from the center to a distant area allows us to analyze the impact of increased distance on the algorithm's efficiency. Existing studies have utilized clustering techniques such as k-medoids with Artificial Bee Colony (ABC), brainstorm optimization with Levy distribution, and Water Strider Algorithm (WSA), which often result in higher computational complexity. In contrast, WAOA employs the Whale Optimization Algorithm (WOA), which provides lower complexity and simpler relationships among nodes. By leveraging the strengths and addressing the limitations identified in prior research, the WAOA introduces a novel approach aimed at significantly enhancing network performance. The following section offers a detailed explanation of the proposed WAOA.

A HYBRID WHALE-ANT OPTIMIZATION ALGORITHM FOR ENERGY-EFFICIENT ROUTING IN WSNS :

The WAOA integrates two powerful algorithms: WOA [37] for selecting Cluster Heads (CHs) and Ant Colony Optimization (ACO) [38] for multi-hop routing. The WOA selects optimal CHs based on energy levels and node proximity, ensuring efficient clustering. Meanwhile, the ACO algorithm optimizes the routing process by utilizing a fitness function to determine the best paths between CHs and the BS.This hybrid approach leverages the unique advantages of both algorithms: WOA offers strong global search capabilities for exploration, while ACO excels at local path optimization.



By combining global exploration with fine-tuned local optimization, WAOA achieves a more effective clustering and routing solution, enhancing both network lifetime and performance. The architecture of WAOA (as shown in Figure 1) reflects this integration, illustrating how these two algorithms interact to deliver optimal routing and clustering outcomes. Through the synergistic combination of WOA and ACO, the proposed WAOA introduces a comprehensive solution for the dynamic and complex environments typical of WSNs.

Notation	Meaning
d	Distance between transmitting and receiving node
$d0$	A threshold value for d for determining the path loss
$EEElec$	model to be used Amplifier Energy
$\xi free$	Energy loss in the free space
ξmul	Transmitter receiver circuit operating energy
$Eamp$	Energy loss in the multipath

CH SELECTION USING WOA:

SeyedaliMirjalili introduced the Whale Optimization Algorithm (WOA) in 2016 [37]. Inspired by the cooperative hunting behavior of humpback whales, WOA replicates their social strategies and collaborative hunting methods [37, 39]. This algorithm is designed to address optimization problems by iteratively refining a population of candidate solutions, referred to as "whales," to discover the best or near-optimal outcome. Throughout the process, the positions of these whales are updated iteratively.

WOA leverages two core behaviors observed in whale hunting: encircling and bubble-net hunting. In the encircling behavior, whales adjust their positions based on the current best solution discovered, effectively converging towards it. This behavior helps them "encircle" the optimal solution. On the other hand, the bubble-net hunting behavior involves choosing a leader whale randomly from the population, with the remaining whales moving in a spiral pattern around the leader. This technique promotes both exploration and exploitation of the search space.

WHALE REPRESENTATION AND INITIALIZATION :

During the CH (Cluster Head) selection process in WOA for sensor networks, the whales determine which sensor nodes (SNs) will serve as CHs. The number of CHs in the network corresponds to the dimensions of each whale. Initially, each whale selects a random node ID between 1 and (N), where (N) represents the

total number of nodes, as summarized in Table [II]. In this context, every whale symbolizes a potential solution for CH selection, with each dimension of the whale indicating a specific SN that will act as a CH.
The initialization phase ensures diversity by randomly assigning node IDs to each whale's position, allowing the algorithm to explore various parts of the network. Let's assume the position of the (i)-th whale is given by:
Wh_i = left(Wh_{i,1}(t), Wh_{i,2}(t), .s, Wh_{i,m}(t)right)
Here, (Wh_{i,varphi}) (where (1 leqvarphileq m)) represents the node identity, and (varphi) defines the number of CHs. For instance, in a network containing 150 SNs, 10% (i.e., 15 nodes) will be selected as CHs. Consequently, each whale will have 15 dimensions, with each dimension initialized to a random number between 1 and 150, representing the total number of SNs. These whale positions are then mapped to the coordinates of the SNs.
During the exploitation phase, whales begin by circling or encircling their prey [40]. This behavior can be mathematically modeled using Eq. (1) and Eq. (2).the current iteration is represented by (t), (X) denotes the positional vector, and (X^) indicates the optimal solution. Coefficient vectors (A) and (C) are computed using Eq. (3) and Eq. (4), as follows:

$$\vec{A} = 2.\vec{a}.\vec{r} - \vec{a} \quad (3)$$
$$\vec{C} = 2.\vec{r} \quad (4)$$

In this context, (r) represents a random vector within the [0, 1] range. The whales (search agents) update their positions based on the best arrangement found so far. The vectors (A) and (C) delineate the region in which a search agent can be located in proximity to the prey [37], [39], [41].The concept of shrinking encircling behavior is illustrated in Figure 2, which is achieved by decreasing the value of (a). The value of (a) in Eq. (3) is computed using Eq. (5):

$$a = 2 - t\frac{2}{Maxt}$$

Here, (t) denotes the iteration number, and (text{Max}_t) is the maximum number of allowed iterations. The distance between (X) and (X^) is calculated to simulate a circular path [42]. Subsequently, the position of the neighboring search agent is defined using a spiral-shaped equation via Eq. (6):

$$\vec{X}(t+1) = W_h' * e^{bl} * cos(2\pi q) + \vec{X} * (t)$$

Where ($Wh = |\vec{X*}(t) - \vec{X}(t)|)|$), which calculates the distance from the (i)-th whale to the best solution identified up to the current iteration (t). The parameter (b) influences the geometric characteristics of the logarithmic spiral, while (q) is constrained within the range of -1 to 1. Eq. (7) illustrates that there is a 50% probability of selecting between the concepts of reducing encircling and spiral-shaped paths during the optimization process:

$$\vec{X}(t+1) = \begin{cases} Eq.(5)\ if\ j < 0.5 \\ Eq.(9)\ if\ j \geq 0.5 \end{cases}$$

Here, (j) is a random number between [0, 1].
In the Exploration Phase, rather than altering the positions of the search agents based solely on the best-performing agent, a random search agent leads the search in WOA to promote exploration [37], [42], [43]. Using a random value, vector (A) is utilized to encourage the search agent to move away from the best search agents, where (A > 1) or (A < 1). The mathematical representation of this behavior is given by Eq. (8) and Eq. (9):

$$\vec{W_h} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}|$$
$$\vec{X}(t+1) = \overrightarrow{X_{rand}}(t) - \vec{A}.\vec{W_h}$$

In this context, (vec{X}_{rand}) refers to a randomly selected whale from the current population.

WOA-BASED LINEAR PROGRAMMING FRAMEWORK FOR CH SELECTION:

The subsequent section presents the framework for the WOA fitness function concerning CH selection.

a) Residual Energy in WSNs: This term refers to the remaining power in SNs after data collection and transmission activities. Effectively managing this energy is crucial for extending the network's lifespan and ensuring reliable operations. The residual energy (RE) is defined in Eq. (10):

$$\text{Minimize} \qquad wf_1 = \sum_{i=1}^{m} \frac{1}{RE_{CH_i}}$$

b) Distance Among Sensor Nodes: This term refers to the physical distance separating individual SNs deployed in the network and is represented as (w_{f2}) in Eq. (11):

c) Distance Between CHs and BS: This refers to the spatial gap separating data-aggregating CHs from the central Base Station (BS), represented as (w_{f3}) in Eq. (12):

d) Node Degree: This term refers to the number of direct connections or neighbors that an SN has within the network, represented as (w_{f4}) in Eq. (13):

e) Node Centrality ((w_{f5})) measures the degree to which a node is centrally positioned among its neighboring nodes, expressed in Eq. (14):

$$\text{Minimize} \quad wf_5 = \sum_{i=1}^{m} \frac{\sum_{j \in n} dist^2(i,j)/n(i)}{Network\ Dimension}$$

Adjacent nodes of (CH_i) are denoted as (n(i)). Each objective is assigned a specific weight value. In the described scenario, these multiple objectives are consolidated into a single objective function by applying their corresponding weights, represented as (¥_1), (¥_2), (¥_3), (¥_4), and (¥_5). The combined single objective function ((F_w)) is expressed in Eq. (15):

$$Fw = wf_1 * ¥_1 + wf_2 * ¥_2 + wf_3 * ¥_3 + wf_4 * ¥_4 + wf_5 * ¥_5$$

$$\text{Where} \qquad \sum_{i=1}^{5} ¥_i = 1, \quad ¥_1 \in (0,1)$$

Where:

sum_{i=1}^{5} ¥_i = 1 quad text{and} quad ¥_i in (0, 1)

The above steps detail the entire process for CH selection utilizing WOA. The algorithm for this procedure is provided in Algorithm 1 as pseudo-code.The process of selecting optimal Cluster Heads (CHs) using the Whale Optimization Algorithm (WOA) involves several key steps. It begins by defining parameters such as the maximum number of iterations (MaxIter), a fitness function to evaluate the effectiveness of each CH candidate, and WOA-specific variables, including coefficient values and movement equations. The algorithm follows a systematic approach, outlined below:Initially, the optimization process starts by setting the MaxIter and creating a population of potential CHs, each with a distinct position. It also initializes variables to track the best CH configuration discovered so far, along with its corresponding fitness value. This ensures that the algorithm can identify and preserve the optimal solution throughout the iterations.

The next step is evaluating the fitness of each CH candidate using the fitness function. This function considers several factors, including residual energy (RE), distances between sensor nodes (SNs), the proximity of CHs to the base station (BS), node degree, and centrality. The fitness value indicates how suitable each candidate CH is for the role. As the algorithm progresses, it continuously compares the fitness values of the current CHs with the best one identified so far. The CH with the highest fitness value is selected as the best candidate for the current iteration, ensuring that the most promising configuration is retained across iterations.

The core functionality of WOA lies in its movement mechanism, where the positions of potential CHs are updated iteratively. This movement mimics the behavior of whales in nature, with CHs adjusting their positions relative to the current best CH in search of better solutions. The movement equations incorporate calculations based on the distance to the best CH, encircling behavior through specific coefficients, and randomization elements to explore the solution space efficiently.

The optimization process repeats these steps—evaluating fitness, updating the best CH, and adjusting positions—until the termination condition is satisfied, typically after reaching MaxIter. At the end of the process, the algorithm outputs the position of the optimal CH configuration found during the iterations. This set of CHs is chosen as the most efficient solution, balancing RE, distances, node degree, and centrality to ensure effective and reliable CH selection for the wireless sensor network (WSN).

b. Alternatively, randomize the movement:
- r1, r2 = **random** () Random values in (0,1)
- **Equation (8):** Distance to the best CH
- **Equation (4):** Coefficient for encircling prey
- $\vec{C} = 2.\vec{r}$
Equation (9): Coefficient for whale's search
- newCHPosition = CHPosition - $W_h.\vec{A}$

5: Convergence Check
Repeat steps 2 to 4 until MaxIter

ACO-BASED MULTI-HOP ROUTING:

Ant Colony Optimization (ACO) is a well-known metaheuristic technique inspired by the foraging behavior of ants. It is frequently employed to solve combinatorial optimization problems【44】【45】. In ACO, ants mimic natural behavior by communicating through pheromone trails, which help them discover optimal routes between their nest and food sources. These pheromone paths guide other ants toward favorable solutions.

The ACO algorithm follows several essential steps. At the beginning, ants are randomly placed across the search space, with each ant representing a potential solution. As they navigate through the problem, each ant builds a solution by sequentially choosing elements or components based on predefined rules. These rules are governed by two main factors: pheromone levels, which reflect the quality of previous solutions, and heuristic information, which provides domain-specific guidance【44】【46】.

The possibility of ant k moving Pij
k
(t) from node i to j is calculated using the following formula and expressed in Eq. (16):

Where $\tau ij$is the pheromone level on the edge between nodes *i* and *j* at iteration *t*, and $\eta ij$is the heuristic information between nodes i and j. The parameters α and β are used to adjust the relativesignificance of the heuristic value and pheromone intensity [47]. The symbol Nkdenotes the set ofnodes that the kthant has not yet visited. CHs information in the routing table updates heuristic andpheromone intensity. The distance between CHs updates the heuristic information, as shown below inEq. (17)

$$\eta_{ij} = \frac{1}{dist_{CH}}$$

LINEAR PROGRAMMING PROBLEM FORMULATION FOR MULTI-HOP ROUTING:

When determining each fitness value, the weight value is taken into consideration.

a) The source node chooses the closest node with the maximum Residual Energy ($\mu 1$) when transmitting over multiple hops in Eq.(20). Maximize $\mu 1$ = Σ 1$REchimi$ =1 (20)

Industrial Engineering Journal
ISSN: 0970-2555
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b) Node Degree refers to the number of direct connections or neighbours a SN has within the network, and expressed as ($\mu 2$) in Eq.(21) Minimize $\mu 2 = \Sigma\ |CLmemith\ |\ CHTotali{=}1$ (21)

c) Node centrality $\mu 3$ refers to the degree to which a node is placed in the middle of its neighboring nodes and expressed in Eq.(22) Minimize $\mu 3 = \Sigma\Sigma dist2\ j{\in}n\ (i,j)/n(i)NetworkDimensionmi{=}1$ (22)

Subsequently, this value is employed to transform the values of the fitness function into a single objective function referred to as route cost. The cost of the route is given by Eq. (23).

$$\text{Minimize} \qquad \mu_3 = \sum_{i=1}^{m} \frac{\sum_{j\in n} dist^2(i,j)/n(i)}{Network\ Dimension}$$

The process of ACO-based routing from the source node to the base station (BS) is detailed in Algorithm 2 through its pseudo code. The algorithm begins by initializing pheromone trails along the edges of the network graph, which reflect the desirability of each edge for the ants. In the simulation, 50 ants are deployed, each starting from a randomly selected Cluster Head (CH). The ants move through the network probabilistically, selecting the next node based on both the pheromone levels and heuristic information, such as distance and cost. As the ants travel across the graph, they evaluate the objective function for the selected path. Once all ants have completed their journeys, the pheromone trails are updated through a process of evaporation and deposition. Evaporation gradually reduces older pheromone concentrations, preventing outdated paths from dominating.

At the same time, pheromone deposition reinforces routes associated with higher objective function values, making them more attractive for future ants. This reinforcement mechanism directs future ant movements toward better paths over time. The steps of ant traversal, path evaluation, and pheromone updates are repeated for a predefined number of iterations. At the end of the process, the algorithm selects the route with the highest pheromone concentration as the optimal path from the CHs to the BS. This path represents the best solution for data transmission, taking into account the network's constraints and the objective function.

By utilizing the collective behavior of ant agents and the feedback loop of pheromone trails, the ACO algorithm efficiently explores and exploits the solution space. This enables it to provide an optimized route selection strategy for CHs to transmit data to the BS in wireless sensor networks (WSNs).

Algorithm 2: CHs to BS Multi-Hop Route Selection by ACO
Input: **1.** Graph G represents CHs and the BS. **2.** fitness function to be optimized. **3.** fitness function Constraints. **4.** Parameters: Total ants(m), MaxIter, pheromone evaporation rate, α and β
Output: Best route from CHs to the BS based on the pheromone trail.
. Initialize Pheromone Trails: **For each** edge e in G: **Set the** initial pheromone value τ(e) to a small positive constant. **2.** Repeat for a specified number of iterations: **For each** ant, i = 1 to A_t **a.** Start from a randomly chosen CH as the current node **b. While** the current node is not the BS:

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i. Calculate the probability using Eq. (16) of moving to each neighboring node based on the pheromone trails and heuristic information
ii. Select the next node based on the probability.
iii. Move to the selected node and update the current node
c. End while
d. Evaluate the fitness function for the route taken by ant i
3. Update Pheromone Trails:
For each edge e in G:
Evaporate pheromone $\tau(e) = (1 - e^{r}) * \tau(e)$ using Eq. (18)
For each ant, $i = 1$ **to** A_t
For each edge e in the route taken by ant i:
Add pheromone to the edge:
$\tau(e) = \tau(e) + 1$ / fitness value of i_{th} ant
4. Find the Best Route:
Choose the route with the maximum pheromone trail as the finest route from CHs to the BS.
5. Output the Best Route.
End Algorithm

WAOA ALGORITHM AND FLOWCHART:

Figure 3 illustrates the overall structure of the proposed WAOA framework. This flowchart demonstrates a hybrid strategy for energy-efficient clustering and routing in wireless sensor networks (WSNs) by combining two metaheuristic algorithms: Whale Optimization Algorithm (WOA) and Ant Colony Optimization (ACO). The primary objective is to determine the optimal data transmission path from multiple sensor nodes (SNs) to Cluster Heads (CHs) while minimizing energy consumption and enhancing network performance. Below is a summary of the WAOA framework and its flowchart.

The algorithm leverages the strengths of both WOA and ACO. WOA focuses on efficient CH selection, while ACO ensures optimal multi-hop routing. Together, they address clustering and routing challenges to achieve energy-efficient communication. The goal is to ensure optimal data transmission, maximizing energy efficiency while meeting network constraints. The WOA algorithm selects the most suitable CHs by evaluating their fitness based on parameters such as residual energy, distance, and network centrality. Once the CHs are selected, the ACO algorithm is used to find the most efficient paths between CHs and the base station (BS). It determines the routes that offer the best trade-off between energy consumption and path cost.

Outcome: By integrating WOA and ACO, the WAOA approach ensures that both clustering and routing are optimized, leading to better resource management, extended network lifetime, and improved performance.This hybrid methodology enables WAOA to efficiently explore the solution space, balancing exploration and exploitation, to find the best possible solution for data transmission in WSNs.

1. Initialize the parameters for ACO and WOA, such as Total number of whales, pheromone intensity,evaporation rate, population size, and update coefficients.
2. Create the pheromone matrix for ACO to represent the attractiveness of paths based on historicalinformation.
3. Generate an initial population of whale positions for WOA, representing different candidate routes.
4. In each iteration until the stopping criteria are met

WOA PHASE:

a. Update the positions and fitness of each whale using the WOA algorithm.
b. Evaluate the fitness of each whale's route, considering factors in the fitness function.
c. Update the global best solution if a better route is found during the WOA phase.
d. Update the position matrix of whales based on ACO pheromone information to balance exploration and exploitation.

ACO PHASE:

e. For each SN, create an ant to find the route using ACO-based routing.
f. Update the pheromone matrix based on the ant's route to enhance the attractiveness of selected paths.
g. Evaluate the fitness of the ant's route, considering factors like distance or energy consumption.
5. Retrieve the best route found by the integrated approach.

The resulting optimal route will simplify efficient data transmission from multiple SNs to the CHs,enhancing overall network performance and extending the network lifetime.

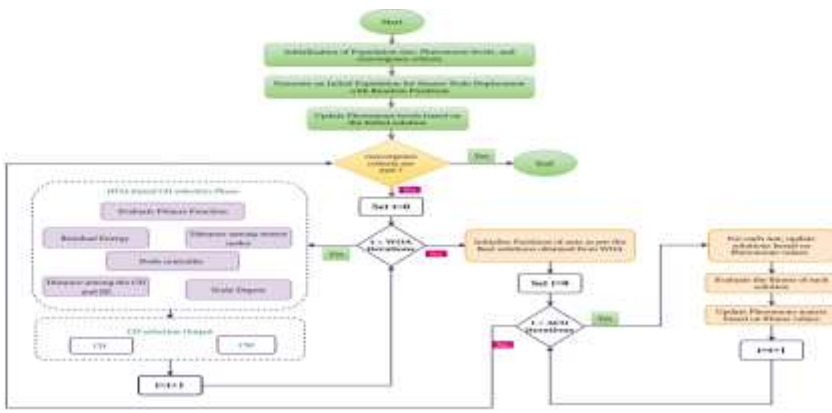

Figure 3: Proposed WAOA flowchart

RESULT ANALYSIS AND DISCUSSION :

This section outlines the simulation outcomes and performance assessment of the WAOA algorithm. The WAOA simulations were executed using MATLAB R2016a, incorporating a custom script to implement energy-efficient routing strategies. The performance of WAOA was analyzed with respect to network lifetime, node centrality, and residual energy (RE). The obtained results were benchmarked against three baseline algorithms: MOORP [16], MMABC [17], and AZEBR [18].

SIMULATION ENVIRONMENT :

The experiments were conducted under two scenarios, considering both homogeneous and heterogeneous environments.

HOMOGENEOUS ENVIRONMENT:

In the homogeneous scenario, simulations were performed assuming that all sensors start with the same amount of initial energy (E_0) in their batteries. The total initial energy for all the sensor nodes (SNs) is expressed by Eq. (24):

E_{text{Total}} = sum E_0 quad text{(for } N text{ nodes)}

Here, (N) represents the total number of nodes in the network.

HETEROGENEOUS ENVIRONMENT:

In the heterogeneous scenario, simulations allowed sensors to start with varying energy levels. The nodes were divided into two categories: Type-1 and Type-2.

Type-1 Nodes: These nodes (normal nodes) have initial energy equal to (E_0).

Type-2 Nodes: These nodes have (δ) times more energy than the Type-1 nodes. A fraction (n) of the total nodes is Type-2 nodes.

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The total energy of the Type-2 nodes is calculated using Eq. (25):
E_{text{Total Type-2}} = N c. (1 - n)E_0 + n c. N c. E_0 (1 + δ) = N c. E_0 (1 + δ)

SCENARIO 1:
In this setup, the base station (BS) is located at the center of the sensor network region, which spans a square area of 125 meters per side (as illustrated in Figure 4).
In Scenario 2, the BS is situated at a more remote location within the network region; to be more Accurate, its distance from the network's edge is (300,125) meters, as shown in Figure 5.
Table III presents the simulation parameters utilized in our research, covering key aspects such as the network's area size, the number of nodes, the BS locations, initial energy levels, and the percentage of cluster heads. These elements play a crucial role in determining the simulation outcomes.

Table III Simulation parameters description

Parameter	Description
Size of the network area	250*250
Total Nodes	150
BS location	125,125 and 125,300
Initial energy	1.5 joules
Percentage of CHs	15%-20%
EE_{elc}	50 nJ/bit
E_{amp}	0.0013 pJ/bit/m^4
ξ_{free}	10 pJ/bit/m^2
d_0	35 m
d_{max}	100 m
Packet size	4000 bits

Table IV summarizes the parameters specific to our WAOA algorithm. The effectiveness and behavior of the optimization algorithms are strongly influenced by these settings, making them critical to the study. The ACO parameters enhance the routing process, improving data transmission reliability and minimizing energy consumption. Meanwhile, the WOA parameters guide the clustering mechanism, ensuring optimal node distribution and improved energy efficiency.

SIMULATION METRICS :
The following performance metrics were evaluated to assess the overall performance of the WAOA and conduct a comparative analysis:
a. Network Lifetime: Network lifetime refers to the total number of operational rounds until all nodes have completely exhausted their energy.
b. Alive Nodes: Alive nodes are those that retain sufficient energy across multiple rounds, contributing to the continued functionality of the network.
c. Residual Energy: A node loses energy during signal transmission and reception. Residual energy is the remaining energy of a node after data transmission.
d. Dead Nodes: Dead nodes are those that have entirely depleted their energy resources, rendering them inactive.

PERFORMANCE ANALYSIS AND COMPARISON :
Our analysis concentrated on the decision-making capabilities of the proposed WAOA in selecting Cluster Heads (CHs) and the CH's ability to determine the most efficient path for transmitting data to the BS.

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Since data packets are sent from the source node to the CH, the CH plays a critical role in selecting the optimal next hop for forwarding the data to the BS. In our study, 150 nodes were randomly distributed within a 250 × 250-meter region surrounding the network.

RESULT ANALYSIS IN TERMS OF NETWORK LIFETIME

In this section, network lifetime is defined as the time span during which all nodes in the network deplete their energy. Three key metrics were examined:

- First Node Died (FND): The round in which the first node runs out of energy.
- Half Node Died (HND): The round in which half of the nodes are depleted.
- Last Node Died (LND): The round in which the final node becomes inactive.
- Figures 6 to 11 illustrate the FND, HND, and LND for both Scenario 1 and Scenario 2, across homogeneous and heterogeneous environments, to evaluate the performance of the proposed WAOA compared to the baseline algorithms: MOORP, MMABC, and AZEBR.

The proposed WAOA demonstrates significant improvements in FND, as shown in Table V and Figures 6 and 7, across all scenarios and environments. These improvements are attributed to WAOA's efficient exploration of the search space and refinement of the routing paths between CHs and the BS. This results in more optimal and energy-efficient solutions compared to the baseline algorithms, which rely primarily on global or local optimization techniques.

The proposed WAOA demonstrates improvements in HND as outlined in Table VI and Figures 8 and 9 across both scenarios and environments. This improvement is mainly due to WAOA's ability to effectively explore the search space, swiftly identifying alternative communication paths and redistributing tasks among available nodes when some nodes fail. By being adaptive and flexible, the network can distribute the workload more evenly among the nodes, reducing energy consumption and enhancing communication routes. This, in turn, boosts the network's performance and prolongs its lifespan.

The improvements in LND are highlighted in Table VII and Figures 10 and 11 for both scenarios and environments. The key factor driving this improvement is WAOA's ability to dynamically redirect data packets and reconfigure the network's topology using pheromone-guided paths managed by the ACO component. This capability enables WAOA to achieve quicker recovery times and minimize downtime, outperforming static or less adaptive routing strategies employed by the baseline algorithms.

Table VI Proposed WAOA Improvement in (%) over Baseline Algorithm for HND

Scenario/ Environment	MOORP	MMABC	AZEBR
Scenario-1/ Homogeneous	10.9	18.6	28.1
Scenario-2/ Homogeneous	5.5	15.3	22.2
Scenario-1/ Heterogeneous	13.89	17.47	22.03
Scenario-2/ Heterogeneous	23.02	44.20	48.23

RESULT ANALYSIS IN TERMS OF DEAD NODES:

Table VIII presents the number of dead nodes corresponding to different rounds. When the network operates for 750 rounds, the dead nodes across all algorithms range between 28 and 39. After 12,000 rounds, however, WAOA records 142 dead nodes, while the three baseline algorithms exhaust their network functionality by the 12,000th round. Figure 12 further illustrates that WAOA maintains a higher percentage of nodes alive after 10,000 cycles.

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Table VIII Number of Dead Nodes for Scenario-1 (Homogeneous)

Number of Rounds	Algorithms			
	WAOA	MOORP	MMABC	AZEBR
750	22	28	33	39
1500	79	83	89	102
3000	103	114	126	147
4500	117	128	146	150
6000	127	133	150	150
7500	132	136	150	150
9000	136	137	150	150
10500	140	143	150	150
12000	142	150	150	150
14014	150	150	150	150

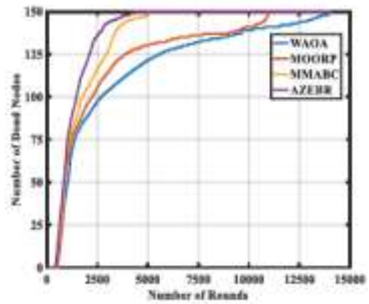

Figure12: Dead Nodes per Round for Scenario-1 (Homogeneous)

This improvement is attributed to WAOA's strategy for selecting CHs, avoiding the pitfall of local optima that can arise when merging WOA and ACO algorithms. In the heterogeneous environment and Scenario 1, the number of dead nodes for each algorithm is shown in Table IX. At 750 rounds, dead nodes range between 11 and 25 across the algorithms, while at 12,000 rounds, WAOA records 146 dead nodes. The three baseline algorithms also lose network connectivity by 12,000 rounds. Figure 13 shows that WAOA sustains a higher percentage of active nodes throughout the rounds.

This enhancement is due to WAOA's ability to efficiently allocate resources by leveraging the fitness function to make optimal routing decisions. It ensures routing paths are optimized and prioritizes nodes with sufficient residual energy, contributing to more efficient usage of sensor nodes (SNs) and extended network longevity.

Table X presents the number of dead nodes alongside the corresponding number of rounds in Scenario 2. From the table, it is evident that after 1,500 rounds, the baseline algorithms lost around 92% of their nodes, while WAOA experienced only 79% node depletion. Figure 14 visualizes the number of inactive nodes per round, showing that after approximately half of the nodes became inactive in each method, WAOA displayed better performance. This improvement stems from the ACO algorithm's ability to identify the most energy-efficient paths for data transmission, resulting in lower energy consumption compared to the baseline algorithms.

Table: X Number of Dead Nodes for Scenario-2 (Homogeneous)

Number of Rounds	Algorithms			
	WAOA	MOORP	MMABC	AZEBR
250	25	31	37	55
500	80	99	96	108
1000	99	124	131	134
1500	119	139	146	141
2000	131	145	148	146
2500	140	147	149	150
3000	144	149	150	150
3500	147	150	150	150
4127	150	150	150	150

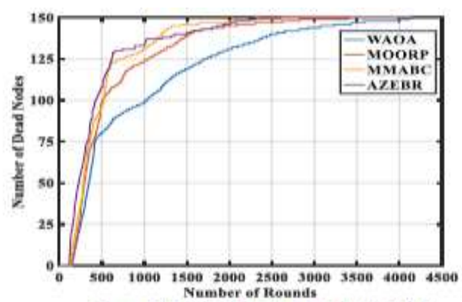

Figure 14: Dead Nodes per Round for Scenario-2 (Homogeneous)

The number of dead nodes for Scenario 2 is further outlined in Table XI, along with the corresponding rounds. The data reveals that after 3,500 rounds, the baseline algorithms lost over 90% of their nodes, whereas WAOA lost only 82%.

The number of inactive nodes present in each cycle is depicted in Figure 15. After approximately half of the nodes in every baseline method died, it is likely observed that the performance of our proposed WAOA is superior to that of baseline methods

RESULT ANALYSIS IN TERMS OF AVERAGE RESIDUAL ENERGY:

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This section assesses the performance of WAOA and the baseline algorithms—MOORP, MMABC, and AZEBR—in terms of average residual energy (RE). In the first scenario, where the base station (BS) is positioned at the center of the area, energy depletion is comparatively lower than when the BS is placed at a more distant location. This is because shorter communication distances to the BS reduce energy consumption.

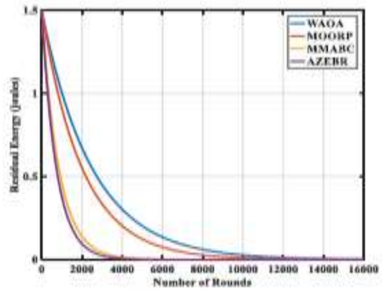

Figure 16: Residual Energy BS (125,125) Homogeneous

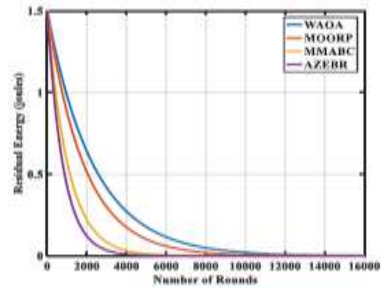

Figure 17: Residual Energy BS (125,125) Heterogeneous

Figure 16 presents a visual comparison between WAOA and the baseline algorithms for Scenario 1 in a homogeneous environment. Within 4,000 rounds, the proposed WAOA shows a reduction in RE by 79.96%. In comparison, the baseline algorithms demonstrate greater energy depletion, with reductions recorded at 86.5%, 99.14%, and 99.59% for MOORP, MMABC, and AZEBR, respectively.In the heterogeneous environment Figure 17, within round 4000, the proposed WAOA demonstratesa reduction in RE by 81.33%. In contrast, the baseline algorithm exhibits a comparatively moresignificant reduction in RE, with specific values recorded at 84.67%, 98.33%, and 99.23% for therespective algorithms: MOORP, MMABC, and AZEBR.

In the homogeneous environment, as shown in Figure 18, WAOA demonstrates a reduction in residual energy (RE) by 84.12% within 1,000 rounds. In comparison, the baseline algorithms exhibit a greater RE reduction, with values of 88.67%, 92.37%, and 96.67% for MOORP, MMABC, and AZEBR, respectively. By 1,500 rounds, as illustrated in Figure 19, WAOA experiences a reduction in energy reserves by 83.98%. Under the same conditions, the baseline algorithms show higher energy consumption, with reductions of 85.57% for MOORP, 92.63% for MMABC, and 94.87% for AZEBR.

RESULT ANALYSIS IN TERMS OF PACKET DROP RATIO AND ROUTING OVERHEAD:

This section provides a detailed comparison of the packet drop ratio and routing overhead between the proposed WAOA and the baseline algorithms. Figures 20 and 21 display the evaluation of the packet drop ratio for WAOA against existing algorithms.

The packet drop ratio measures the percentage of packets lost during transmission—a lower value indicates more reliable and efficient network performance. The figures reveal that WAOA consistently achieves a lower packet drop ratio than the baseline algorithms, underscoring its effectiveness in preserving data integrity and ensuring reliable communication.

the routing overhead for WAOA compared to other state-of-the-art algorithms. Lower routing overhead reflects more efficient utilization of network resources. The results show that WAOA not only reduces the packet drop ratio but also minimizes routing overhead, making it a more efficient and scalable solution for network routing.

The improved performance of WAOA is attributed to its efficient fitness function, which helps prevent node failures during route generation, resulting in a higher packet reception rate at the BS. This capability ensures reliable data delivery and reduces overhead by optimizing the paths and minimizing packet loss during transmission.

CONCLUSION AND FUTURE WORK :

This paper introduces a Hybrid Whale-Ant Optimization Algorithm (WAOA) designed for energy-efficient routing in Wireless Sensor Networks (WSNs) by leveraging the clustering capability of the Whale Optimization Algorithm (WOA) and the routing efficiency of the Ant Colony Optimization (ACO) algorithm. The goal of the proposed WAOA was to improve network performance by maximizing residual energy (RE) and extending network lifetime. WAOA effectively identifies the optimal cluster head (CH) and establishes efficient communication paths between cluster members and CHs, as well as between CHs and the base station (BS).

Through comprehensive simulations and comparisons with baseline algorithms such as MOORP, MMABC, and AZEBR, the results demonstrate the superior performance of WAOA. These findings highlight that WAOA surpasses the baseline algorithms in terms of network lifetime, residual energy, and node centrality. Performance evaluations under different environments and scenarios show that the proposed WAOA achieves 5.78%, 16.11%, and 18.52% improvements in network lifetime compared to MOORP, MMABC, and AZEBR, respectively.

FUTURE WORK:

Future research will involve conducting stress tests and scalability assessments to evaluate how the algorithm performs as network size and complexity grow. Further work will also focus on addressing security and privacy challenges to ensure safe data transmission, along with implementing authentication mechanisms and privacy-preserving techniques. Additionally, future efforts will explore integrating edge computing with WAOA, facilitating distributed data processing and real-time decision-making at the network edge. This will help reduce latency and enhance the responsiveness of WSN applications, improving overall network efficiency and performance.

REFERENCES :

[1]. B. Fan and Y. Xin, “A Clustering and Routing Algorithm for Fast Changes of Large-Scale WSNin IoT,” IEEE Internet Things J., vol. 11, no. 3, pp. 5036–5049, Feb. 2024, doi:10.1109/JIOT.2023.3302874.

[2]. Z. Wang, H. Ding, B. Li, L. Bao, and Z. Yang, “An Energy Efficient Routing Protocol Based onImproved Artificial Bee Colony Algorithm for Wireless Sensor Networks,” IEEE Access, vol. 8,pp. 133577–133596, 2020, doi: 10.1109/ACCESS.2020.3010313.

[3]. P. Karpurasundharapondian and M. Selvi, “A comprehensive survey on optimization techniquesfor efficient cluster-based routing in WSN,” Peer-to-Peer Network. Application., Jun. 2024, doi:10.1007/s12083-024-01678-y.

[4]. R. Mishra and R. K. Yadav, “Energy Efficient Cluster-Based Routing Protocol for WSN UsingNature Inspired Algorithm,” Wireless Personal Communication, vol. 130, no. 4, pp. 2407–2440,Jun. 2023, doi: 10.1007/s11277-023-10385-5.

[5]. Qureshi, KashifNaseer, Bashir, Muhammad Umair, Lloret, Jaime, Leon, Antonio, “OptimizedCluster-Based Dynamic Energy-Aware Routing Protocol for Wireless Sensor Networks inAgriculture Precision”. Journal of Sensors. 2020. 1-19. doi: 10.1155/2020/9040395.

[6]. S. Chaurasia, K. Kumar, and N. Kumar, “EEM-CRP: Energy-Efficient Meta-Heuristic Cluster-Based Routing Protocol for WSNs,” IEEE Sensors J., vol. 23, no. 23, pp. 29679–29693, Dec. 2023,doi: 10.1109/JSEN.2023.3322631.

[7]. Jain, D., Shukla, P.K. &Varma, S. Energy efficient architecture for mitigating the hot-spotproblem in wireless sensor networks. Journal of Ambient Intelligence and HumanizedComputing14, 10587–10604 (2023). https://doi.org/10.1007/s12652-022-03711-5.
[8]. GiadaSimionato, Mario G.C.A. Cimino, Swarm intelligence for hole detection and healing inwireless sensor networks, Computer Networks, Volume 250, 2024, 110538, ISSN 1389-1286,https://doi.org/10.1016/j.comnet.2024.110538.
[9]. Jianpo Li, Qing Han, Wenting Wang, “Characteristics analysis and suppression strategy of energyhole in wireless sensor networks,” Ad Hoc Networks, Volume 135, 2022, 102938, ISSN 1570-8705, https://doi.org/10.1016/j.adhoc.2022.102938.
[10]. A. Mehmood, Z. Lv, J. Lloret and M. M. Umar, "ELDC: An Artificial Neural Network BasedEnergy-Efficient and Robust Routing Scheme for Pollution Monitoring in WSNs," in IEEETransactions on Emerging Topics in Computing, vol. 8, no. 1, pp. 106-114, 1 Jan.-March 2020,doi: 10.1109/TETC.2017.2671847
[11]. K. Dionisis et al., LEACH-based hierarchical energy-efficient routing in wireless sensor networks,AEU - International Journal of Electronics and Communications, Volume 169, 2023, 154758,ISSN 1434-8411, https://doi.org/10.1016/j.aeue.2023.154758.
[12]. Mohan, Y., Yadav, R.K. &Manjul“Seagull optimization algorithm for node localization inwireless sensor networks. Multimedia Tools and Applications 83, 70793–70814 (2024).https://doi.org/10.1007/s11042-024-18331-8.
[13]. Dohare and K. Singh, “Energy-Aware Clustering and Routing Protocol for Wireless SensorNetwork: Chicken Swarm Optimization based Approach.” Jun. 28, 2023. doi: 10.21203/rs.3.rs-2566665/v1.
[14]. S. Al-Otaibi, A. Al-Rasheed, R. F. Mansour, E. Yang, G. P. Joshi, and W. Cho, “Hybridization ofMetaheuristic Algorithm for Dynamic Cluster-Based Routing Protocol in Wireless SensorNetworks,” IEEE Access, vol. 9, pp. 83751–83761, 2021, doi: 10.1109/ACCESS.2021.3087602.
[15]. N. E. H. Bourebia and C. Li, “A novel raccoon optimization algorithm with multi-objectiveclustering strategy-based routing protocol for WSNs,” Peer-to-Peer Network. Application. vol.16, no. 4, pp. 1624–1640, Aug. 2023, doi: 10.1007/s12083-023-01479-9.
[16]. S. Chaurasia and K. Kumar, “MOORP: Metaheuristic Based Optimized Opportunistic RoutingProtocol for Wireless Sensor Network,” Wireless Personal Communications, vol. 132, no. 2, pp.1241–1272, Sep. 2023, doi: 10.1007/s11277-023-10659-y.
[17]. S. S. Sefati, M. Abdi, and A. Ghaffari, “QoS-based routing protocol and load balancing in wirelesssensor networks using the Markov model and the artificial bee colony algorithm,” Peer to PeerNetwork. Appl., vol. 16, no. 3, pp. 1499–1512, May 2023, doi: 10.1007/s12083-023-01502-z.
[18]. D. S. Kumar and S. S. Sundaram, “Associative Zone Based Energy Balancing Routing forExpanding Energy Efficient and Routing Optimization Over the Sensor Network,” Wireless.Personal.Communication., vol. 124, no. 3, pp. 2045–2057, Jun. 2022,
[19]. Anandh, S.J., Baburaj, E. Energy Efficient Routing Technique for Wireless Sensor NetworksUsing Ant-Colony Optimization. Wireless PersCommun 114, 3419–3433 (2020).https://doi.org/10.1007/s11277-020-07539-0.
[20]. Priyanka, B.N., Jayaparvathy, R. &DivyaBharathi, D. Efficient and Dynamic Cluster HeadSelection for Improving Network Lifetime in WSN using Whale Optimization Algorithm.Wireless Personal Communication 123, 1467–1481 (2022). https://doi.org/10.1007/s11277-021-
[21]. Rawat P, Chauhan, S. Particle swarm optimization-based energy efficient clustering protocol inwireless sensor network. Neural Computing & Applications 33, 14147–14165 (2021).https://doi.org/10.1007/s00521-021-06059-7.

[22]. G. Han and L. Zhang, “WPO-EECRP: Energy-Efficient Clustering Routing Protocol Based onWeighting and Parameter Optimization in WSN,” Wireless Personal Communications, vol. 98, no.1, pp. 1171–1205, Jan. 2017, doi: 10.1007/s11277-017-4914-8.
[23]. Nagadivya, S., Manoharan, R. Energy efficient fuzzy logic prediction-based opportunistic routingprotocol (EEFLPOR) for wireless sensor networks. Peer-to-Peer Netw.Appl. 16, 2089–2102(2023). https://doi.org/10.1007/s12083-023-01516-7
[24]. M. Moshref, R. Al-Sayyed, and S. Al-Sharaeh, “An Enhanced Multi-Objective Non-DominatedSorting Genetic Routing Algorithm for Improving the QoS in Wireless Sensor Networks,” IEEEAccess, vol. 9, pp. 149176–149195, 2021, doi: 10.1109/ACCESS.2021.3122526.
[25]. C. Xu, Z. Xiong, G. Zhao, and S. Yu, “An Energy-Efficient Region Source Routing Protocol forLifetime Maximization in WSN,” IEEE Access, vol. 7, pp. 135277–135289, 2019,
[26]. N. Kumar and D. P. Vidyarthi, “A Green Routing Algorithm for IoT-Enabled Software DefinedWireless Sensor Network,” IEEE Sensors Journal, vol. 18, no. 22, pp. 9449–9460, Nov. 2018, doi:10.1109/JSEN.2018.2869629.
[27]. Z. Wang, H. Ding, B. Li, L. Bao, and Z. Yang, “An Energy Efficient Routing Protocol Based onImproved Artificial Bee Colony Algorithm for Wireless Sensor Networks,” IEEE Access, vol. 8,pp. 133577–133596, 2020, doi: 10.1109/ACCESS.2020.3010313.
[28]. T. Kaur and D. Kumar, “MACO-QCR: Multi-Objective ACO-Based QoS-Aware Cross-LayerRouting Protocols in WSN,” IEEE Sensors Journal, vol. 21, no. 5, pp. 6775–6783, Mar. 2021, doi:10.1109/JSEN.2020.3038241.
[29]. R. Chaudhry and N. Kumar, “A Multi-Objective Meta-Heuristic Solution for Green Computing inSoftware-Defined Wireless Sensor Networks,” IEEE Transactions on Green Communications andNetworking vol. 6, no. 2, pp. 1231–1241, Jun. 2022,
[30]. V. Agarwal, S. Tapaswi, and P. Chanak, “Energy-Efficient Mobile Sink-Based Intelligent DataRouting Scheme for Wireless Sensor Networks,” IEEE Sensors J., vol. 22, no. 10, pp. 9881–9891,May 2022, doi 10.1109/JSEN.2022.3164944.
[31]. Ojha and P. Chanak, “Multi-objective Gray-Wolf-Optimization-Based Data Routing Scheme forWireless Sensor Networks,” IEEE Internet Things J., vol. 9, no. 6, pp. 4615–4623, Mar. 2022, doi:10.1109/JIOT.2021.3105425.
[32]. Seyyedabbasi, F. Kiani, T. Allahviranloo, U. Fernandez-Gamiz, and S. Noeiaghdam, “Optimaldata transmission and pathfinding for WSN and decentralized IoT systems using I-GWO and Ex-GWO algorithms,” Alexandria Engineering Journal, vol. 63, pp. 339–357, Jan. 2023, doi:10.1016/j.aej.2022.08.009.
[33]. S. Al-Otaibi, A. Al-Rasheed, R. F. Mansour, E. Yang, G. P. Joshi, and W. Cho, “Hybridization ofMetaheuristic Algorithm for Dynamic Cluster-Based Routing Protocol in Wireless SensorNetworks,” IEEE Access, vol. 9, pp. 83751–83761, 2021, doi: 10.1109/ACCESS.2021.3087602.
[34]. X. Xue, R. Shanmugam, S. Palanisamy, O. I. Khalaf, D. Selvaraj, and G. M. Abdulsahib, “AHybrid Cross Layer with Harris-Hawk-Optimization-Based Efficient Routing for Wireless SensorNetworks,” Symmetry, vol. 15, no. 2, p. 438, Feb. 2023, doi10.3390/sym15020438.
[35]. Kooshari, M. Fartash, P. Mihannezhad, M. Chahardoli, J. AkbariTorkestani, and S. Nazari, “AnOptimization method in wireless sensor network routing and IoT with water strider algorithm andant colony Optimization algorithm,” Evolutionary. Intelligence., Apr. 2023, doi: 10.1007/s12065-023-00847-x.