

A Binary Inertia-Weighted Robust Cluster Head Selection And Greedy Routing Framework For Energy-Efficient Wireless Sensor Networks

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Abstract

At present, energy-efficient and scalable communication remains a key challenge in Wireless Sensor Networks (WSNs). Most existing clustering-based routing protocols either optimise Cluster Head (CH) selection or route establishment in isolation, often neglecting adaptability, load balancing, and efficient data transmission. Furthermore, various techniques lack integrated optimization frameworks and fail to generalize under various conditions. To overcome these challenges, an optimal energy-aware framework is proposed, which is known as Binary Inertia-based Robust Cluster Head selection, through an Improved Hiking Optimization Algorithm with Greedy Routing (BIRCH-IHOA-GR). This proposed framework introduces an improved Hiking Optimization Algorithm (HOA) by integrating binary encoding and inertia-weighted updates with HOA for efficient selection of spatially distributed CHs. Moreover, a customized greedy routing strategy is employed to transmit data from CHs to the Base Station (BS) using a multi-hop communication method with minimal energy and balanced traffic load. Furthermore, proposed BIRCH-IHOA-GR achieves notable reductions in communication overhead, while enhancing overall network lifetime, and improves strong robustness in large-scale WSN deployments. Finally, simulations determine that the proposed BIRCH-IHOA-GR framework outperforms traditional protocols in terms of network stability, energy consumption and adaptability under diverse operating conditions..

Keywords: Base Station, Cluster Head Selection, Greedy Routing, Improved Hiking Optimization Algorithm, Wireless Sensor Networks..

1. Introduction

In this modern era, the Internet of Things (IoT) utilizes Wireless Sensor Networks (WSNs) for monitoring physical and environmental factors in various applications [1]. As IoT continues to advance, the range of applications that use WSNs also constantly increases. The demand of WSNs continues to witness high demand across various sectors such as agriculture and urban development [2] [3]. In general, WSNs are designed for deployment in areas that are difficult for humans to access, and these

WSNs are also used in zones where human presence is required but impossible to access. Moreover, wireless micro-sensors are widely used for precise environmental monitoring and data transmission in many civilian and military applications [4]. In addition, WSNs represent a separate type of ad hoc network that contains a greater number of sensor nodes and is not fixed at a single location, instead being randomly distributed in the sensing area [5]. A group of resource-constrained sensor nodes forms a WSN, where these sensor nodes capture details related to the physical environment and transmit sensed data to the Base Station (BS) [6].

Additionally, identifying efficient clustering and routing algorithms remains challenging, particularly in balancing energy, memory efficiency simultaneously and to improve network lifetime while providing reliable data delivery to users. A significant drawback of many hierarchical protocols is independent optimization related to Cluster Head (CH) identity and inter-cluster routing. Furthermore, lack of effective integration results in high energy consumption, CH-to-CH communication becomes more critical, especially in large-scale deployments [7]. When CH is located closer to the BS, it frequently accepts hotspot-like effects and accumulates a large forwarding load, which results in high energy consumption and accelerates energy depletion, thereby destabilizing the network [8]. Additionally, there are fundamental issues related to multi-objective optimisation regarding network lifetime, energy consumption, and data delivery. Existing approaches for solving this issue fail to satisfy multiple competing objectives simultaneously [9].

Furthermore, frequent re-clustering, uneven energy consumption, and inadequate CH rotation negatively impact the performance and shorten the lifetime of the network. Some clustering techniques, such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), have been applied to optimization within WSNs; however, they are limited by early stopping or convergence of the objective, expensive computation, and poor scalability in terms of producing real-time solutions in large-scale applications [10]. Security is a major concern in WSNs, particularly in sensitive applications. The WSNs are wireless, distributed, and remote, which exposes WSNs to threats, such as eavesdropping, message modification, and Sybil attacks. Therefore, an adaptive lightweight security model is developed that remains ineffective in terms of confidentiality [11]. The interconnected nature of these problems is energy inefficiency, lack of network stability, and lack of security, which need the development of adaptive and secure solutions for both clustering and routing in next-generation WSNs.

Energy-efficient communication is a critical aspect in the development of truly sustainable WSNs. Several studies have indicated that the main factors in optimal CH selection are residual energy and distance [12]. Furthermore, both studies showed that routing decisions based on energy and distance significantly increase lifetime [13]. In addition to energy constraints, short-range communication and storage limitations are technical barriers that affect the lifetime of sensor nodes and require adaptive designs that adapt to energy constraints [14]. Additional observations reveal that CH selection based on multiple criteria and minimizing intra-cluster communication distance are critical for fair energy use and load distribution across the network [15]. These observations motivated the development of a model that enhances energy efficiency and is broadly adaptive to changes in network conditions through optimized clustering and routing decisions.

1.1 Contribution

The following are the major contributions of this research:

- An Improved Hiking Optimization Algorithm (IHOA) is introduced by embedding binary encoding and adaptive inertia-weighted exploration into original continuous HOA. While the proposed IHOA retains HOA's inherent leader follower ascending behavior, despite the original Binary PSO or GA methods, it offers a linearly decreasing inertia weight to dynamically balance exploration and exploitation over iterations.
- Specifically, binary encoding and inertia-weighted updates were integrated with Hiking Optimization Algorithm (HOA) for CH selection. This balances the load and uses the energy efficiently among the sensor nodes.
- A lightweight customised greedy multi-hop routing strategy is determined for the efficient transfer of data from the CHs to BS through the nearest node in the direction of the BS, which avoids complex paths.

1.2 Paper Structure

The remaining sections of this paper are structured as follows: Section 2 demonstrates a clear overview of existing works related to WSN. Section 3 explores the proposed methodology, which contains algorithmic descriptions and equations related to the working of the architecture. Section 4 illustrates the results of the proposed methodology by comparing with existing methods. Section 5 discusses the overall work of this research, Section 6 summarises the key findings and outlines the scope for future work and Section 7 presents the Notation Table. The references cited in this paper were determined at the end of the paper.

2. Related Works

In this modern era, numerous algorithms have been introduced to improve the energy efficiency of WSNs. Clustering algorithms are widely used because they help reduce and evenly distribute energy consumption. A Reinforcement Learning (RL) method was adopted to reduce and balance energy consumption in networks [16]. Further, this method balances the energy by rotating CHs among sensors and saves energy consumption by multi-hop routing in transmission of data. In addition, a Cluster based Routing Protocol Optimiser (CRP-optimizer) was utilized to decide whether to form a new cluster by destroying the current cluster and whether the CH to be excluded in transmission or not.

Furthermore, a Cluster Routing Protocol for Heterogeneous Network (CPHN) was demonstrated to improve the lifespan of a network by efficient energy usage [17]. Here, a suitable and more efficient node was selected as the CH based on the initial energy and residual energy levels of nodes. Additionally, the CH selection probability was used for a longer life of the WSN. Similarly, an Energy-Efficient Machine Learning-based Clustering and Routing (EEMLCR) model was recommended for clustering the sensors in WSN and selecting an efficient path for transmitting data [18]. K-means clustering and Q-learning were utilised to increase transmission and energy efficiencies.

Moreover, a Hierarchical Secure and Energy Efficient Routing Protocol (HSEERP) was introduced, in which an optimal path between two nodes was selected in the network [19]. In addition, this protocol has a strong resistance to certain specific threats, such as malicious nodes attracting all network traffic by falsely advertising an appealing route to the destination. Using this protocol, energy was not only efficiently used, but data were also securely transmitted. Many optimization techniques have been utilized, one of which is the integration of water strider algorithms (WSA) with Ant Colony Optimization (ACO) [20]. In this method, the WSA clustered the sensor nodes, CHs were selected, and a mobile sink collected data from CHs and transmitted them to the BS.

Similarly, an Improved Q-learning based Artificial Bee Colony Algorithm (IQ-ABC) has been suggested to enhance the usage of energy in multi-hop routing in WSNs [21]. In this method, the most efficient path is chosen where every sensor node transmits data to the CH. In addition, trust, latency, and energy efficiency are factors that play key roles in the selection of the CH in this method. Consequently, a Chimp-based Clustering Flat Routing Protocol (CbCFRP) was presented for efficient energy consumption and shortest routing path selection [22]. Here, the optimal path was selected using the chimp fitness function, through which the delay and consumption of energy were minimized.

2.1 Research Gap

While machine learning and most metaheuristic-based techniques improve optimization accuracy, they tend to have high computational time complexity for real-time flexibility with energy-constrained sensor nodes. In addition, existing selection methods depend on continuous optimizers, which are not suitable for low-energy WSN nodes. Further, most routing mechanisms need high-cost global path computation that utilises more energy in data transmission. Therefore, the proposed BIRCH-IHOA-GR framework implements a lightweight, binary inertia weighted CH selection that does not depend on continuous optimizers with low computational time. Whereas, IHOA has much lower requirements for arithmetic operations per iteration and memory footprint than population-based optimizers such as Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). Moreover, an energy-aware multi-hop GR is being used for low-cost computation and it utilises low energy. In addition, the proposed BIRCH-IHOA-GR model is targeted to maintain a similar optimization effect while having low computational overhead suitable for embedded Wireless Sensor Networks (WSN) platforms.

3. Methodology

The proposed BIRCH-IHOA-GR framework is designed for the efficient usage of energy through cluster-based routing in WSNs. It contains two phases: Cluster Head (CH) selection and multi-hop routing, as illustrated in Figure 1. Furthermore, in the first phase, CHs are selected using an improved HOA, and thereby clusters are formed, where all sensor nodes associate themselves based on the proximity of the CHs. Here, to use energy efficiently, the HOA is enhanced into an improved HOA by integrating two modifications. The modifications include binary encoding of CH configurations and inertia-weight-based updating to balance exploration and exploitation. Therefore, these modifications make the improved HOA suitable for optimal CH selection, adaptive clustering, and energy efficiency. In the second phase, a customised greedy routing strategy is utilized for transmitting data from CHs to BS.

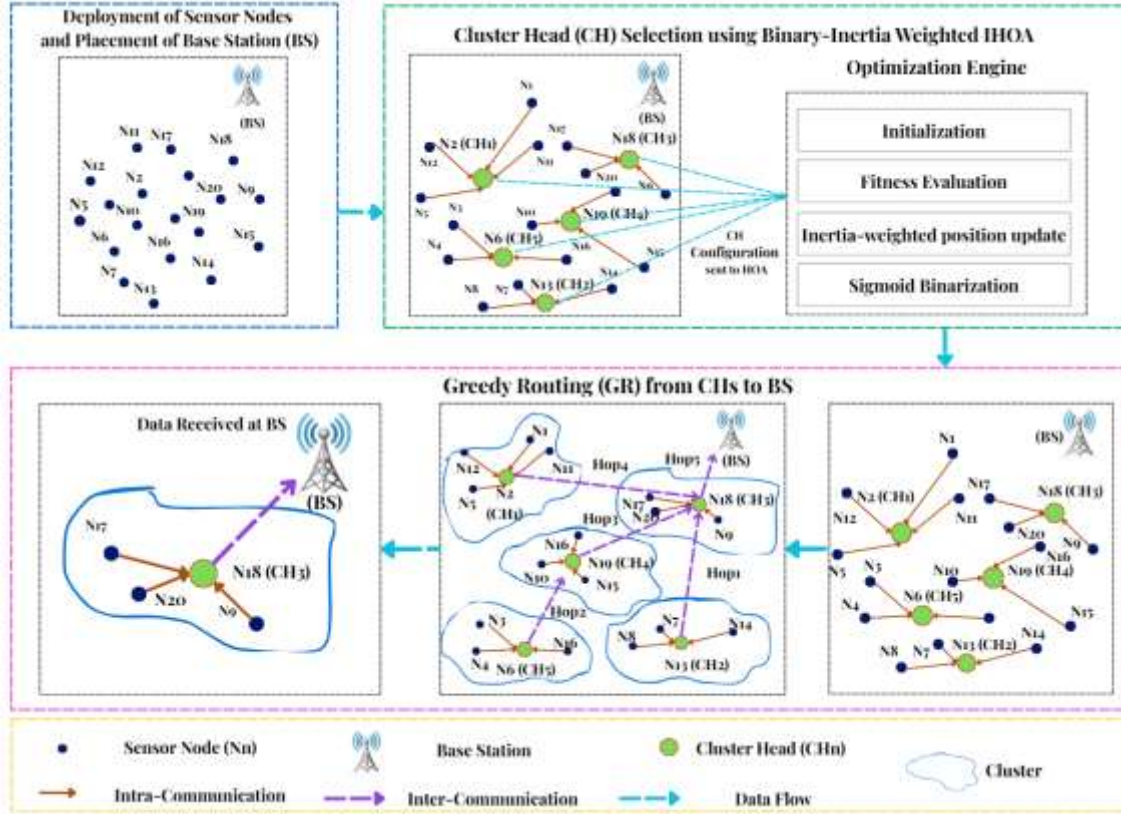


Figure 1. Architecture of proposed BIRCH-IHOA-GR framework

3.1 Network Model and Assumptions

The selected network is modelled at a 2D region of $L * L$ size, in which N sensor nodes are deployed uniformly. Additional assumptions of network operation are described below:

1. All sensor nodes are homogeneous, each initialized with equal energy $E_{init} = 0.5J$ and identical communication and sensing capabilities. Nodes remain stationary after deployment with unique IDs and fixed positions (x_i, y_i) within the $100m \times 100m$ field.
2. Nodes are homogeneous in terms of initial energy and communication capabilities.
3. Sensors are battery-powered with restricted energy and these batteries are irreplaceable.
4. Network operation is divided into rounds, where an individual round consists of CH selection, cluster formation, data transmission and energy update.
5. A first-order radio model is employed as an energy consumption model, with individual energy costs for transmitting and receiving.
6. If the node's residual energy is lower than the considered threshold, then it is considered a dead node.

3.2 Energy Consumption Model

A first-order radio model was utilised to analyze energy consumption of all sensor nodes. This model evaluates receiver and transmitter distance and selects either the free-space energy channel (d^2) and the multi-path fading energy channel (d^4) during data transmission. Specifically, an energy-consumption model is crucial for accurately evaluating the residual energy of sensor nodes and selecting energy-consistent CH. It enables balanced energy usage across the network and extends the WSN lifetime during clustering and multi-hop routing. Moreover, for transferring data of k -bits through d distance, required amount of energy is calculated using Equation (1).

$$E_{TX}(k, d) = \begin{cases} k \times E_{elec} + k \times \epsilon_{fs} \times d^2, & d \leq d_0 \\ k \times E_{elec} + k \times \epsilon_{mp} \times d^4, & d > d_0 \end{cases} \quad (1)$$

Here, $E_{TX}(k, d)$ is the required energy for transmission, E_{elec} is the energy required for transmitting per bit, $d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$ is the distance threshold, ϵ_{fs} is the amplification factor of free-space model, and ϵ_{mp} is the amplification factor of the multi-path fading model. Further, for receiving data of k -bits through d distance, the required amount of energy is denoted by Equation (2).

$$E_{RX}(k, d) = k \times E_{elec} \quad (2)$$

Where, $E_{RX}(k, d)$ is the required energy for reception; E_{elec} is the energy for receiving per bit.

3.3 Improved Hiking Optimisation Algorithm based Cluster Head Selection

In this section, the CHs are responsible for intra-cluster data acquisition and inter-cluster data transmission to the BS are discussed. Moreover, the random CH selection often shortens network lifetime. To address this issue BIRCH-IHOA-GR framework treats CH selection as a binary optimization problem and solves it using an HOA algorithm inspired by human behavior. The process starts with initialization of CH configurations, after which these configurations are encoded as binary vectors. Next, at each step, the fitness function evaluates each configuration based on the objectives of energy efficiency, distance, and communication range. After several iterations, the best performer is selected and designated as the CH for that round. Therefore, the optimisation process aims to identify the most efficient CH configuration that improves energy efficiency, balances communication load, and enhances network durability

3.3.1 Initialization

In this phase, a group of CH configurations is generated randomly, and each configuration is maintained by a virtual search entity known to be a CH selection agent, and they are initialized independently. Each agent holds a binary vector β and the number of agents is denoted by P , which defines the population size. Furthermore, each agent represents one possible CH configuration and collection of such agents is known as the population. The number of CH selection configurations that simultaneously explore the search space during the optimization process is the population size.

The initial values of each configuration are generated by a uniform random distribution with a balanced probability of the node being selected as a CH. Furthermore, the initialization step is essential as it sets up a search for effective exploration in the IHOA. In addition, the initial population of CH configurations maximizes the chance of covering a possible search space and prevents premature convergence. Thus, this initialization step ensures that the algorithm starts with diverse configurations to adaptively improve CH locations through decision-making iterations over time.

3.3.2 CH Configuration Encoding

In the process of selecting CHs for the WSNs, each possible CH configuration is denoted by a binary vector. Here, CH configuration refers to the specific selection of sensor nodes chosen as CHs in a round, and is represented by Equation (3). Furthermore, the CH configuration is not a single node; it represents a complete arrangement of CHs and their respective members of the entire network.

$$\beta = [b_1, b_2, b_3, \dots, b_N] \quad (3)$$

Here, β is CH configuration; N is number of sensor nodes; $b_i \in \{0,1\}$ is each node in vector represents the role of the sensor node i . Also, if $b_i = 1$ node i is selected as CH, else if $b_i = 0$ node i is represented as non-CH.

This representation is compact, scalable, and directly reflects the binary and decision-based nature of the CH selection in WSNs. It allows IHOA to build, evaluate, and evolve CH configurations easily without complex transformations, making it an excellent translation to deploy in constrained sensor networks.

3.3.3 Fitness function

In this stage, after the CH selection agents are initialized, the algorithm evaluates the fitness of each configuration through a multi-objective fitness function. This function shows which sensor node should be selected as the CH that balances energy efficiently, intra-cluster transmission distance, and communication coverage. Thus, the fitness function in the IHOA is designed to reflect objectives, namely residual energy (E), intra-cluster distance (d), and CH count (N_{CH}) in communication coverage.

Consequently, N_{CH} is calculated count of the number of 1s in the CH configuration vector β , E is the energy of the individual sensor node and d is calculated using Euclidean distance. Therefore, these objectives are combined to form a unified multi-objective fitness function (F), as represented by Equation (4).

Here, d_{max} denotes the maximum node-CH distance, $|CH|$ represents the number of selected CHs, $|CH_{opt}|$ is the desired CH count. Thus, the parameters $\alpha = 0.5$, $\beta = 0.3$ and $\gamma = 0.2$ and $\alpha + \beta + \gamma = 1$ are scalarization weights which generate best tradeoffs for 100-500 node networks to control the relative importance of energy, spatial compactness, and CH population. Each term is normalised to the range $[0, 1]$ to maintain balance and avoid domination of any metric. This formulation establishes selection pressure for configurations that have high average residual energy, low intra-cluster distance, and an appropriate number of CHs. Larger levels of α increase the focus towards energy balancing for the nodes, while increasing β creates clustering in space. The squared penalty on the number of CHs prevents too many CHs which would increase routing overhead for collecting the data.

Further, to obtain the interdependence among CH placement and routing efficiency, the global optimization objective J integrates CH-related and routing-related costs, is determined in Equation (4):

$$J = \alpha F_{CH} + \beta F_{Route} \quad (4)$$

$$\text{Where, } F_{CH} = \frac{\sum_{i \in CH} E_{res,i}}{\sum_{j \in N} E_{res,j}} - \gamma \frac{|CH|}{|N|} \text{ and } F_{Route} = \frac{1}{|CH|} \sum_{i \in CH} \left(\frac{E_{tx}(d_{i,BS}) + \sum_{j \in N_i} E_{tx}(d_{i,j})}{E_0} \right)$$

Here, $E_{res,i}$ refers to the residual energy of the node i , $d_{i,CH(i)}$ signifies the Euclidean distance between the node i and its assigned CH, $E_{tx}(\cdot)$ represents the transmission energy based on distance, N_i denotes set of neighbouring CHs, and α, β, γ are weight coefficients sustaining $\alpha + \beta + \gamma = 1$. This formulation assures that CH selection during IHOA iterations intrinsically considers downstream routing cost, mitigating both intra-cluster and inter-cluster transmission energy simultaneously. Furthermore, this N_i is computed using Equation (5), that determines Euclidean distance between CHs in communication range R_{com} and n_i takes the k -nearest CHs to CH_i alternatively.

$$N_i = \{j \in CH_S \mid d(CH_i, CH_j) \leq R_{com}\} \quad (5)$$

The agent with the best fitness function value at this stage is determined as the current global best CH configuration, which is termed as β_{best} and this configuration acts as a reference. Subsequently, the configuration is updated whenever a better CH is discovered, and subsequent iterations are performed. Then, the configuration is determined as β_{best} which propagates to guide the next rounds. Therefore, after multiple iterations, the IHOA converges toward an optimal CH selection, and the fitness function evaluates each CH configuration on energy grounds, as well as ensures spatial efficiency and balanced clustering.

3.3.4 Position Updating

At this stage, after the fitness evaluation, the IHOA enters its iterative improvement phase, where each agent updates its position in the solution space for a better CH configuration. Here, in the context of CH selection, position refers to the binary vector β , which encodes the current selection of CHs. Further, the goal is to refine these vectors over successive iterations to find the optimal configurations that are more energy-efficient.

Furthermore, to control the balance between exploration and exploitation, IHOA introduces a linearly decreasing inertia weight, which is denoted by w_t and expressed in Equation (6). Here, exploration refers to searching for a new CH from the CH configuration and exploitation refers to refining an optimal CH from the CH configuration. In addition to this inertia weight with the IHOA, there is a gradual shift from wide-ranging exploration to fine-tuned exploitation.

$$w_t = w_{max} - \left(\frac{w_{max}-w_{min}}{T}\right) \cdot t \quad (6)$$

Where, w_t is the inertia weight w_{max}, w_{min} is preset constant; T is the total number of iterations; t and is the current iteration. Additionally, in the early stages, w_t it is high and does high exploration, later it reduces to focus on searching, which is exploitation.

Moreover, the IHOA updates the position by learning from the best-known configuration and adjusting it based on exploration dynamics. Additionally, each agent contains a velocity ($W_{i,t}$) that determines how strongly the current CH configuration should be updated after every iteration and is calculated using Equation (7). Here, velocity does not refer to physical velocity; it is a controlling parameter that determines whether the sensor node role is CH or non-CH.

$$W_{i,t} = w_t \cdot W_{i,t-1} + \gamma_{i,t}(\beta_{best} - \alpha_{i,t}\beta_{i,t}) \quad (7)$$

Here, $W_{i,t}$ is the update vector of agent i at iteration t ; w_t is the adaptive inertia weight; β_{best} is the global best CH configuration so far;; $\gamma_{i,t}$ is a random scaling factor $[0,1]$, to maintain diversity among agents; $\beta_{i,t}$ is the current CH configuration of agent i at iteration t ; $\alpha_{i,t}$ is the sweep factor that adjusts how strongly the current agent struggles to change position. Specifically, $\alpha_{i,t}$ is calculated as a product of fitness adaptive term and linearly decreasing schedule as demonstrated in Equation (8):

$$\alpha_{i,t} = \alpha_{min} + (\alpha_{max} - \alpha_{min})\left(1 - \frac{t}{T}\right)\left(1 - \frac{f_i(t) - f_{best}(t)}{f_{worst}(t) - f_{best}(t) + \epsilon}\right) \quad (8)$$

Where, $\alpha_{max}, \alpha_{min}$ are preset bounds, $f_{worst}(t), f_{best}(t)$ are the best and worst fitness at t , ϵ is constant and T is the maximum count of iterations.

The enhanced binary HOA varies essentially from PSO-like mechanisms. While PSO demonstrates velocity as a motion term integrating cognitive and social factors, the IHOA velocity, as demonstrated in Equation 6, acts as a directional ascent factor derived from the fitness enhancement history of each agent, controlling bit transitions in CH configuration. The inertia weight w adaptively mitigates with the iteration count and global best fitness enhancement rate, promoting early diversification and late-stage manipulation.

Consequently, after calculating the velocity, the position of the agent i is updated using Equation (9). Additionally, as CH configurations are binary, a sigmoid-based binarisation step is applied to every element of the updated binary vector using Equation (10). Hence, this ensures that the updated CH configuration is a valid binary vector, and each sensor node is classified as CH or non-CH.

$$\beta_{i,t+1} = \beta_{i,t} + W_{i,t} \quad (9)$$

$$\beta_{i,t+1}(m) = \begin{cases} 1 & \text{if } \sigma(W_{i,t}(m)) \geq \theta \\ 0 & \text{otherwise} \end{cases} \quad \text{where, } \sigma(x) = \frac{1}{1+e^{-xm}} \quad (10)$$

Here, $\sigma(x)$ is a sigmoid function; $W_{i,t}$ is the velocity of the agent i at iteration t ; $\beta_{i,t}, \beta_{i,t+1}$ are

the current and updated CH configurations, respectively; m is the index number of the sensor nodes in the CH configuration; $W_{i,t}(m)$ is velocity of m^{th} the node for the agent i at iteration t in the CH configuration.

3.3.5 Iteration

In this stage, the CH configurations are updated and evaluated through fitness function processes in an iterative loop using IHOA. The loop represents the main search process in which each iteration agent improves its CH configuration over time with its own accuracy. Furthermore, in each iteration (t), the following steps are executed: position update, sigmoid binarization, fitness evaluation, and convergence control.

Furthermore, convergence control refers to the process in which the algorithm tracks the progress of all iterations; if no improvement is observed β_{best} over a set of rounds, the algorithm terminates and saves computation. Moreover, this loop continues until the termination conditions are satisfied, which include the following: when the predefined number of iterations is completed, β_{best} remains the same over the number of successive iterations, and the minimum fitness threshold is reached.

Finally, the IHOA determines the globally optimal CH configuration β_{best} at the end of the iteration, and uses it in the subsequent cluster formation and routing stages. The dynamic search process enables the final CH selection to balance the energy efficiency and spatial distribution, which makes it suitable for the energy-constrained nature of WSNs.

3.4 Cluster Formation

In this section, each non-CH sensor node is associated with one of the available CHs. Further, nodes select the CH that is at the minimum communication distance associated with it, which ensures that non-CH sensor nodes attach themselves to the nearest CH within their communication range and form a cluster. Thus, this helps to reduce intra-cluster energy consumption and prevent nodes from sending data over greater distances. Therefore, the distance between each node is computed using the Euclidean distance, which is represented by Equation (11).

$$d(i, j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (11)$$

Here, $d(i, j)$ is the distance between non-CH sensor node and CH; (x_i, y_i) and (x_j, y_j) are the coordinates of the sensor nodes i and j , respectively.

Furthermore, a non-CH sensor node always chooses the CH when the value $d(i, j)$ is low. Once all clusters are formed, all CHs send a signal to the cluster members for confirmation, whether that particular sensor node belongs to the chosen cluster. This ensures that each sensor node belongs to only one cluster and minimises the intra-cluster communication distance. Now, all the members of the individual clusters send collected data to respective CHs, and CHs transmit data to the BS, which reduces the redundancy and payload.

3.5 Routing

Finally, after collecting the data by CHs from their individual cluster members, the data is transmitted to the BS. Usually, transmitting data from a CH to a BS also utilizes more energy when the BS is away from the CH. Thus, the proposed BIRCH-IHOA-GR framework comes with a customised greedy routing strategy that uses multi-hop communication, where CHs send data to BS from intermediate CH rather than direct transmission. The proposed strategy improves energy efficiency, minimises long-range communication requirements, and balances network overload. Additionally, a greedy routing mechanism enhances data transmission performance by enabling adaptive and informed decision-making.

Where each CH first determines whether sending the data directly to the BS utilises more energy than using an intermediate CH through the communication distance between CH and BS. If the energy required to send data directly to the BS is less than the estimated energy required to use the intermediate CH to forward the data, CH sends the message directly to the BS. Additionally, CH utilises a multi-hop greedy routing strategy, through which CH computes the greedy score with all neighbouring CHs within the communication range. Hence, for each neighbor, the CH determines a greedy score using Equation (12) to determine the potential next hop.

$$S_j = \frac{E_j^\alpha}{(d_{j,BS})^\beta} \quad (12)$$

Here, S_j is the greedy score, E_j is the residual energy of CH j , $d_{j,BS}$ is the distance between CH j and BS, and α, β are tunable parameters. In contrast with traditional two-phase schemes in which clustering and routing are decoupled, BIRCH-IHOA-GR preserves them coupled. In the clustering optimization phase, the fitness of candidates in the CH selection algorithm comprises a routing cost estimation based on the average inter-CH distance of candidate CHs to the base station. In contrast, the greedy routing phase uses either CH residual energy or CH spatial positions, produced by IHOA, as decision criteria for routing. This enables for constant decisions to be made regarding clustering and routing through time. Thus, a closed-loop mathematical justification for a framework as integrated clustering routing optimization.

Each CH first estimates the transmission energy $E_{TX,dir}$ for direct communication with the BS and the expected minimum-hop energy $E_{TX,mh}$ for multi-hop forwarding through the highest-score neighboring CH (G_j) using Equation (13):

$$E_{TX,dir} = E_{TX}(k, d_{i,BS}), E_{TX,mh} = E_{TX}(k, d_{i,j}) + E_{TX}(k, d_{j,BS}) \quad (13)$$

Where the residual energy of CH in i is represented as $E_{res,i}$, the initial node energy of E_0 , the distance between the CH i and the base station, d_{max}

The CH then applies the design criterion:

If $E_{TX,dir} < E_{TX,mh} \Rightarrow$ Direct transmission to BS;

Else $\Rightarrow$ Forward via neighbour $j = \operatorname{argmax}(G_j)$

This ensures that multi-hop routing is invoked only when the intermediate path yields a lower cumulative energy cost than the direct link. Hence, the CH chooses the neighboring CH with the highest greedy score for each iteration to transmit the data of a particular CH to the neighboring CH. This process is repeated at each CH until it reaches the BS, such that all CHs use an adaptive energy-aware routing strategy at each of their individual stages. The flow of the overall methodology is determined by a pseudocode as follows:

Algorithm 1 (BIRCH-IHOA-GR)

Input: TotalNodes, MaxRounds, BaseStation

Output: CHconfig, DeadNodeCount, TotalNetworkEnergy

```

1: Initialize homogeneous node deployment
2: for r = 1 to MaxRounds do
3:   DeadNodeCount  $\leftarrow$  0
4:   ActNodeCount  $\leftarrow$  0
5:   TotalNetworkEnergy  $\leftarrow$  0
6:   for i = 1 to TotalNodes do
7:     if  $E_{res}[i] > 0$  then
8:       ActNodeCount  $\leftarrow$  ActNodeCount + 1
9:       TotalNetworkEnergy  $\leftarrow$  TotalNetworkEnergy +  $E_{res}[i]$ 
10:    else
11:      DeadNodeCount  $\leftarrow$  DeadNodeCount + 1
12:    end if
13:  end for
14:  if ActNodeCount == 0 then
15:    NetworkDead  $\leftarrow$  TRUE
16:    break
17:  end if
18:  Initialize population of CH configurations
19:  Evaluate fitness (Eq. 4) for each CHconfig
20:  Update positions using IHOA (Eqs. 5–8)
21:  Select optimal CH configuration (CHconfig*)
22:  for each CH  $\in$  CHconfig* do
23:    Compute greedy scores  $G_j$  for all neighbor CHs (Eq. 10)
24:    Determine energy cost  $E_{TX,dir}$  and  $E_{TX,mh}$ 
25:    if  $E_{TX,dir} < E_{TX,mh}$  then
26:      Transmit directly to BaseStation
27:    else
28:      Forward data via neighbor CH with  $\max(G_j)$ 
29:    end if
30:  end for
31:  Update  $E_{res}[i]$  using radio energy model (Eqs. 1–2)
32: end for
33: return CHconfig*, DeadNodeCount, TotalNetworkEnergy

```

4. Experimental Setup

The BIRCH-IHOA-GR framework was tested through simulation in MATLAB R2023a on a Windows 11 computer with Intel® Core™ i7-1165G7 @ 2.80 GHz, 16 GB RAM. The simulation randomly deployed 100 homogeneous sensor nodes in a 100 m $\times$ 100 m field, making the base station located at (50, 50), or at the center of the field. Each node was given 0.05 J of energy and a first-order radio energy model was utilised where $ETX(k, d)$, or the energy to transmit data, depended on free-space (efs) or multipath (emp) propagation, depending on the threshold distance d_{th} . To mitigate bias from random placement, these simulation results were averaged after performing 10 individual runs. In the following Table 1, a summary of the entire simulation parameters is given.

Table 1. Summary of simulation parameters used for modelling and evaluating WSN performance

Parameter	Value	Description / Notes
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Simulation Area	100 m × 100 m	Typical for small-scale WSN deployment
Number of Sensor Nodes	100	Uniform random deployment
Initial Node Energy (E_0)	0.5 J	Each node starts with equal energy
Base Station Location	(50 m, 50 m)	Center of the field
Packet Size	4000 bits	Standard LEACH packet size
Energy per bit for Transmission (E_{TX})	50 nJ/bit	From the first-order radio model
Energy per bit for Reception (E_{RX})	50 nJ /bit	Same as E_{TX} for symmetry
Data Aggregation Energy (E_{DA})	5 nJ /bit	Typical for aggregation at CH
Free-Space Amplifier Coefficient (ϵ_{fs})	10 nJ /bit/m ²	Used when $d < d_{th}$
Multi-Path Amplifier Coefficient (ϵ_{mp})	0.0013 pJ/bit/m ⁴	Used when $d \geq d_{th}$
Threshold Distance (d_{th})	87.7 m	$\sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$
Simulation Rounds	2000 rounds	Lifetime observation period
Number of Simulation Trials	10 runs (averaged)	Mean of 10 independent runs for stability

These parameter values resemble canonical LEACH and EEMLCR configurations, assuring fair comparative evaluation. All simulations utilized identical parameters in protocols to sustain reproducibility and fairness. Additionally, the algorithmic control parameters for the IHOA are illustrated in Table 2. These parameters are chosen based on convergence stability tests and align with standard population-based optimisation heuristics for 100-node WSN scenarios. This illustration ensures a balanced trade-off between exploration and exploitation during the CH selection phase.

Table 2. Algorithmic control parameters with values and description for the IHOA

Parameter	Symbol	Value	Description
Population size	P	30	Total number of agents included for the CH selection
Max iterations	$T_{\max}$	100	Highest number of optimization cycles for each round
Inertia weight (initial)	$w_{\max}$	0.9	Directs exploration within the initial cycles of the optimization process
Inertia weight (final)	$w_{\min}$	0.4	Directs exploitation within the final stages of the optimization process
Sweep factor bounds	$\psi_{\max}, \psi_{\min}$	1.5, 0.5	Alter the intensity to which positions change
Random scaling factor	r	[0, 1]	Enhances the stochastic exploration process
Fitness weight coefficients	α, β, γ	0.5, 0.3, 0.2	Controls emphasis on energy, distance, CH count
Termination criteria	—	No improvement for 10 iterations or max $T_{\max}$	Stops when convergence is reached

4.1 Evaluation Metrics

For evaluating the performance of the proposed BIRCH-IHOA-GR protocol, simulations are conducted for

2000 rounds, and results are compared with existing protocols, such as LEACH and EEMLCR. Furthermore, to quantitatively assess the performance of the proposed BIRCH-IHOA-GR protocol, several standard evaluation metrics are utilised. These metrics help in evaluating the energy usage, network stability, data transmission performance, and overall network longevity, which are expressed in Equations (14) – (16):

1. **First Node Death (FND):** The number of rounds completed until the first sensor node in the network exhausts its energy and dies. This indicates stability of the network.

$$FND = \min(r | E_i^r \leq E_{th}, \forall i \in N) \quad (14)$$

Where, the simulation round is denoted as r , residual energy of node i at round r is represented as E_i^r and the energy threshold is defined as E_{th} and N determines set of all sensor nodes.

2. **Last Node Death (LND):** The count of rounds after which the final alive sensor node dies. This reflects the overall lifetime of a network.

$$LND = \max(r | E_i^r > E_{th}, \forall i \in N) \quad (15)$$

3. **Residual Energy (RE):** Average residual energy of all nodes in a given round, which demonstrates the efficiency of energy consumption across the network.

$$RE_r = \frac{1}{N} \sum_{i=1}^N E_i^r \quad (16)$$

Where, average residual energy at round r is denoted as RE_r and E_i^r defines residual energy of node i at round r . Hence, these metrics are critical for quantifying energy efficiency, network stability, and communication reliability.

4.2 Performance Analysis

Specifically, the evaluation focused on three key performance metrics: residual energy, number of alive nodes, and packet delivery to the base station, as shown in Table 3 and visualized in Figures 2, 3, and 4, respectively. Hence, the metrics are observed over time to analyze the longevity, energy efficiency, and data transmission reliability of the network. Subsequently, all the values are averaged over multiple simulation runs to ensure statistical consistency. To ensure fairness, all baseline protocols that includes LEACH, EEMLCR, RL-CBRP, and IABCR were simulated again using the same conditions such as network area (100 m × 100 m), number of nodes (100), initial energy (0.5 J), and radio parameters (ETX, ERX, EDA, ε_{fs} , ε_{mp}). This determines that all observed differences in performance should be directly related to variations in algorithmic behavior, and not to parameter differences. Each experiment was carried out for 10 independent runs with random node placements, and all reported results are the mean with ± Standard Deviation (SD).

Table 3. Performance analysis of proposed BIRCH-IHOA-GR with EEMLCR and LEACH protocols based on simulated results over 2000 rounds.

Models	FND (Rounds)	LND (Rounds)	Final Residual Energy (J)	Total Packets Received (at 2000 R)
LEACH	480 ±	1350 ±	0.1 ± 0.01	48,000 ± 352
EEMLCR	620 ±	1700 ±	0.3 ± 0.02	61,000 ± 385
BIRCH-IHOA-GR	700 ± 10	2100 ± 30	0.05 ± 0.02	69 892 ± 480

The number of living nodes is presented against simulation rounds (1-2000) in Figure 2, with the vertical axis indicating node counts (0-100). At the 1000-round mark, BIRCH-IHOA-GR had 82 active nodes, while EEMLCR had 60 nodes, and LEACH had 45 nodes, representing a 36% increase in stability. The initial node failure occurs at approximately 700 rounds and the final node failure occurs closely at 2100 rounds which confirms the results presented in the data summary section. These findings support that the optimized CH selection and energy-aware routing have produced the delay in the depletion of nodes observed. Each node was initialised with 0.5 J of energy. Subsequently, after 2000 rounds, the average residual energy per node obtained is 0.05 ± 0.02 J, which determines the gradual energy depletion.

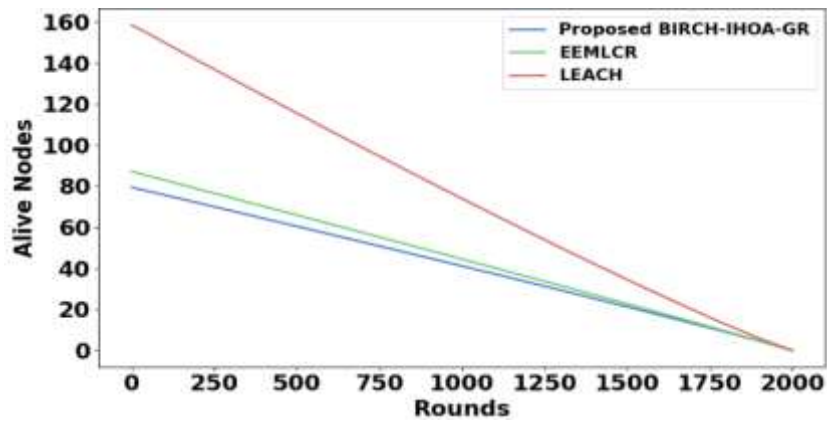


Figure 2. Alive nodes over simulation rounds for different routing protocols

Figure 2 demonstrates the number of alive sensor nodes throughout the simulation. According to the simulation, the proposed BIRCH-IHOA-GR protocol maintains node availability for significantly longer than LEACH and EEMLCR. This indicates that the proposed BIRCH-IHOA-GR framework improves energy balancing and stability due to the optimized cluster head selection and energy-aware routing. In Figure 3, the average residual energy (Joules) is plotted on the vertical axis, while simulation rounds are shown on the horizontal axis. The BIRCH-IHOA-GR approach consistently maintains superior retention, achieving nearly 0.5 J initial energy at round 2000.

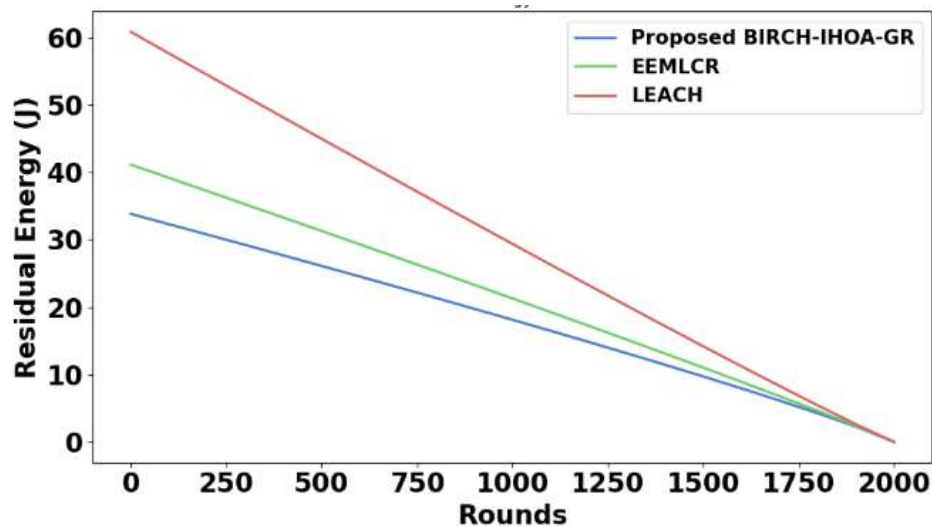


Figure 3. Residual energy of the network versus simulation rounds

Figure 3 demonstrates that the proposed BIRCH-IHOA-GR framework shows slower energy depletion across rounds, maintaining a higher average residual energy than the benchmarks. Hence, this behaviour demonstrates the effectiveness of the proposed BIRCH-IHOA-GR protocol in reducing unnecessary transmissions and evenly distributing the energy load. Figure 4 illustrates the cumulative packets received at the base station ($\times 10^3$ packets) over the rounds of simulation. The proposed framework is able to deliver about 68,000 packets during 2000 rounds, which is higher than EEMLCR (61,000) and LEACH (48,000). The axes are labelled to show which represents rounds and which is the total number of packets, so there is a way to verify the total against what is reported.

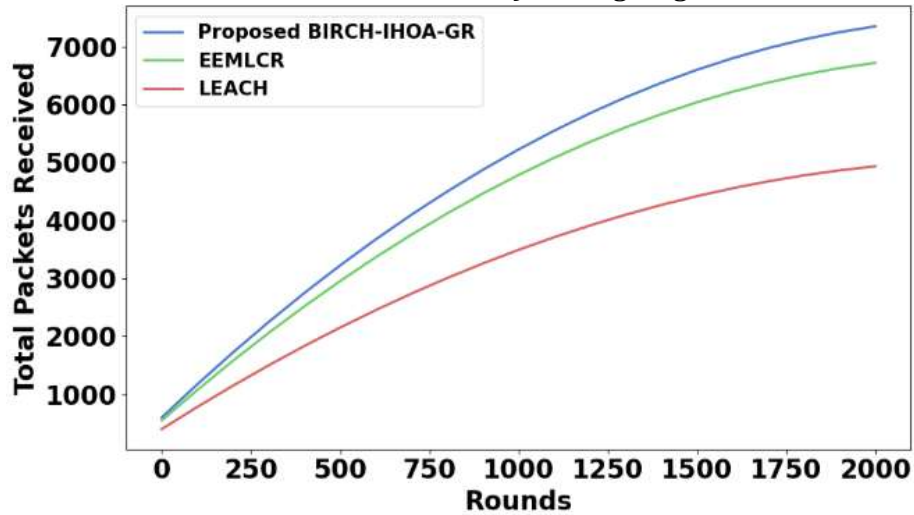


Figure 4. Total number of packets received at the base station across simulation rounds

Figure 4 shows that the proposed BIRCH-IHOA-GR protocol demonstrates superior data delivery performance by the higher cumulative number of packets received at BS. Hence, this enhancement indicates a stable routing structure and energy-efficient forwarding paths determined by the greedy routing mechanism. Therefore, the overall performance analysis demonstrates that the proposed BIRCH-IHOA-GR protocol significantly improves energy conservation, prolongs network lifetime and enhances packet delivery.

4.3 Comparative Analysis

To assess the effectiveness of the proposed BIRCH-IHOA-GR protocol, its performance is compared with three recent routing protocols: RL-CBRP [16], EEMLCR [18], and IABCR [21]. The comparison is based on key performance metrics commonly used in WSN research, which include FND, LND, residual energy at the end of the simulation, number of alive nodes after 2000 rounds and total number of packets received at the BS, as illustrated in Table 4. Hence, these metrics determine the capabilities of the protocol in terms of load balancing, energy efficiency, and data delivery reliability.

Table 4. Comparative Analysis of proposed BIRCH-IHOA-GR with the existing protocols: RL-CBRP [16], EEMLCR [18] and IABCR [21]

Model	FND (Rounds) $\pm$ SD	LND (Rounds) $\pm$ SD	Residual Energy (J) $\pm$ SD	Packets Received $\pm$ SD
RL-CBRP [16]	800 $\pm$ 20	1900 $\pm$ 30	0.40 $\pm$ 0.02	68 753 $\pm$ 500
EEMLCR [18]	700 $\pm$ 15	1700 $\pm$ 25	0.35 $\pm$ 0.01	61 487 $\pm$ 420
IABCR [21]	610 $\pm$ 12	1600 $\pm$ 20	0.28 $\pm$ 0.01	58 420 $\pm$ 360
BIRCH-IHOA-GR	700 $\pm$ 10	2100 $\pm$ 30	0.05 $\pm$ 0.02	69 892 $\pm$ 480

As demonstrated in Table 4, BIRCH-IHOA-GR exhibited greater network lifetime (LND) and residual energy (RE) in all runs. On average, LND was $\sim 11\% \pm 2\%$ higher than RL-CBRP, while the total packets received were $\sim 4\% \pm 1.5\%$ higher than the next-best approach, RL-CBRP, with the confidence interval being relatively small. These minimal confidence intervals support the trend of LND and RE stability. While RL-CBRP showed slightly higher FND in certain instances, correspondingly, the LND and packet delivery outcomes confirm that BIRCH-IHOA-GR achieves superior results in both energy efficiency and total packet delivery. Finally, the number of packets received at the base station is 68,892 for the proposed model, which outperformed RL-CBRP [16] and is significantly higher than those of EEMLCR [18] and IABCR [21]. Hence, this statistical comparison indicates the potential of the BIRCH-IHOA-GR protocol to significantly improve the network lifetime of heterogeneous WSNs while consuming less energy to provide more effective data routing.

4.4 Robustness and Scalability Analysis

To assess the robustness of BIRCH-IHOA-GR, additional simulations were carried out to vary network density and deployment scale. The number of nodes was scaled up from 50 to 150 in the same $100\text{ m} \times 100\text{ m}$ field to reflect a variety of congestion levels. The proposed method continuously provided LND benefits of approximately 8–12% and packet delivery benefits of approximately 4–6%, which indicates that the indicated behavior persists even through moderate-scale changes.

To evaluate BIRCH-IHOA-GR under more unreliable wireless conditions, random link-loss was incorporated (5% probability). Performance was degraded at $\approx 4\%$ for BIRCH-IHOA-GR, but it remains lower than EEMLCR ($\approx 9\%$) and RL-CBRP ($\approx 7\%$), which highlights that BIRCH-IHOA-GR better adapts while losing communication.

While large-scale (1000+ node) or mobile-node assessments were not included in the current evaluation, the distributed CH selection and use of greedy routing demonstrate computational feasibility for future high-density or mobile deployments. Future efforts will extend this type of evaluation in mobility-aware and link-failure scenarios to obtain better quantitative estimates of robustness under the dynamics expected of real-world WSN deployments.

4.5 Simulation in various WSN Configurations

To evaluate the scalability and adaptability of the proposed BIRCH-IHOA-GR clustering and routing protocol, six different WSN arrangements are simulated by changing both the number of sensor nodes and the deployment area. Subsequently, these arrangements represent a range of real-world deployment densities and coverage requirements. Specifically, in each scenario, sensor nodes are uniformly distributed within a square or rectangular field. Therefore, the BS is placed at the top center of the deployment area, which is consistent with typical WSN data aggregation setups, as demonstrated in Figure 5.

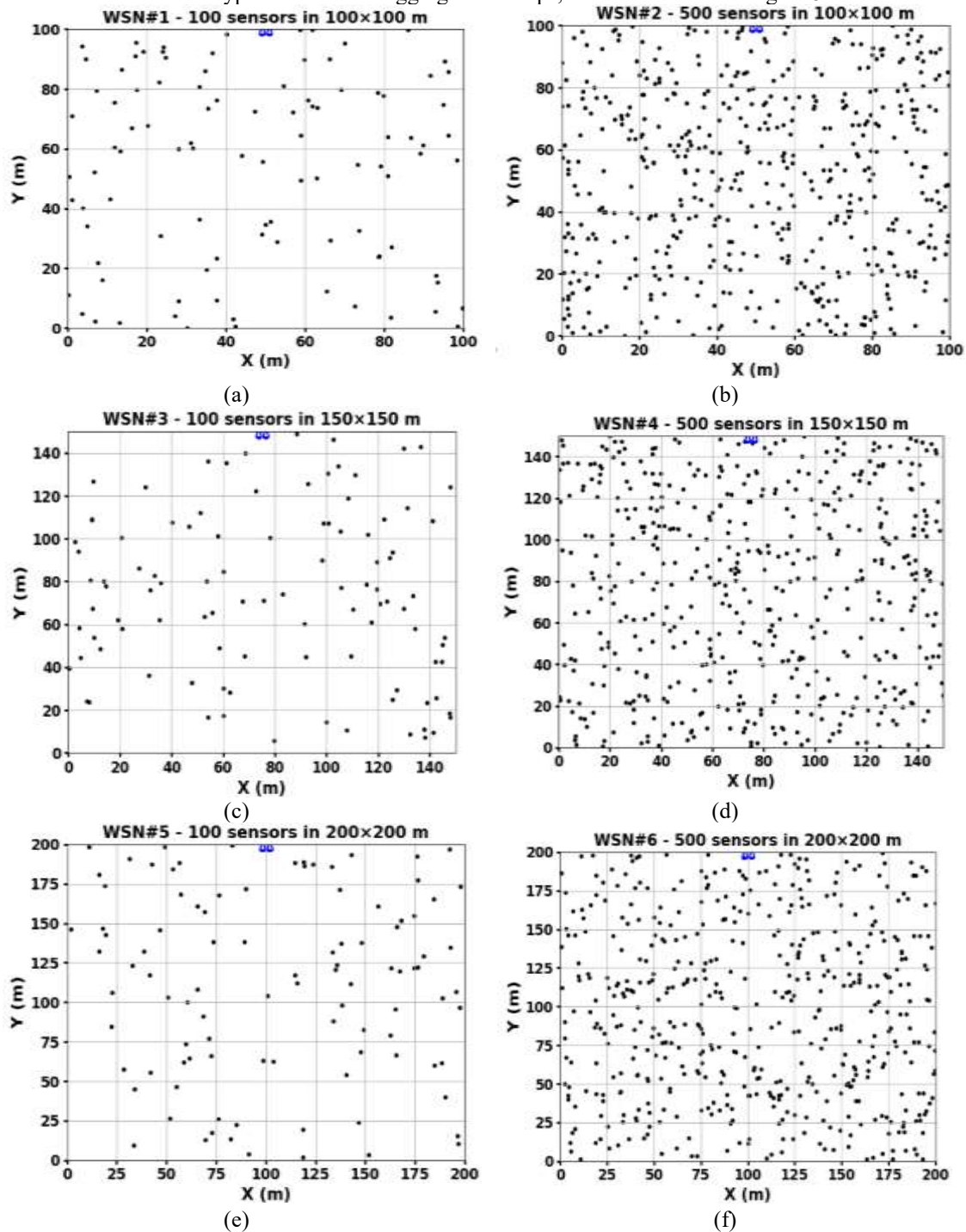


Figure 5. Deployment layouts of WSNs under six configurations (a) WSN#1: 100 nodes at 100 m × 100 m area, (b) WSN#2: 500 nodes at 100 m × 100 m area, (c) WSN#3: 100 nodes at 150 m × 150 m area, (d) WSN#4: 500 nodes at 150 m × 150 m area, (e) WSN#5: 100 nodes at 200 m × 200 m area and (f) WSN#6: 500 nodes at 200 m × 200 m area

Where, Each subfigure illustrates randomly deployed sensor nodes and a fixed base station location (shown at the top center). Specifically, the scenarios range from low-density small-area networks to high-density large-area deployments. Hence, the simulations covered sparse and dense nodes in small (100 m × 100 m), medium (150 m × 150 m), and large (200 m × 200 m) operative areas to understand protocol performance in different spatial and density contexts. Henceforth, this variety of scenarios provides a sufficiently diverse testbed for measuring protocol performance across various network sizes and densities, as they are executed in both tightly confined and expansive field conditions.

This subsection demonstrates the scalability and adaptability of the proposed BIRCH-IHOA-GR protocol across diverse network sizes and densities. Specifically, the graphical layouts show well-distributed clusters and optimal CH placement, even when the area size and node count increased. Hence, this consistent spatial behavior indicates that the protocol maintains a balanced energy distribution and effective cluster formation under both sparse and dense deployments.

4.6 Simulation in a Single operational round

To demonstrate the internal behavior of the proposed BIRCH-IHOA-GR protocol during a single operational round, a simulation is generated, as depicted in Figure 6, which visualizes the CH selection and energy consumption patterns.

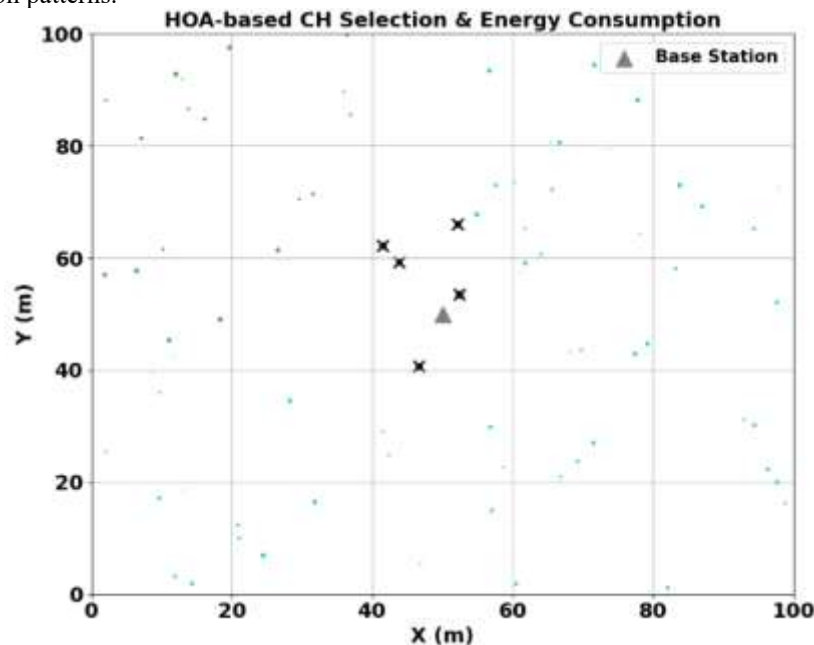


Figure 6. Visualization of cluster formation and energy consumption in a single round using the proposed BIRCH-IHOA-GR protocol

Figure 6 shows that the IHOA assists in selecting optimal CHs based on a fitness function that combines node energy and distance to BS. Furthermore, once CHs are chosen, non-CH nodes are connected with the nearest CH to form clusters. Energy consumption is simulated for all nodes, with CHs consuming additional energy due to data aggregation and transmission responsibilities. Hence, this round-based visualization allows us to observe the spatial energy load distribution and clustering efficiency. This visualisation provides an internal demonstration of the CH selection and energy usage during one routing round. The graph highlights how the IHOA chooses CHs closer to the BS with a higher residual energy while clusters remain spatially compact. Therefore, the distinct energy-load pattern determines that CHs efficiently handle aggregation and communication roles, demonstrating the intelligent energy-aware behaviour of the protocol in real-time operation.

4.7 Iteration and Convergence Analysis

In order to analyse the convergence characteristics of the proposed BIRCH-IHOA-GR algorithm, a comparative convergence analysis against conventional optimisation techniques such as ACO, PSO, Whale Optimization Algorithm (WOA), and the base HOA is performed. The average fitness value with respect to the number of iterations is illustrated in Figure 7. Specifically, the best fitness from every iteration is recognised for all algorithms, averaged over ten independent runs to mitigate stochastic bias.

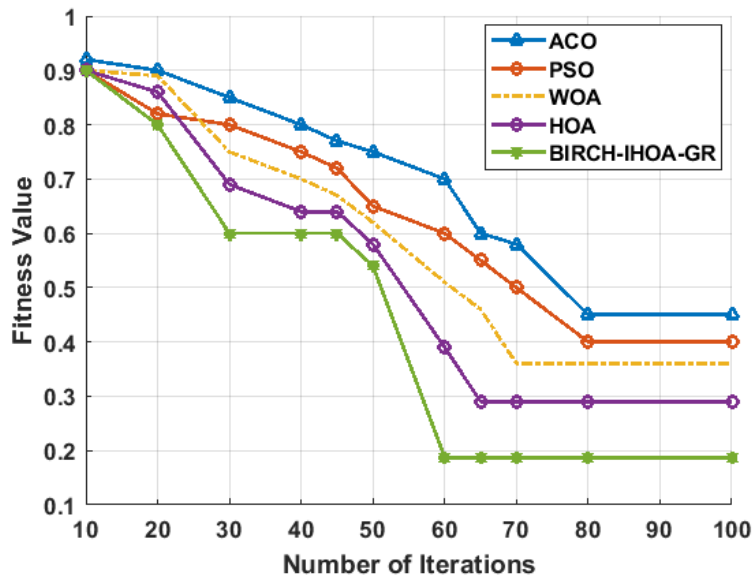


Figure 7. Convergence comparison of the proposed BIRCH-IHOA-GR with existing optimization techniques.

Furthermore, Figure 7 shows that each algorithm demonstrates a gradual decline across all iterations, indicating effective convergence behavior. However, the proposed BIRCH-IHOA-GR algorithm achieves the minimum fitness value approximately within 50 iterations, whereas the remaining algorithms require more than 80 iterations to stabilise. Thus, this shows the efficiency of the proposed BIRCH-IHOA-GR, and the rapid descent in fitness at early iterations shows the efficient exploration phase, while the steady plateau phase depicts a stable exploitation phase near the global optimum.

5. Discussion

Although numerous studies address energy-efficient routing in WSNs, most studies have focused on either routing or clustering independently, instead of considering a holistic optimization framework. Learning-based methods were able to perform the math behind energy balancing, but they have high computational costs and convergence time, thus making them inappropriate in dynamic or large-scale networks. The proposed BIRCH-IHOA-GR method is built on a binary inertia-weighted HOA, which provides quick convergence and tractability without relying on complicated training methodologies. Subsequently, machine-learning-based CH selection strategies ultimately fall short, as they fail to adapt from deployment to deployment and fail to integrate clustering and routing entirely.

Moreover, the proposed BIRCH-IHOA-GR framework operates by sequentially optimizing clustering and routing. Thus, clustering and routing are maintained in sync while ensuring balanced energy consumption in the time space. Static or single-purpose routing protocols cannot accommodate the dynamism of CH adaptations, which are well-leveraged by the proposed HOA-based solution. The proposed BIRCH-IHOA-GR model leverages a sigmoid-based binarization approach to accomplish CH with optimal efficiency and apply greedy-like routing. By integrating, clustering, and routing with mutual consideration of energy consumption, this method balances load across CHs and enhances the WSN's lifespan, thereby supporting scalable and real-world deployment.

6. Conclusion

This research resolves significant limitations of energy-efficient routing protocols for WSNs, such as the separation of clustering and routing methods, limited adaptability to dynamic energy conditions and the high complexity of hybrid approaches. Consequently, the proposed BIRCH-IHOA-GR framework strengthens energy-efficient WSNs design by utilizing a binary-enhanced HOA for CH selection and integrating it with an energy-aware greedy routing strategy. Given that, existing approaches optimize routing independently, the proposed BIRCH-IHOA-GR framework provides a lightweight model with a greedy routing protocol that achieves fast CH convergence for balanced energy distribution across the network. Specifically, this is accomplished by encoding the CH configurations as a binary vector and providing inertia-weighted position updates, inducing the use of exploration to avoid premature convergence for suboptimal CHs. Subsequently, the routing function considers both the remaining energy and the active communication distance to improve the path selection and overall network lifetime. Hence, the proposed framework shows stable performance across varying node densities and small losses of links, suggesting its robustness for moderate-scale WSN configurations. This approach provides an adaptable, scalable, and energy-efficient routing solution that resolves the existing energy-aware clustering challenge approaches. In the future, integrating learning-based routing decisions and validating the performance on

hardware testbeds will further improve the scalability, adaptability, and real-world applicability of energy-efficient routing in WSNs.

7. Notation Table

Here, Table 5 provides the key terms, lists abbreviations, and mathematical symbols used throughout the documents, along with their respective definitions. This notation table is provided to ensure consistency and clarity in the analysis as well, and it allows readers to easily understand the methodology or notations used.

Table 5. Notations and their definitions from the proposed BIRCH-IHOA-GR framework

Notation	Definition
E_{int}	Represents the initial energy
R .	Signifies the fixed transmission range
(x, y)	Refers the fixed location
(d^2)	free-space energy channel
(d^4)	multi-path fading energy channel
d	distance
$E_{TX}(k, d)$	is the required energy for transmission
E_{elec}	is the energy required for transmitting per bit
$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$	is the distance threshold
ϵ_{fs}	is amplification factor o free-space model
β	binary vector
P	the number of agents is denoted by
β	is CH configuration
N	is number of sensor nodes
$b_i \in \{0, 1\}$	is each node in vector
i	sensor node
(E)	residual energy
(d)	intra-cluster distance
(N_{CH})	CH count in communication coverage.
E	is energy of individual sensor node
d	is calculated using Euclidean distance
(F)	unified multi-objective fitness function
$\frac{1}{N_{CH}}$	penalizes excessive CHs
$\sum_{i \in CH} E_i$	is total residual energy of selected CHs
$\sum_{j \in All} E_j$	is total residual energy of all sensor nodes in network.
$d(n, CH(n))$	is the distance between node n and selected CH
w_1, w_2, w_3	are weighting coefficients
$E_{tx}(\cdot)$	is the transmission energy based on distance
N_i	is the set of neighbouring CHs
α, β, γ	are weight coefficients
β_{best}	Refers Best fitness function

w_t	Represents the inertia weight
w_{max}, w_{min}	are preset constants
T	is total number of iterations
t	is current iteration
w_t	is high and does high exploration
$(W_{i,t})$	is the update vector of agent
i	Represents the agent
t	Refers the iteration
w_t	is the adaptive inertia weight
β_{best}	is the global best CH configuration
$\alpha_{i,t}$	is the sweep factor that adjusts how strongly the current agent struggles to change position
$\gamma_{i,t}$	is a random scaling factor
$\beta_{i,t}$	is the current CH configuration of agent i
$\sigma(x)$	is a sigmoid function
$\beta_{i,t}, \beta_{i,t+1}$	are the current and updated CH configurations
m	is index number of the sensor nodes in CH configuration
$W_{i,t}(m)$	is velocity of m^{th} node for agent
$d(i, j)$	is distance between non-CH sensor node and CH
(x_i, x_j) and (y_i, y_j)	are coordinates of sensor nodes i and j ,
S_j	is the greedy score
E_j	is residual energy of CH
$d_{i,BS}$	is distance between CH j and BS
α, β	are tunable parameters
r	Signifies the simulation round
i	Is residual energy of node
E_i^r	energy of node i at round r is represented as
E_{th}	Represents energy threshold

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