Energy-Efficient Cluster Head Rotation in WSNs Using Bee Colony Optimization

Azamuddin Bin Ab Rahman, Sakib Iqram Hamim
Faculty of Computing, Universiti Malaysia Pahang Al-Sultan Abdullah, Pahang, 26600, Malaysia

***Abstract*—In this study, we present a method designed to improve energy efficiency and balance the workload across Wireless Sensor Networks (WSNs). Our approach dynamically selects and rotates cluster heads (CHs) based on factors such as remaining energy, node mobility, distance to the base station, and data processing needs. By focusing on nodes with more energy and lower mobility, we aim to extend the network's operational life and prevent any single node from being overburdened. At the heart of our method is the Artificial Bee Colony (ABC) optimization algorithm, which mimics the foraging behavior of bees. This algorithm helps to identify the best nodes to act as CHs, balancing the energy load across the network and maintaining strong connectivity within clusters. Our simulations show that this method outperforms existing protocols like FEEC and PSAP-WSN, particularly when it comes to distributing energy more evenly and extending the network's lifespan. By continuously rotating the CHs, we ensure that energy consumption is spread out, leading to improved network performance and sustainability. The results indicate that this dynamic and adaptive approach is highly effective in maintaining a balanced energy distribution, making it a robust solution for energy management in WSNs.**

Keywords*—*Energy efficiency; load balancing; cluster head rotation; bee colony optimization; metaheuristic clustering; Wireless Sensor Network

I. Introduction

WSNs are becoming a crucial part of modern life, helping us in areas like environmental monitoring, healthcare, and even the development of smart cities [1]. These networks, made up of small sensor nodes, are designed to collect and send data, often operating in places where it's difficult for humans to reach [2]. But despite their usefulness, WSNs face a major challenge. Their nodes run on limited battery power, and managing this energy efficiently is key to keeping the network alive for as long as possible. One of the biggest problems comes from the cluster heads (CHs), which handle most of the heavy lifting by collecting and transmitting data. Since these CHs use more energy than other nodes, they tend to drain their batteries faster, which can shorten the overall network's lifespan [3].

To solve this issue, researchers have been focusing on ways to make energy use more balanced across the network [4]. One promising idea is to rotate the CH role among different nodes, which helps spread out the energy consumption more evenly and prevents any single node from wearing out too quickly. This technique has been proven to extend the life of WSNs by avoiding the early failure of key nodes like CHs.

Artificial intelligence (AI) techniques are playing an increasingly important role in improving how WSNs function [5]. By applying smart algorithms, we can tackle a range of challenges, like managing energy use more efficiently, gathering data more effectively, and detecting potential faults before they become serious problems. Machine learning, for example, helps predict when parts of the network might fail or when energy is being used inefficiently, allowing us to adjust ahead of time to keep the network running longer [6]. Similarly, nature-inspired methods, like swarm intelligence, are being used to better decide which sensor nodes should take on more demanding roles, such as cluster heads [7]. This ensures that energy is shared more evenly among all the nodes, which helps the network stay alive and operate smoothly over time. However, there are some downsides to using AI in these networks. Many AI techniques [8] are quite complex and require a lot of computing power, which can be a big problem since WSNs often work in environments where resources are limited. In addition, these algorithms usually need a large amount of data to learn from, and it might not always be possible to gather that data in real-time.

More recently, nature-inspired algorithms have shown great promise in addressing this problem. Algorithms like the Artificial Bee Colony (ABC) mimic the way bees work together to find food, using this behavior as a model for selecting CHs more effectively [9]. By rotating the CH role based on factors like energy levels and proximity to other nodes, these methods help keep the network running smoothly and efficiently for a longer time [10].

In this study, we propose a new approach for choosing CHs in WSNs using the ABC optimization algorithm. Through simulations and detailed analysis, we show how this method not only balances the energy load across the network but also helps the network last longer.

The rest of the study is organized as follows: Section II looks at the related works, Section III describes the system model, and Section IV details the PSAP-WSN CH selection with ABC. Section V presents the results and analysis, and Section VI wraps up the study.

II. Related Work

WSNs have become a cornerstone in the development of Internet of Things (IoT) applications, particularly in areas where scalable and energy-efficient communication is critical [11]. The primary challenge in WSNs lies in maintaining energy efficiency while ensuring scalability and reliability [12].

Various multi-tier clustering frameworks and load balancing protocols have been proposed to address these challenges. This systematic literature review explores key contributions in this area, analyzing the effectiveness of multi-tier clustering and load balancing strategies in WSNs and their impact on network lifetime, scalability, and energy efficiency.

Multi-tier clustering frameworks have gained significant attention due to their ability to manage large-scale networks by breaking them into smaller, manageable segments. Shukla and Tripathi (2020) presented a multi-tier-based clustering framework aimed at enhancing the scalability and energy efficiency of WSN-assisted IoT networks [13]. Their approach focused on distributing the network load across multiple tiers, thus minimizing long-distance communication and transforming it into shorter, more manageable hops. This method not only conserved energy but also improved the network's overall scalability by ensuring that sensor nodes operate within their energy constraints, thereby extending the network's lifetime.

Several algorithms have been proposed to address this issue, including Sparrow Search Algorithm (SSA), Grey Wolf Optimization (GWO), and Bat Algorithm (BA) [14]. While these approaches offer notable improvements in energy consumption and CH selection, the Artificial Bee Colony (ABC) algorithm generally outperforms them due to its superior exploration-exploitation balance and adaptability.

SSA and GWO, for instance, focus on optimizing CH selection by mimicking the behaviors of sparrows and wolves, respectively, to enhance energy efficiency and prolong network lifetime [15]. SSA uses a multi-objective approach to distribute energy consumption across nodes, while GWO employs a hierarchical approach to cluster head selection. However, both algorithms have a limited capacity to dynamically adapt to rapidly changing network conditions. SSA and GWO tend to converge prematurely on suboptimal solutions, particularly in large-scale networks, due to their deterministic search processes. In contrast, ABC, which simulates the foraging behavior of bees, allows for continuous refinement of solutions by balancing local and global search through different types of bee agents (employed, onlooker, and scout bees) [16]. This adaptability ensures that ABC maintains higher energy efficiency even as the network topology evolves.

Similarly, BA uses echolocation to explore and exploit solutions but often struggles with scalability issues in larger WSNs due to its inherent complexity [17]. ABC's iterative nature and robust exploration strategies make it more effective in preventing energy depletion across network nodes, ensuring optimal CH selection across various WSN topologies. In essence, while the algorithms referenced offer valuable contributions, ABC's dynamic adaptability, superior balance between exploration and exploitation, and energy optimization make it a more effective approach for CH selection in WSNs [18].

Golden Eagle Optimization (GEO) is a recent metaheuristic algorithm inspired by the hunting behaviors of golden eagles [19]. Its application in Wireless Sensor Networks (WSNs) focuses on optimizing the selection of CHs to balance energy consumption and enhance network longevity. Although GEO has shown effectiveness in this area by simplifying cluster topology and extending the operational lifetime of WSNs, the ant and bee colony optimization algorithms are often considered superior for certain tasks within WSNs.

Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithms are bio-inspired by the foraging behavior of ants and bees, respectively [20]. These algorithms excel in multi-objective optimization tasks and have demonstrated strong performance in dynamic and distributed network environments like WSNs. The primary reason ACO and ABC are often preferred over GEO is their inherent ability to handle large, complex networks with unpredictable changes [21]. ACO, for instance, simulates the pheromone trail-laying behavior of ants, which enables robust and efficient pathfinding in routing protocols, especially under dynamic network conditions. Similarly, the ABC algorithm, inspired by the food foraging behavior of bees, is excellent at finding globally optimal solutions through efficient exploitation and exploration strategies, particularly in optimizing energy consumption.

While GEO can optimize CH selection by imitating eagle predation, it lacks the adaptive feedback mechanisms inherent in ACO and ABC [22]. These mechanisms allow ACO and ABC to dynamically adjust their search patterns based on real-time changes in network conditions, improving resilience to node failures and mobility. Additionally, ACO's pheromone-based learning facilitates quick convergence towards the optimal path, which is crucial for time-sensitive WSN operations. Consequently, for larger and more complex WSNs, ACO and ABC often provide better scalability and adaptability than GEO, making them more suitable for real-world deployments where network dynamics are a critical concern [23].

III. The System Model

A. Network Model

Fig. 1 illustrates a network model of a 2-Tier WSN network, where S fixed number of sensors are randomly distributed in an M × M area. The network section is of two types: in direct nodes and cluster nodes. A cluster, in general, can be defined as a collection of nodes that are functioning in adjacent regions. In Tier 1, child nodes in each cluster sent the data to their respective CHs. Then, CHs collected the aggregated data from their child nodes to send them to the relay nodes. Next, relay nodes forwarded the data to the BS. Dissimilar to Tier 1, the relay nodes of Tier 2 would pass the data to the relay nodes of Tier 1 before reaching the BS. The multi-hop transmission was based on a triple-hop in Tier 1 and a quad-hop in Tier 2. The required energy of the BS during the movement is not too high, because its energy is significantly higher than that of the sensor nodes. Rounds are defined as the period where the data packets are exchanged among different groups of sensor nodes, their CH, and the data sink [24], [25].

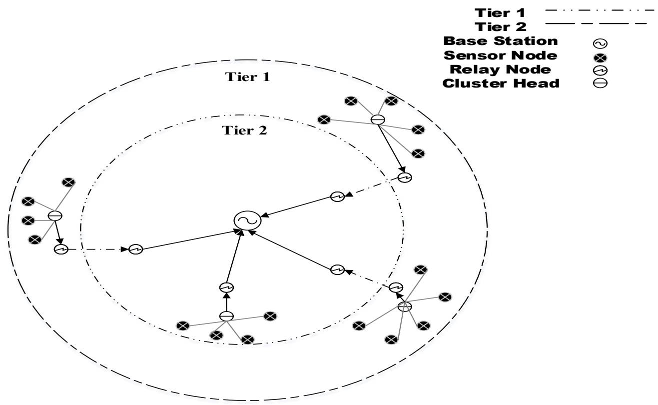

Fig. 1. 2-Tier Network model.

B. Energy Model

The constituents of the sensor node are the processing circuit, sensor interfacing circuit, and radio frequency connections. Transmission of data in WSNs consumes considerably high power and, therefore, can be considered as one of the major energy-consuming operations. Data transmission has energy loss at both the transmitter and receiver ends and the energy loss occurs at the rate of $\frac{E_{elect}}{k\ bits}$ bits. Therefore, communication network energy is utilized by both the sender and the receiver as per a specialized wireless energy consumption model, as shown in Fig. 2.

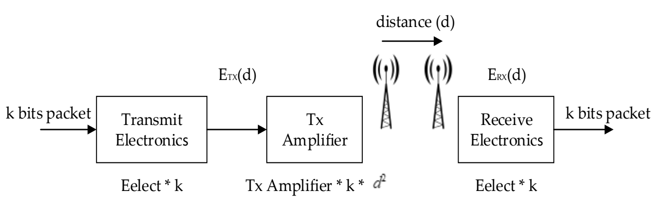

Fig. 2. Energy model.

The energy used to transmit a message of k bits over a distance of d meters is expressed in Eq. (1) below:

$$E_{TX}(k.d) = \begin{cases} k * E_{elect} + k * \varepsilon_{fs} * d^2, & d \le d_o \\ k * E_{elect} + k * \varepsilon_{mp} * d^4, & d \ge d_o \end{cases} \quad (1)$$

where, E_{elect} is the energy expended for the electronic circuit at the sender's end. The energy expended for the sensor nodes to send data through a free space channel is represented by ε_{fs}, the energy to transmit through the multipath channel is represented as ε_{mp}. The distance threshold d_o incorporates the values which are [see Eq. (2)]:

$$\sqrt{\varepsilon_{fs}/\varepsilon_{mp}} \quad (2)$$

The energy consumed to receive a message of k bits over a distance d is expressed as Eq. (3):

$$E_{RX} = k * E_{elect} \quad (3)$$

C. Proposed Technique

The proposed method for energy-aware cluster head rotation in WSNs focuses on optimizing energy efficiency and load balancing. The approach involves dynamically selecting and rotating cluster heads based on multi-factor decision-making models that consider key parameters such as residual energy, node mobility, distance to the base station, and the length of data queues. Initially, nodes with higher energy levels and lower mobility are preferred for cluster head roles to minimize energy consumption across the network.

The main idea of the proposed scheme is to balance the load among clusters, keeping in mind factors like residual energy, the amount of nodes a cluster head (CH) is connected to and the distance between the cluster head (CH) and the base station (BS), which eventually improves the availability of the network and increases the lifespan of the network. The method operates in several phases: discovery of locations and neighboring nodes, formation of initial clusters, energy-efficient balanced clustering, and identification of the rendezvous point (RP) for data collection. This energy-aware approach effectively balances the network's load by dynamically rotating cluster heads, thereby mitigating rapid energy depletion of individual nodes and improving overall network performance.

D. Location and Neighbor Identification

Imagine the deployment area as a rectangular grid with dimensions *D1* × *D2*. Each node in the network sends out its *ID* at synchronized intervals and gathers information about its nearest neighbors. This data is then stored in a list specific to each node, called N_List[i]. The Mobile Data Gathering Unit (MDGU) moves through the area following a planned route to collect details about the location, remaining energy (RE), and neighbors of each node.

The MDGU begins at a point R out of the upper-left of the area and travels to the right at spacing intervals of R√2. It proceeds in a left-to-right and top-to-bottom direction until it has occupied the whole area, depending upon the method mentioned in [26]. At each stopping point, the *MDGU* sends out a signal ("1") to all devices within range. Devices that receive the signal respond with their *ID*, location (*Xi*,*Yi*), remaining energy *REi*, and their neighbor list N_List[i].

This process allows the MDGU to gather and organize information on all devices in the area. This data is stored in a table, as shown in Table I. Initially, every node is in an "UNMARKED" state, indicated by Flag = 0. When a node is chosen as either a cluster head (CH) or a cluster member (CM), its state changes to "*MARKED*" (Flag = 1). At the same time, the neighbor pointer *NLPointei* is updated. The structure that stores data about device i at the MDGU includes *IDi,* (*Xi*, *Yi*), *REi*, Flag, and *NLPointerj*.

E. Centralized Clustering Formation Algorithm

Here, we present a centralized clustering formation algorithm that is to cluster the devices and identify the initial group of CH. The algorithm is initiated by picking the node that has the most energy to be the initial CH. All the nodes in the neighborhood list of this node (NL[i]) will constitute the first cluster. Subsequently, the status of the selected CH and its associated members is updated to "MARKED" (Flag set to 1). The process then iterates, choosing the next CH from the set of "UNMARKED" nodes with high energy, which, together with its neighbor nodes, forms the subsequent cluster. This iterative process continues until all nodes are transitioned into the "MARKED" state, as detailed in Algorithm 1.

Algorithm 1: Initial Cluster Formation

```
Input: Nodes Placement [1,…..,N]
Output: Set of 'M' CHs [1,…M]

For i=1,…N do
        Flagi = 0
End For
M = 0
While (there exists i such that 1 <= i <= N and Flagi = 0) do
  | M = M + 1
  | CH[M] = {}
  | c = MaxEnergyNode()
  | CH[M] = c
  | Flagc = 1
  | For (j = 1,..., n) do
  | Flag_neighbor(c,j) = 1
  | End For
  | End
  | Return CH[1,...,M]
```

In this algorithm, the initial loop sets a flag for all nodes in line 8 of the algorithm, marking them as "UNMARKED". The main loop then proceeds by identifying nodes with the highest residual energy, marking them as CHs, and subsequently marking their neighboring nodes. This process ensures that all nodes are clustered efficiently, based on energy availability, ensuring optimal distribution of CHs across the network. The process concludes when no unmarked nodes remain, indicating the successful formation of all clusters [see Eq. (4)].

$$Centroid = \frac{\sum \mu_i * (x) * x}{\mu_i * (x)} \tag{4}$$

where, μ_i is the set of membership functions. Finally, a defuzzifier produces a crisp output for the fuzzy system obtained from the inference engine. Thus, the output for CH selection is obtained by a centroid defuzzification method.

F. Concept Behind ABC

ABC is a nature-inspired optimization method based on the way honeybees search for food. There are three kinds of bees used in this technique: employed bees, onlookers, and scouts. The working bees seek sources of food and relay this to the onlookers, who then choose the source to concentrate on depending on the waggle dance of the bees. Scouts explore new areas randomly to find fresh food sources. Throughout the search process, the colony adjusts its focus, starting with a broad exploration of different areas and gradually narrowing down to the best available food sources as they are found. If a better source is discovered during this process, the bees shift their attention to it.

IV. PSAP-WSN CH Selection with ABC

The first group of CHs is created on the basis of maximum energy by Algorithm 1. It returns *'M'* CHs from a given set of *'N'* nodes. Therefore, the dimension of the bee's search space is *'M'*. Assume that there are 'P' search agents (Bees: Employed Bees B1, B2, ..., BP, B2, ..., B2, ..., BP). Each bee defines a memory of dimension *M*. The first group of CHs is stored as the first solution in the memory of the first bee (Bee 1). Other bees are initialized with random node *IDs*.

TABLE I. Agent and its Dimension in ABC

Agent	Dimension 1	Dimension 2	...	Dimension M
Bee1	B11	B12	...	B1M
Bee2	B21	B22	...	B2M
...	...	...	...	...
BeeP	BP1	BP2	...	BPM

Every bee, which is employed, estimates the fitness of the current solution (i.e., food source in its memory) and updates it as the best food source that it has ever visited. It then shares this information with the onlooker bees, which decide which food source to focus on based on the fitness evaluation. Onlooker bees move to the new food source and evaluate its fitness. They update the new food source in their memory if it is superior to the stuff they already knew. This process is repeated for all bees. Additionally, scout bees explore new areas randomly to find fresh food sources. If a bee discovers a better food source, the colony shifts its attention to it. After a predefined number of iterations, all bees will have converged towards the best food source with the highest fitness. This method focuses on four parameters for selecting the best solution in each iteration. The objective function is framed using connectivity, average energy of CHs, balancing factor of each cluster, and cohesion between CHs and Cluster Members (CMs).

The objective function of connectivity focuses on ensuring that all nodes are included within at least one cluster, where the total number of CHs and CMs equals the total number of nodes, N. The set CM_j represents the members connected to *CHj*., and the aim is to maximize network connectivity by ensuring proper clustering of each node. To further enhance network performance, especially in applications like Low-Rate Wireless Personal Area Networks (LR-WPAN), energy-efficient clustering is vital. The average energy of CHs, defined as the ratio of the total energy of all CHs to their number, helps maintain energy-balanced clusters, contributing to the network's longevity and sustainable operation.

In addition, the balancing factor (BF) and cohesion are critical metrics for optimizing cluster performance. The balancing factor minimizes the variation in the number of nodes connected to each CH by calculating the difference between the actual and optimal node distribution, ensuring even load distribution across clusters. This factor, determined using the formula BF=∣V∣×0.1, ranges between [0,1] and helps prevent cluster imbalances. Cohesion, on the other hand, measures the proximity of CMs to their respective CHs by assessing the average distance between them. A higher cohesion value indicates tighter clusters, resulting in better communication efficiency within the cluster structure.

A. Explanation of ABC Objective Functions:

1) Connectivity (f_1): This ensures that every node in the network is connected to a CH, maximizing the cluster membership and ensuring robust connectivity across the network.

2) Average anergy (f_2): This function seeks to maintain a high level of energy across all CHs, which is essential for prolonging network lifetime by ensuring that CHs can sustain their roles effectively.

3) Balancing factor (f_3): The balancing factor minimizes the uneven distribution of nodes across CHs. By keeping this factor low, the algorithm ensures that all CHs handle a similar load, which is crucial for network stability and performance.

4) Cohesion (f_4): This function aims to minimize the average distance between CHs and their CMs. Lower cohesion values indicate tighter clusters, which enhance communication efficiency within each cluster.

5) Overall fitness function (f): The overall fitness function combines these objectives using weighted averages to find the optimal CH selection. The weights w_1, w_2 and w_3 determine the emphasis on energy, balancing, and cohesion, respectively, ensuring a well-rounded solution that balances network longevity, performance, and efficiency.

B. Key Parameters in the ABC Approach for CH Selection

The final fitness function, *f*, aims to maximize all the key parameters involved in the ABC approach to CH selection. The sum of the weighted averages of these parameters is computed to derive f, as given in Eq. (5). The weights are assigned as w_1= 0.5, w_2= 0.4, and w_3= 0.1.

The objective functions in the ABC approach for CH selection are as follows:

$$Maximize\ f_1 : M + \left[\bigcup_{j\in CH[m]} CM[j]\right] \quad 1 \le m \le M \quad (5)$$

Here, f_1 represents the connectivity, ensuring that all nodes are connected to at least one CH.

$$Maximize\ f_2 : AvgE = \frac{\sum_{i=1}^{M} Energy(CH[i])}{M} \quad (6)$$

In Eq. (6), f_2 calculates the average energy of CHs, which is critical for maintaining energy-efficient clusters [see Eq. (7)].

$$AverageBF, BF_{mw} = \frac{BF\ of\ each\ CH}{Total\ number\ of\ clusters} \quad (7)$$

The balancing BF_H ensures that nodes are evenly distributed across clusters. It is computed using Eq. (8):

$$BF_H = \left|(n_H - n_{opt})\right| \text{ X } 0.1 \quad (8)$$

And the network-wide balancing factor is given by Eq. (9):

$$Minimize\ f_3 : BF_{mw} = \frac{\sum_{j=1}^{M}\sum_{i=1}^{N} Dist(Node_i \in cluster_j, CH_j}{N \text{ X } R} \quad (9)$$

This function f_4 measures cohesion, which is the average distance between CHs and their corresponding CMs, aiming to minimize this distance for better intra-cluster communication.

Finally, the overall fitness function f combines these factors [see Eq. (10)]:

$$Maximize\ f : f_1 + w_1 f_2 + w_2(1 - f_3) + w_3(1 - f_4) \quad (10)$$

V. Performance Evaluation

In this section, we provide a detailed discussion on the experimental setup and evaluate the performance of the proposed method. The cluster-based routing technique is assessed using a range of performance metrics, including the number of alive and dead nodes, average energy consumption, delay, total packets transmitted, throughput, as well as the times to the first, half, and last node deaths (FND, HND, and LND, respectively). The proposed approach was implemented and validated using MATLAB. MATLAB was selected due to its robust capabilities in mathematical operations and data analysis. In the experiment, 300 sensor nodes were randomly deployed across a 100 m × 100 m sensing area. To analyze the performance of the proposed method in comparison with other routing protocols, we adopted the radio energy model, with key parameters being $E_{elect} = 50nJ/bit$, $\varepsilon_{fs} = 110pJ/bit$, and $\varepsilon_{mp} = 0.001310pJ/bit$.

The simulation scenarios' settings are presented in Table II. The primary objective was to minimize the overall energy consumption of each node in the network. To achieve this, a load-balancing approach was developed, employing ABC-based CH selection. The inputs for optimal CH selection through ABC included residual energy, node degree, distance to neighbors, distance to the BS, and node centrality. This proposed method was benchmarked against traditional energy-efficient approaches such as LEACH and DEEC, as these protocols are widely utilized to enhance energy efficiency in WSNs. Additionally, comparisons were made with other existing methodologies, including PSAP-WSN [27], DESK, CIRP, ALOC [28], and FLION [29].

TABLE II. Experiment Scenarios for Network Lifetime

Scenario 1	• 100 sensor nodes • Initial energy of 1 J
Scenario 2	• 200 sensor nodes • Initial energy of 1 J
Scenario 3	• 100 sensor nodes • Random energy (0.5 to 2 J)

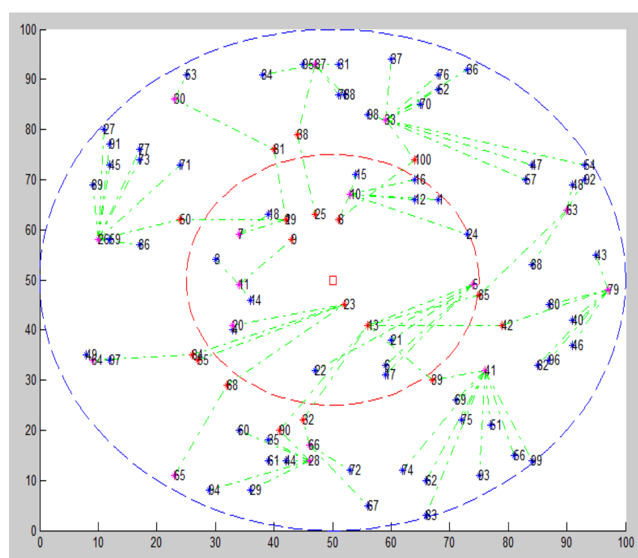

Fig. 3. Network model of scenarios 1 and 3.

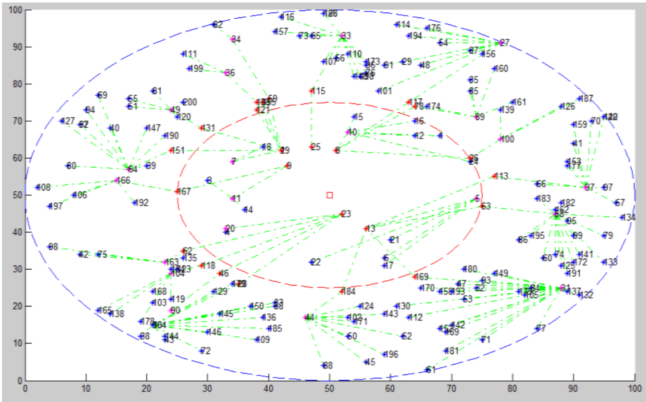

Fig. 4. Network model of scenario 2.

Fig. 3 and Fig. 4 show the network mode with distributed nodes for experimental Scenarios 1, 3 and 2 in the simulation.

A. Network Lifetime

The effectiveness of the proposed method is evaluated by testing the performance of active nodes across different scenarios and varying node quantities, comparing it to established algorithms like FEEC and PSAP-WSN. For example, both the proposed method and the existing algorithms were simulated using 100 and 200 sensor nodes. Fig. 5, Fig. 6, and Fig. 7 illustrate the performance of active nodes when using the proposed method in comparison to the FEEC and PSAP-WSN algorithms. These figures demonstrate how long the nodes last in terms of when the First Node Dies (FND) and the Last Node Dies (LND) across three distinct scenarios.

To carry out the evaluation of these two kinds of transmission, the performance criteria of FND, LND, and number of dead nodes were observed.

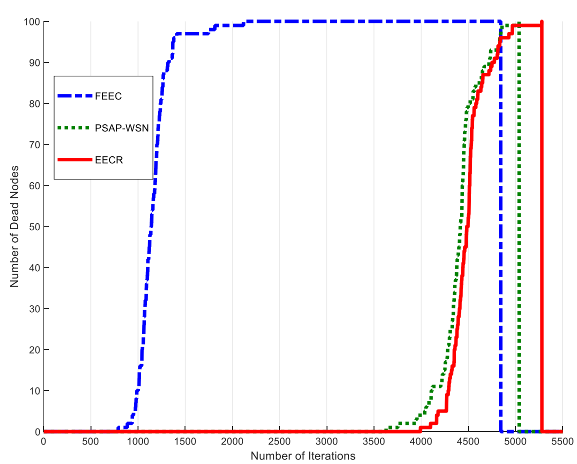

Fig. 5. The FND and LND of EECR, FEEC, and PSAP-WSN for scenario 1.

In Fig. 5, the FEEC exhibits the earliest First Node Death (FND) at the 827th iteration, followed by PSAP-WSN and EECR at the 4017th and 4024th iterations, respectively. As for the Last Node Death (LND), it was first recorded in FEEC at the 4917th iteration, with PSAP-WSN and EECR reaching LND at the 5227th and 5281st iterations, respectively.

Initially, all sensor nodes had high energy levels, leading to the absence of dead nodes. However, over time, the first node death was observed in FEEC at the 3666th iteration as energy began depleting due to data transmission processes. During this phase, child nodes attempted to transmit data to their respective cluster heads (CHs), then from the CHs to the relay nodes, and finally from the relay nodes to the base station (BS).

A similar pattern of node mortality emerged in PSAP-WSN, FEEC, and EECR, with a gradual increase in the number of dead nodes. Around the 4800th iteration, the number of dead nodes stabilized for PSAP-WSN and EECR, coinciding with the decrease in the number of active nodes. The slow rate of energy dissipation observed in this phase was attributed to the reduced number of active sensor nodes, leading to a deceleration in node death.

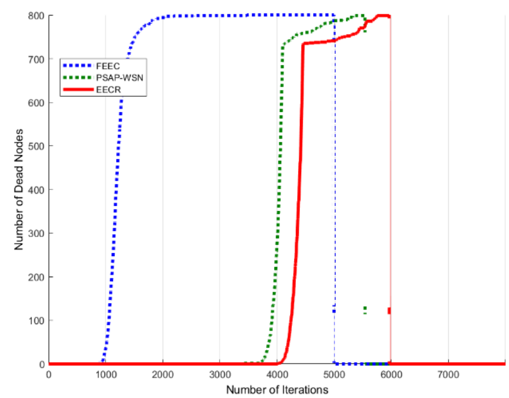

Fig. 6. The FND and LND of EECR, FEEC, and PSAP-WSN for scenario 2.

In this scenario, the number of nodes is increased to 800, each with an initial residual energy of 1 J. As illustrated in Fig. 6, the First Node Death (FND) occurred at the 4124th, 3896th, and 966th iterations for EECR, PSAP-WSN, and FEEC, respectively. Similarly, the LND took place at the 5856th, 5742nd, and 4845th iterations for these protocols. This demonstrates a slower trend in the number of dead nodes, which can be attributed to the higher number of nodes, ultimately contributing to an extended network lifetime. Around the 5000th iteration, the trends in EECR and FEEC stabilized and slowed, primarily due to a reduced number of alive nodes, which led to less competition for data transmission. Consequently, the remaining nodes were able to sustain their operation for a longer period.

Fig. 7 illustrates the network lifetime of EECR, FEEC, and PSAP-WSN under a scenario where the initial energy distribution is randomized. In this case, the higher initial energy of certain nodes results in the longest network lifetime across all three scenarios. The FND was recorded at the 4703rd, 4007th, and 1286th iterations for EECR, FEEC, and PSAP-WSN, respectively. Regarding the LND, it occurred at the 11997th, 11260th, and 10144th iterations, respectively. This marks a significant difference in the number of dead nodes compared to Scenario 1. By the steady-state phase, around the 7000th iteration, EECR had only 29 dead nodes, while PSAP-WSN and FEEC recorded 37 and 43 dead nodes, respectively. Due to the randomized initial energy distribution, the network lifetime for PSAP-WSN and FEEC was approximately twice as long as in Scenarios 1 and 2.

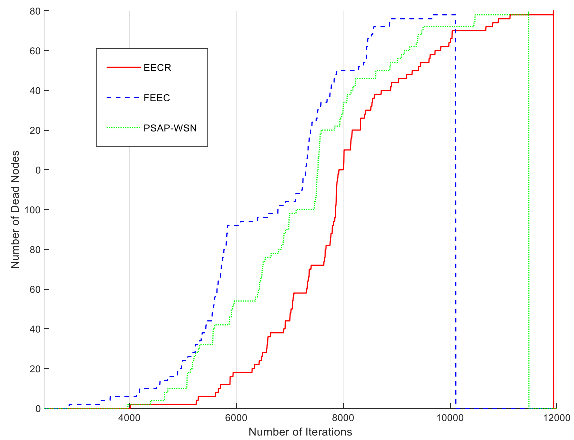

Fig. 7. The FND and LND of EECR, FEEC, and PSAP-WSN for scenario 3.

The proposed method for energy-aware cluster head rotation in WSNs is designed to improve energy efficiency and balance the load across the network. The approach dynamically selects and rotates cluster heads based on several important factors, including the remaining energy of the nodes, their mobility, distance to the BS, and the amount of data they need to process. By prioritizing nodes with higher energy and lower mobility, the method helps reduce energy consumption and extends the overall network lifetime.

At the heart of this method is the goal of evenly distributing the workload across different clusters. It does so by considering key elements like how much energy each node has left, how many devices are connected to each CH, and how far each CH is from the base station. This strategy leads to better network stability and longer operational periods, as it helps prevent individual nodes from draining their energy too quickly. The process unfolds in four main stages: discovering node locations and neighbors, forming the initial clusters, clustering in an energy-efficient manner, and rotating the CHs to collect and transmit data. By continuously rotating the cluster heads, the method prevents any single node from being overburdened, leading to better network performance.

The first phase focuses on gathering information about the network. Each node broadcasts its identity and tracks its closest neighbors. Meanwhile, a mobile data-gathering unit (MDGU) moves through the network, recording each node's location, remaining energy, and its neighboring connections. This data is stored centrally, providing a clear picture of the network's overall status.

Once the information is collected, the network forms its clusters. The node with the most energy is selected as the first cluster head, and its nearby nodes become part of its cluster. This process continues until all nodes are grouped into clusters, ensuring that the nodes are clustered efficiently based on their energy and location.

The method also integrates the ABC algorithm, which further refines the selection of cluster heads. This algorithm mimics the behavior of bees searching for food, where nodes with the best energy levels and cluster configurations are selected as cluster heads. ABC helps optimize the process by improving the connectivity, balancing the workload, and ensuring that clusters are tightly bound together.

By combining dynamic cluster head rotation with ABC, the method successfully extends the lifespan of the network while ensuring that it runs smoothly and efficiently. This not only enhances energy conservation but also boosts overall performance, allowing the WSN to operate longer and more effectively.

B. Energy Balance

In this section, the energy balance of EECR protocols that utilized the ABC algorithm was assessed under varying data aggregation values. The experimental setups are outlined in Table III.

TABLE III. EXPERIMENT SCENARIOS FOR ENERGY BALANCE

Scenario 1	100 sensor nodes Data aggregation value of 5 nJ/bit/signal
Scenario 2	200 sensor nodes Data aggregation value of 10 nJ/bit/signal

The methodology for calculating data aggregation follows the approach discussed. These parameters were used to quantify the energy consumption in various configurations of input parameters, focusing on the cost of transmission and data aggregation within cluster heads (CHs). Consequently, the scenarios were classified into two categories: 1) Normal data aggregation ratio and 2) High data aggregation ratio. In the analysis of these scenarios, the standard deviation of residual energy (SDRE) served as a key metric, reflecting the energy distribution across sensor nodes. A higher SDRE indicates greater energy imbalance, signifying uneven energy depletion among the nodes. Therefore, minimizing SDRE is a crucial objective for EECR in these evaluations.

Fig. 8 and Fig. 9 illustrate the standard deviation of residual energy (SDRE) for the EECR, FEEC, and PSAP-WSN protocols over multiple iterations in Scenarios 1 and 2. Each scenario exhibited distinct variations in SDRE across the different input parameter combinations.

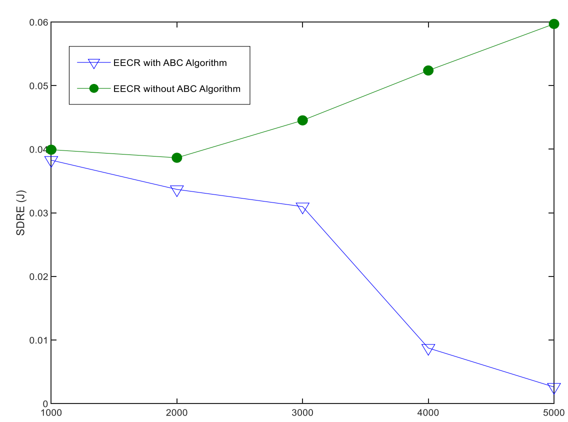

Fig. 8. The SDRE for scenario 1.

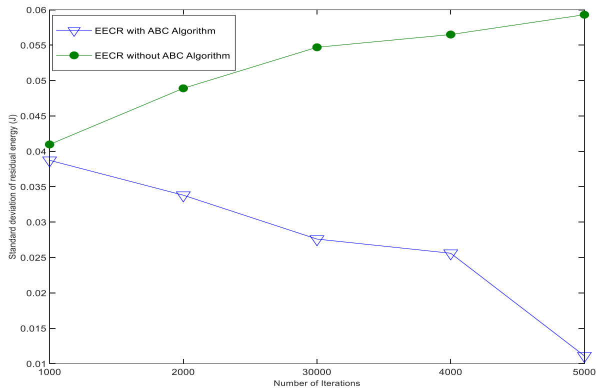

Fig. 9. The SDRE for scenario 2.

In contrast, the SDRE of EECR 2 without the ABC algorithm for 100 nodes experienced a gradual increase up to the 5000th iteration. A similar upward trend in SDRE was observed when the node count increased to 200 in the absence of the algorithm. Conversely, the model integrated with the ABC algorithm for 200 nodes followed the same trend as seen with 100 nodes, with a pronounced drop in SDRE between the 4000th and 5000th iterations. When comparing the two scenarios, the SDRE for EECR 2 with the ABC algorithm and 200 nodes was significantly lower than the model without the algorithm. Meanwhile, the SDRE for EECR 2 without the ABC algorithm with 200 nodes was notably higher than for 100 nodes, displaying a distinct contrast in behavior between the models.

The figures provide clear insights into how much the ABC algorithm enhances the energy balance in the EECR 2 model. When using 100 nodes, the system with the ABC algorithm showed a dramatic improvement in SDRE efficiency, dropping from 0.0346 to 0.0089 after the 4000th iteration. This reflects the impact of integrating the algorithm, achieving almost 94% better energy balance compared to not using it. Without the algorithm, the SDRE values steadily increased across iterations, and this trend only intensified as we added more nodes. Interestingly, for 200 nodes, the ABC algorithm once again proved its effectiveness, as we saw another significant decrease in SDRE, whereas the model without the algorithm showed even higher SDRE values as the node count increased. These results underscore the role of the ABC algorithm in maintaining energy balance, especially as the system scales in complexity.

VI. Conclusion

In this study, we introduced an energy-aware CH rotation and load-balancing approach for WSNs that leverages the ABC optimization algorithm. The method was designed to address one of the most pressing challenges in WSNs: the uneven energy depletion across nodes, particularly among cluster heads. By dynamically rotating CHs and considering multiple factors such as residual energy, node mobility, and proximity to the base station, our approach successfully distributes the energy load across the network, thereby enhancing both energy efficiency and network longevity. Through simulations, the proposed method demonstrated significant improvements over traditional protocols like FEEC and PSAP-WSN. The results show that our method consistently maintains a more even energy distribution across nodes, preventing early node failures and extending the operational lifetime of the network. This is particularly important in large-scale networks where the sustainability and performance of the system are critical. Additionally, the integration of the ABC optimization algorithm provided a robust framework for CH selection, ensuring that the network adapts dynamically to changing conditions without compromising on efficiency. Overall, the proposed method offers a practical and effective solution for energy management in WSNs. By optimizing CH rotation and load balancing, it not only prolongs the network's lifespan but also ensures stable and reliable performance, making it a valuable contribution to the field of WSNs. This work paves the way for future research on enhancing energy efficiency in WSNs through bio-inspired optimization techniques and other adaptive approaches.

Acknowledgment

The authors are grateful to Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) for providing the funding under the Fundamental Research Grant Scheme (FRGS Grant (RDU230128)). In addition, we would like to thank the Faculty of Computing (UMPSA) and specifically our Computer Network Research Group (CNRG) for their support and facilities.

References

[1] M. Nasri, M. Omari, and M. Kaddi, "The Application of Multihop HEED Protocol in Wireless Sensor Networks," in Artificial Intelligence and Heuristics for Smart Energy Efficiency in Smart Cities: Case Study: Tipasa, Algeria, Springer, 2022, pp. 557–565.

[2] R. Dhiman and J. Thakur, "Evolution of WSN into WSN-IoT: A Study on its Architecture and Integration Challenges," in International Conference on Innovative Computing and Communications: Proceedings of ICICC 2022, Volume 3, Springer, 2022, pp. 185–207.

[3] K. N. Dattatraya and K. R. Rao, "Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN," Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 3, pp. 716–726, 2022.

[4] A. A. Jasim, M. Y. I. Idris, S. Razalli Bin Azzuhri, N. R. Issa, M. T. Rahman, and M. F. b Khyasudeen, "Energy-efficient wireless sensor network with an unequal clustering protocol based on a balanced energy method (EEUCB)," Sensors, vol. 21, no. 3, p. 784, 2021.

[5] A. K. Koshariya, D. Kalaiyarasi, A. A. Jovith, T. Sivakami, D. S. Hasan, and S. Boopathi, "Ai-enabled iot and wsn-integrated smart agriculture system," in Artificial Intelligence Tools and Technologies for Smart Farming and Agriculture Practices, IGI Global, 2023, pp. 200–218.

[6] P. Yadav and S. C. Sharma, "A systematic review of localization in WSN: Machine learning and optimization-based approaches," International journal of communication systems, vol. 36, no. 4, p. e5397, 2023.

[7] Q. Tang and F. Nie, "Clustering routing algorithm of wireless sensor network based on swarm intelligence," Wireless Networks, pp. 1–12, 2023.

[8] A. Benfradj, A. Thaljaoui, T. Moulahi, R. U. Khan, A. Alabdulatif, and P. Lorenz, "Integration of artificial intelligence (AI) with sensor networks: Trends, challenges, and future directions," Journal of King Saud University-Computer and Information Sciences, vol. 36, no. 1, p. 101892, 2024.

[9] G. Santhosh and K. V Prasad, "Energy optimization routing for hierarchical cluster based WSN using artificial bee colony," Measurement: Sensors, vol. 29, p. 100848, 2023.

[10] J. Wang, Y. Liu, S. Rao, X. Zhou, and J. Hu, "A novel selfadaptive multi-strategy artificial bee colony algorithm for coverage optimization in wireless sensor networks," Ad Hoc Networks, vol. 150, p. 103284, 2023.

[11] R. Ramya and T. Brindha, "A Comprehensive Review on Optimal Cluster Head Selection in WSN-IoT," Advances in Engineering Software, vol. 171, p. 103170, 2022.

[12] B. R. Al-Kaseem, Z. K. Taha, S. W. Abdulmajeed, and H. S. Al-Raweshidy, "Optimized energy–efficient path planning strategy in WSN with multiple Mobile sinks," IEEE Access, vol. 9, pp. 82833–82847, 2021.

[13] A. Shukla and S. Tripathi, "A multi-tier based clustering framework for scalable and energy efficient WSN-assisted IoT network," Wireless Networks, vol. 26, no. 5, pp. 3471–3493, Jul. 2020, doi: 10.1007/s11276-020-02277-4.

[14] Y. Yue et al., "Review and empirical analysis of sparrow search algorithm," Artif Intell Rev, vol. 56, no. 10, pp. 10867–10919, Oct. 2023, doi: 10.1007/s10462-023-10435-1.

[15] S. Kumar and R. Agrawal, "A comprehensive survey on meta-heuristic-based energy minimization routing techniques for wireless sensor network: classification and challenges," J Supercomput, vol. 78, no. 5, pp. 6612–6663, Apr. 2022, doi: 10.1007/s11227-021-04128-1.

[16] F. Akram, S. Aziz, N. A. Khan, S. A. Faizi, and K. Raza, "Integrating Artificial Bee Colony Algorithms for Deep Learning Model Optimization: A Comprehensive Review," 2024, pp. 73–102. doi: 10.1007/978-981-97-7344-2_5.

[17] J. Murali and T. Shankar, "A survey on localization and energy efficiency in UWSN: bio-inspired approach," Discover Applied Sciences, vol. 6, no. 12, p. 633, Nov. 2024, doi: 10.1007/s42452-024-06318-x.

[18] S. I. Hamim and A. B. A. Rahman, "Optimizing Wireless Sensor Networks: A Survey of Clustering Strategies and Algorithms," International Journal of Computer Networks and Applications, vol. 11, no. 5, pp. 673–689, Oct. 2024, doi: 10.22247/ijcna/2024/42.

[19] T. Magesh, G. Devi, and T. Lakshmanan, "Improving the performance of grid connected wind generator with a PI control scheme based on the metaheuristic golden eagle optimization algorithm," Electric Power Systems Research, vol. 214, p. 108944, Jan. 2023, doi: 10.1016/j.epsr.2022.108944.

[20] T. Islam, M. E. Islam, and M. R. Ruhin, "An Analysis of Foraging and Echolocation Behavior of Swarm Intelligence Algorithms in Optimization: ACO, BCO and BA," Int J Intell Sci, vol. 08, no. 01, pp. 1–27, 2018, doi: 10.4236/ijis.2018.81001.

[21] T. R. Beegum, M. Y. I. Idris, M. N. Bin Ayub, and H. A. Shehadeh, "Optimized Routing of UAVs Using Bio-Inspired Algorithm in FANET: A Systematic Review," IEEE Access, vol. 11, pp. 15588–15622, 2023, doi: 10.1109/ACCESS.2023.3244067.

[22] S. A. Al-shalif et al., "A systematic literature review on meta-heuristic based feature selection techniques for text classification," PeerJ Comput Sci, vol. 10, p. e2084, Jun. 2024, doi: 10.7717/peerj-cs.2084.

[23] E. H. Houssein, M. R. Saad, Y. Djenouri, G. Hu, A. A. Ali, and H. Shaban, "Metaheuristic algorithms and their applications in wireless sensor networks: review, open issues, and challenges," Cluster Comput, vol. 27, no. 10, pp. 13643–13673, Dec. 2024, doi: 10.1007/s10586-024-04619-9.

[24] A. A. Rahman and S. I. Hamim, "Improved K-means clustering and adaptive distance threshold for energy reduction in WSN-IoTs," Array, vol. 27, p. 100436, Sep. 2025, doi: 10.1016/j.array.2025.100436.

[25] A. A. Rahman, M. N. M. Kahar, and W. I. S. W. Din, "Distance based thresholds for 2-tier relay nodes selection in WSN," Comput Stand Interfaces, vol. 66, p. 103359, Oct. 2019, doi: 10.1016/j.csi.2019.103359.

[26] S. Sumithra and R. Vadivel, "Analyzing the Effectiveness of TCA-CBB by Comparing Various VANET Broadcasting Algorithms in Terms of Quality of Service," Wirel Pers Commun, vol. 124, no. 1, pp. 261–282, May 2022, doi: 10.1007/s11277-021-09337-8.

[27] X. Li, S. Liu, S. Kumari, and C.-M. Chen, "PSAP-WSN: A Provably Secure Authentication Protocol for 5G-Based Wireless Sensor Networks," Computer Modeling in Engineering & Sciences, vol. 135, no. 1, pp. 711–732, 2023, doi: 10.32604/cmes.2022.022667.

[28] R. Punithavathi, C. Kurangi, S. P. Balamurugan, I. V. Pustokhina, D. A. Pustokhin, and K. Shankar, "Hybrid BWO-IACO Algorithm for Cluster Based Routing in Wireless Sensor Networks," Computers, Materials & Continua, vol. 69, no. 1, pp. 433–449, 2021, doi: 10.32604/cmc.2021.018231.

[29] P. Suman Prakash, D. Kavitha, and P. Chenna Reddy, "Safe and secured routing using multi-objective fractional artificial lion algorithm in <scp>WSN</scp>," Concurr Comput, vol. 34, no. 21, Sep. 2022, doi: 10.1002/cpe.7098.