MOBES : A MODIFIED BALD EAGLE SEARCH BASED TECHNIQUE FOR OPTIMAL CLUSTERING IN WIRELESS SENSOR NETWORK

Vipan KUSLA[1], Gurbinder Singh BRAR[2]

Energy efficiency has emerged as a critical concern in Wireless Sensor Networks (WSN). Sensor nodes deplete their energy faster and die earlier making whole network unstable due to poor clustering in the network. Therefore, Optimal clustering is considered as a crucial technique for enhancing the performance of WSNs, with the objective of optimizing efficacy of active nodes. Metaheuristic optimization is commonly used due to its efficiency, therefore, the Bald Eagle Search (BES) algorithm is used in this research. This paper improves the efficacy of a BES algorithm by avoiding problems with local optima stagnation. By improving the exploration phase, a variant of the BES algorithm called Modified Bald Eagle Search (MoBES) is developed and implemented in WSN. MoBES based technique gives an optimal set of nodes selected as Cluster Heads (CH) to which nearest normal nodes join to form a balanced cluster for clustering process. The objective function used in this technique considers intra-cluster distance, inter-cluster distance and equipoise cluster formation using node degree. The performance of this proposed technique is compared to other common metaheuristic algorithms by varying different node densities and making use of evaluation parameters namely average energy consumption, network residual energy, active nodes, dead nodes, and network lifetime. Based on the findings, the proposed technique, which employs a modified Bald Eagle Search algorithm demonstrates reduction in energy consumption thus improves network lifetime when compared with Artificial Bee Colony (ABC), Biogeography-Based Optimization (BBO), Harmony Search Optimization (HS), Salp Swarm Algorithm (SSA) and Bald Eagle Search Algorithm (BES).

Keywords: Wireless Sensor Network (WSN), Bald Eagle Search Algorithm (BES), Network Lifetime, Cluster Heads (CHs), Clustering

1. Introduction

Wireless Sensor Network (WSN) is a comprehensive source of innovative technologies for a wide range of modern Internet of Things (IoT) applications. WSN employs smart sensor nodes capable of sensing data from their surroundings, such as light, pressure, motion detection, temperature, sound, vibration, and so on

[1] Research Scholar, Department of Computer Science and Application, CT University, Ludhiana, Punjab, India, e-mail: vipankusla@gmail.com
[2] Department of Computer Science and Engineering, CT University, Ludhiana, Punjab, India, e-mail: gurbinder17934@ctuniversity.in

[1]. The WSN transmits the acquired data to the sink node over a wireless channel. Healthcare, home automation, warfare, traffic management, industrial control, military surveillance, habitat monitoring, and other domains have been identified where WSNs play a significant role. It can even operate independently in high-risk areas where human presence is almost impossible. WSN provides several advantages, including low deployment costs, flexibility, and ease of sensor node deployment. Aside from these advantages, the main disadvantages of WSN are its non-rechargeable battery and the difficulty in sustaining network lifespan [2]. Increasing the lifetime of WSN networks and reducing the energy consumption of sensor nodes are important subjects for researchers all over the world.

WSN network lifetime and battery energy usage [3] can be increased by achieving effective clustering and optimizing the cluster head selection process [4]. Clustering is the process of grouping nodes into small clusters based on a range of characteristics. Cluster Heads (CHs) are nodes chosen from these small groupings depending on energy and distance for each cluster.

The selection of Cluster Head (CH) can be distinguished by two methods: common Cluster Head Selection (CHS) based on some probability and optimum CHS based on heuristic and metaheuristic procedures [5]. Heuristics denote solutions or procedures for a specific problem, whereas meta-heuristic refer to a solution or procedure at a higher level for indeterminate problems. Heuristic processes are numerically inefficient for large-scale and high-dimensional problems; however, metaheuristic approaches handle large-dimensional, complex optimization challenges to produce better results.

Regardless of meta-heuristic algorithms, the search process can be divided into two phases: exploration and exploitation [6]. The exploration phase implies a comprehensive assessment of probable regions over the whole search area. The ability to broaden one's search beyond the initial promising regions uncovered during exploration is referred to as "exploitation."

The genetic algorithm and differential evolution are both examples of evolutionary algorithms. Swarm intelligence comprises a wide range of optimization approaches, including Ant Colony Optimization (ACO) [7], Artificial Bee Colony Optimization (ABC) [8], Bacterial Foraging Optimization (BFO) [9], Firefly Algorithm (FA) [10], Particle Swarm Optimization (PSO) [11], etc. Due to the efficiency of metaheuristic algorithms, the majority of the strategies proposed by researchers are used to accomplish clustering using these algorithms in WSNs.

The remaining part of the paper is organized as follows: The relevant work is presented in Section 2. Section 3 contains a description of both the energy model and the network model. The Standard Bald Eagle Search algorithm is outlined as background in Section 4. Section 5 discusses the improved Bald Eagle Search technique. In Section 6, the simulations' results are provided, and Section 7 wraps up the paper.

2. Related Work

Studies that use metaheuristic-based clustering techniques in an effort to prolong network life and increase WSN efficiency are available in the literature.

In 2011, Liu and Ravishankar described GA-LEACH, which used a Genetic-Algorithm to choose a cluster head based on the ideal value of the probability that it would be the cluster head. It provided the maximum number of nodes with the lowest energy usage that may be chosen as cluster heads [12]. In 2012, Singh & Lobiyal proposed Particle Swarm Optimization based Cluster Head Selection in which residual energy, intra-cluster distance, node degree and head count were used to formulate its objective function. Network lifetime [13]. In 2013, Hoang et al. proposed centralized cluster based protocols using a harmony search algorithm to minimize the intra-cluster distances between the cluster nodes and cluster heads [14]. In 2014, based on the bat swarm optimization algorithm, Sharwai et al. suggested a method to choose optimum cluster heads by decreasing the intra-cluster compactness with a minimum distance between nodes in the same cluster. [15].

In 2015, using residual energy as a metric, Gupta and Sharma proposed a modified ant colony optimization-based clustering approach [7]. In 2016, Ari et al proposed a cluster-based routing strategy that makes use of an artificial bee colony metaheuristic. It takes into account factors like energy usage and communication quality for the selection of cluster heads [16]. In 2017, Sengottuvelan and Prasath suggested an enhanced Breeding Artificial Fish Swarm Algorithm. The end-to-end delay and energy are the foundation of the multi-objective function [17]. In 2018, using residual energy and distance as its metrics, Lalwani et al. suggested an energy-saving routing architecture based on biogeography for the best cluster head selection and routing in WSN [18]. In 2019, Chandirasekaran and Jayabarathi introduced a Cat Swarm Optimization-based approach taking into account received signal strength, intra-cluster distance, and battery residual energy [19]. In 2021, a new fruit fly optimization method (IFFOA) was presented by Poluru and Kumar [20] for choosing the CH. This algorithm considers a number of factors, including the connection, the nodes' residual energy, the base station’s (BS) overall distance, and the distances between the nodes. In 2022, using a hybrid meta-heuristic-based LEACH protocol, Nagarajan et al. [21] demonstrated energy-efficient routing for WSN. Limit-based Jaya Sail Fish Optimization, a hybrid meta-heuristic technique combining Sail Fish Optimization with the Jaya Algorithm, produced superior cluster head selection (L-JSFO).

In context with the literature review, it has been found that numerous methods for choosing cluster heads for the clustering process are efficient. Both balanced clustering and optimal cluster head selection have attracted the attention of researchers. However, more work needs to be done to stabilize energy and increase the WSNs' lifespan. Researchers have proposed a wide variety of methods for clustering in WSN, the vast majority of which rely on metaheuristic techniques. So, considering this as motivation, a modified Bald Eagle Search based technique for optimal clustering in WSN is proposed.

The following are the main contributions of this paper:

1. A modified metaheuristic-based technique using the Bald Eagle Search algorithm is proposed to improve clustering and the selection of cluster heads in the WSN network.
2. Improvements in the exploration phase of the current BES algorithm and using a fitness function with three parameters network scalability, network coverage, and equipoise cluster formation using node degree have helped to make the network last longer.
3. Analysis of the performance is made using commonly used metaheuristic techniques namely ABC, BBO, HS, SSA and BES.

3. Preliminaries

The network model and the energy model, both of which are utilized throughout this study, are dissected and explored in this part.

3.1. Energy Model

Heinzelman et al. suggested a radio model [22], which is used in the proposed technique. The power amplifier and radio circuitry are powered by the transmitter, which consumes energy in the process. In order to provide power to the radio circuitry, the receiver depletes some of its stored energy. The amount of data sent and the distance traveled determine the node's energy usage. The following formula in equation (1) shows how much energy each node in the network needs to use to send the x bit data packet.

$$Eg^{trs} = \begin{cases} Eg^{ele} \times x + E_{fsp} \times x \times dt^2 & if\ dt < R_{thr} \\ Eg^{ele} \times x + E_{mlp} \times x \times dt^4 & if\ dt \geq R_{thr} \end{cases} \tag{1}$$

Where, E_{fsp} and E_{mlp} are the energy needed by the amplifier to transmit data over a distance dt in the free-space channel and multi-path channel. A multi-path channel is utilized where the distance between transmitting and receiving SN is greater than R_{thr}, else free-space channel is used. The electronics circuit's energy needed to deliver $1 - bit$ data over the distance dt is denoted by Eg^{ele}. R_{thr} is calculated using $R_{thr} = \sqrt{\frac{E_{fsp}}{E_{mlp}}}$. Furthermore, the amount of energy that was used to receive x bit is presented below:

$$E^{rcv} = x \times Eg^{ele} \tag{2}$$

3.2. Network Model

The WSN scenario used in this paper has the following properties in common with existing algorithms. The sensors are dispersed randomly across the field. After deployment, it is assumed that all sensor nodes are fixed, and nodes can work in both the cluster head node and the normal sensor node. Every node does sensing regularly, so it always has information to send to its Cluster Head (CH) or Base Station (BS). Depending on how far away the data is being sent to the CH or BS, sensors use different amounts of transmission power. All sensor nodes are the same and have the same processing and communication abilities.

4. Background

In 2020, Alsattar et al. [23] suggest the standard Bald Eagle Search (BES) algorithm. It looks for food by imitating the way bald eagles hunt. Bald eagles hunt in three steps: deciding what to hunt (selecting stage), looking for it (searching stage), and flying down to catch it (swooping stage). In selecting a stage, the algorithm identifies a region with the highest concentration of prey. In the searching phase, the predator seeks the optimal hunting position within the identified region. During the swooping phase, the eagle pursues its prey from the optimal position determined during the searching phase.

4.1 BES Algorithm

The following sections elaborate on the stages listed above:

Select Stage

The selection phase comprises recognizing and choosing the ideal area for the eagle to seek prey at the chosen site. To express it mathematically, the equation (3) is given below:

$$M_{i,new} = M_{bst} + \alpha \times rnd\ (M_{mean} - M_i) \tag{3}$$

where, α is used to manage position changes and has a value ranging from 1.5 and 2, whereas rnd represents a zero-to-one random number. The bald eagles' current search space is M_{bst} based on their last search's best position. M_{mean} denotes that these eagles have exhausted all of the prior points' data.

Search Space

Bald eagles search for prey in the defined area and fly in various directions inside a spiral region. The mathematical expression for the best swooping location is expressed below in equation (4) [23].

$$M_{i,new} = M_i + q(i) \times (M_i - M_{i+1}) + p(i) \times (M_i - M_{mean}) \quad (4)$$

Where, $p(i) = \frac{xd(i)}{max(|xd|)}, q(i) = \frac{yd(i)}{max(|yd|)}$ ....(a)

$xd(i) = d(i) \times \sin(\emptyset(i)),\ \mathrm{yd}(i) = d(i) \times \cos(\emptyset(i))$ .....(b)

$\emptyset(i) = a \times \pi \times rand$ ..... (c)

$\mathrm{r}(i) = \emptyset(i) + R_{val} \times rand$ .... (d)

where, α is an algorithmic parameter in the range [1.5, 2], rnd represents a zero-to-one random number, i represents the total number of search agents.

Swooping stage

Bald eagles swing from their best position to their goal position during the swooping stage. The mathematical explanation for the swooping stage is expressed in equation (5) as follows:

$$M_{i,new} = rand \times M_{best} + x1(i) \times (M_i - c1 \times M_{mean}) + y1(i) \times (M_i - c2 \times M_{best}) \quad (5)$$

where, $x1(i) = \frac{xd(i)}{max(|xd|)}$, $y1(i) = \frac{yd(i)}{max(|yd|)}$,

$xd(i) = r(i) \times \sin h(\emptyset(i)),\ yd(i) = r(i) \times \cos h(\emptyset(i))$

where, $\emptyset(i) = a \times \pi \times rand$ and $\mathrm{r}(i) = \emptyset(i)$

$c1, c2 \in [1,2]$

where, α is used to manage position changes and has a value ranging [1.5,2], rnd denotes a random number between range [0,1]. The movement of the bald eagle has a variety of patterns. Because parameters $c1$ and $c2$ increase the intensity of bald eagle movement towards the best and center points, the best solution must be multiplied by a random number.

5. Proposed Modified Bald Eagle Search Technique

BES has the potential to become mired in locally optimal regions, which prevents it from discovering the best possible solutions globally. This is a problem in many optimization situations, especially when the task is challenging or has a lot of dimensions [24]. As a result of local optima stagnation, the conventional BES cannot ensure optimal solutions. This weakness during the exploration phase is remedied by employing the replacement technique described below.

5.1 MoBES Architecture

The standard BES algorithm suffers from the problem of local optima stagnation as it just searches inside the selected region of the search space. Therefore, a modified bald eagle search technique is introduced using a replacement strategy. This replacement strategy replaces the worst five individuals in the population with new randomly initialized individuals to maintain the population's diversity. This strategy helps the algorithm explore more and avoid getting stuck in a local optimal condition. The mathematical formulation of the proposed strategy is shown in equation (6).

$$M_{new} = lb\ (ub - lb\ ) \times rnd \tag{6}$$

where, lb, ub are lower bounds and upper bounds of the search space, rnd represents a zero-to-one random number. In addition, this strategy retains the individuals with the best fitness among the worst and new randomly initialized individuals for the consecutive iterations as shown in equation (7).

$$\begin{aligned} &if\ fit(M_{new}) < fit(M_i) \\ &M_i = M_{new} \end{aligned} \tag{7}$$

The pseudo-code for the suggested MoBES is shown in the algorithm below.

Algorithm 1. Steps of the proposed MoBES technique

1. Initialize the search agents (P_i) randomly
2. Calculate the fitness of each search agent ($fit(P_i)$)
3. Select the best search agent (P_{best}) of the current iteration.
4. Set the current iteration (t) = 1
5. Repeat steps 6 to10 until termination criteria met
6. Perform Select stage

   $M_{new} = M_{best} + \alpha \times rnd\ (M_{mean} + M_i)$

   $\boldsymbol{if} fit(M_{new}) < fit(M_i)$

   $M_i = M_{new}$

   $\boldsymbol{if} fit(M_{new}) < fit(M_{best})$

   $M_{best} = M_{new}$

   $\boldsymbol{end}$

   $\boldsymbol{end}$

7. Perform Search stage

   $M_{new} = M_i + q_i\ (M_i - M_{i+1}) + p_i\ (M_i - M_{mean})$

   $\boldsymbol{if} fit(M_{new}) < fit(M_i)$

   $M_i = M_{new}$

   $\boldsymbol{end}$

   $\boldsymbol{if} fit(M_{new}) < fit(M_{best})$

   $M_{best} = M_{new}$

   $\boldsymbol{end}$

8. Perform Swooping stage

$$M_{new} = rnd \times M_{best} + p1_i\,(M_i - c1 \times M_{mean}) + q1_i\,(M_i - c2 \times M_{best})$$

$\boldsymbol{if} fit(M_{new}) < fit(M_i)$

$M_i = M_{new}$

$\boldsymbol{end}$

$\boldsymbol{if} fit(M_{new}) < fit(M_{best})$

$M_{best} = M_{new}$

$\boldsymbol{end}$

9. Replace the worst n candidates

$M_{new} = lb\,(ub - lb\,) \times rnd$

$\boldsymbol{if} fit(M_{new}) < fit(M_i)$

$M_i = M_{new}$

$\boldsymbol{end}$

$\boldsymbol{if} fit(M_{new}) < fit(M_{best})$

$M_{best} = M_{new}$

$\boldsymbol{end}$

. 10. Update the current iteration $(t) = t + 1$

5.2 MoBES for Clustering in WSN

Based on the modification done in BES mentioned in Section 5, the best CHs are chosen in this work for the clustering process. The population is initially thought to represent the total number of homogenous nodes. Fitness is calculated for each node. In this context, “fitness function" refers to the probability that each node will be chosen as the cluster head. The best cluster head selected using MoBES is used for the clustering process, in which the nearest nodes join to form an optimal cluster based on the Euclidean distance between nodes. Once clusters are formed, the data transmission process begins. The workflow diagram for the clustering process using MoBES is shown below in Fig.1.

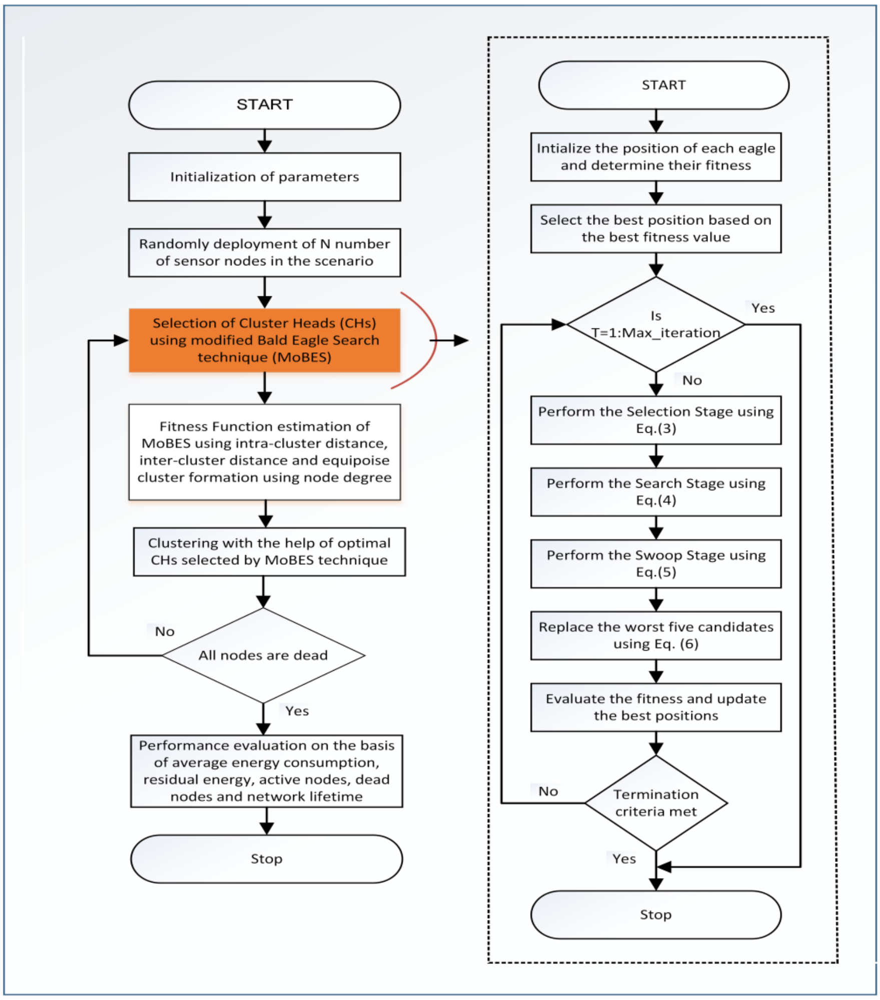

Fig. 1. Workflow Diagram for Clustering Process using MoBES Technique

For fitness calculations, three parameters are considered as network coverage P_{NC}, network scalability P_{NS} and equipoise clusters P_{EC}. The following equation can be used to determine the optimum CH for each distinct category of nodes:

$$FF(i) = P_{NC} + \frac{1}{P_{Ns}} + P_{EC} \quad (8)$$

where, P_{NC} denotes network coverage, P_{Ns} denotes network scalability and P_{EC} denotes equipoise clusters.

Network Coverage: To provide efficient network coverage for the selected CH in the WSN network, the Euclidean distance between the CH and SN needs to be minimized. Because if the distance between the SN and CH is short, then it minimizes the energy required by the SN to transfer data to the CH. Also, the energy requirement of the whole cluster is minimized if this distance is reduced. P_{NC} denotes a function to represent the network coverage and it is formulated as :

$$P_{NC} = \sum_{i=1}^{N} D_{s_i}^{ch^k} \tag{9}$$

where, $D_{s_i}^{ch^k}$ denotes the intra-cluster distance for the k^{th} cluster with N sensor nodes.

Network Scalability: To make the WSN network scalable, well-proportioned CHs should be chosen uniformly across the network even when the size and density of the network increase. To achieve this, the average euclidean distance between the CHs should be maximized, ensuring that no two CHs are chosen in close proximity to one another. P_{NS} denotes a function to represent network scalability and it is formulated as :

$$\mathrm{P_{NS}} = \frac{\sum_{i=1}^{K}\sum_{j=1}^{K} D_{ch_i}^{ch_j}}{K} \tag{10}$$

where, $D_{ch_i}^{ch_j}$ denotes the distance between cluster heads.

Equipoise Clusters: To make the network's clusters equal, the difference between the intra-cluster distance and node degree of different CHs needs to be kept as small as possible. This reduces the energy utilization of the entire cluster by selecting CHs with the smallest intra-cluster distance and lowest node degree. P_{EC} denotes a function to make equipoise clusters in the network and it is formulated as

$$P_{EC} = \sqrt{\frac{\sum_{i=1}^{k}(CD_i - \overline{CD})^2}{K-1}} + \sqrt{\frac{\sum_{i=1}^{k}(ND_i - \overline{ND})^2}{K-1}} \tag{11}$$

Where, CD_i denotes intra cluster distance of the network, ND_i denotes node degree of the clusters.

6. Results and Discussion

In this paper, we propose a method of optimal clustering by utilizing MoBES and a fitness function that takes into account intra-cluster distance, inter-cluster distance, and Equipoise Clusters as taking into account the node degree of each cluster. This is done to ensure that the method uses the least amount of energy possible so that nodes may remain active for an extended period of time within the network. To determine the effectiveness of the proposed technique for different scenarios, the node density varied from 100 to 150 nodes, and then the density was doubled from 100 to 200 nodes. They are all in a network simulation area of $100 \times 100\ m^2$. Table 1 shows the parameters used in the simulation.

Table 1

Simulation Parameters

Parameter	Notation	Value
Sensing Area	$m \times m$	$100 \times 100\ m^2$
Number of Sensor Nodes	N	100, 150, 200
Number Cluster Head	K	10% of Sensor Nodes
Position of Sink Node	S_{bs}	Centre (50,50)
Cluster Head	CH	
Set of SNs	$S = \{S_1, S_2 \ldots S_N\}$	
Set of CHs	$S_{CH} = \{CH_1, CH_2 .. CH_K\}$	
Initial Energy of SNs	E_{init}	$1\ Joule$
Energy required to transmit/receive a bit	E_{elect}	$50\ nJ/bit$
Amplifier Energy for Free Space	E_{fs}	$10\ \mathrm{pJ/bit}/m^2$
Amplifier Energy for Free Space for Multi Path	E_{amp}	$0.0013\ \mathrm{pJ/bit}/m^4$
Energy consumed for Data Aggregation	E_{da}	$5\ nJ/bit$
Packet Length		$6400\ bits$
Distance Between SN S_i and cluster head CH_j	$D_{s_i}^{CH_j}$	
Distance Between CH CH_j and Sink Node S_{bs}	$D_{CH_j}^{S_{bs}}$	
Network scenarios	WSN~1 WSN~2 WSN~3	WSN~1 = Size 100 x 100, nodes=100 WSN~2 = Size 100 x 100, nodes=150 WSN~3 = Size 100 x 100, nodes=200)

In this section, we evaluate the performance of the proposed technique and compare it with ABC [25], BBO [18], HS [14], SSA [26], and BES [23] using the simulation parameters residual energy of the network, average energy consumption, active nodes/dead nodes, and network lifetime based on the first node die and half nodes die. To compute the network lifetime, the simulation was run for 20,000 rounds. But 1,000 rounds are used to measure how well these techniques work in some ways. Fig.2. depicts a WSN scenario for an area of $100 \times 100\ m^2$.

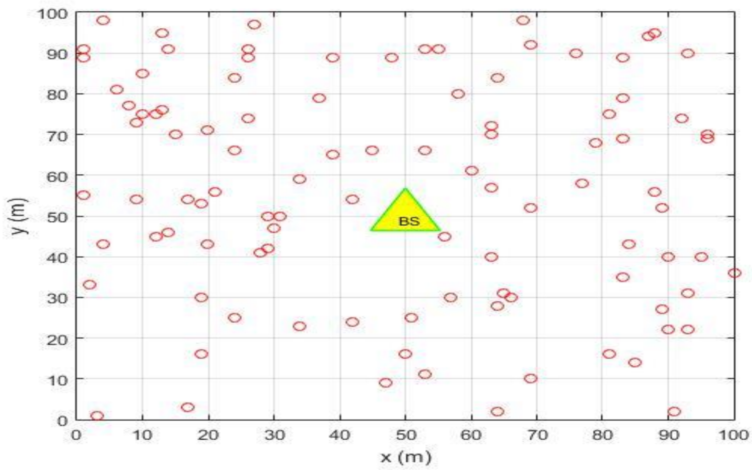

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Fig.2. A WSN Scenario

6.1 Simulation Setup

The performance of the clustering techniques has been simulated in MATLAB-2018b on a platform running Windows 10 Professional OS and equipped with an Intel Core i7 processor running at 3.1 GHz and 8 GB of RAM.

With performance evaluation metrics Average Energy Consumption, Residual Energy, Active Nodes, Dead Nodes, and Network Lifetime based on First Node Die and Half Nodes Die, the results are analyzed for all three scenarios.

6.2 Performance Metrics

The following performance metrics have been employed in the analysis of the suggested technique:

a) **Average Energy Consumption**: It determines the average amount of energy that is dissipated between each node's starting level and its current level. In the WSN network, it refers to the amount of energy that a node expends during the course of one round in order to transmit the data.

b) **Residual Energy of the Network**: Each node uses some amount of energy whenever it communicates with the network's other nodes or with the sink, the network's total energy, also known as the sum of the energies of all of the network's nodes, steadily decreases while the data transmission continues. With the help of this statistic, the state of the residual energy of the network is computed at the end of 1,000 rounds.

c) **Stability Period (Active Node/ Dead Node):** This component is essential to the network's stability since it ensures the reliable transmission of data originating from the network. To generate the value of the stability period in tabular form, a fixed criterion of 2,000 rounds is used.

d) **Network lifetime**: The lifespan of a network may be evaluated based on a variety of factors. In contrast, a WSN's lifespan is measured in iterations, or the time between the network's initial setup and the occurrence of the First Node Die (FND). Eventually, Half Nodes Die (HND) is also computed in this paper to determine the network stability when 50% of the nodes die due to complete depletion of the nodes energy.

6.2.1 Comparison of Average Energy Consumption

Average Energy Consumption has been computed for the proposed MoBES based technique, which is compared with ABC [25], BBO [18], HS [14], SSA [26], and BES [23]. Average energy consumption after 1000 rounds for three different scenarios WSN~1, WSN~2 and WSN~3 is plotted to demonstrate the efficacy of the suggested method. The size of network in all three scenarios is constant i.e. $100 \times 100\ m^2$. but the number of nodes are varying, such that the number of nodes in WSN~1 is 100, number of nodes in WSN~2 is 150 and the number of nodes in WSN~3 is 200.

It is seen from the Fig.3. that the proposed MoBES based technique consumes less average energy per node in all three scenarios as compared to the rest of the techniques. The ABC technique has maximum average energy consumption among these techniques.

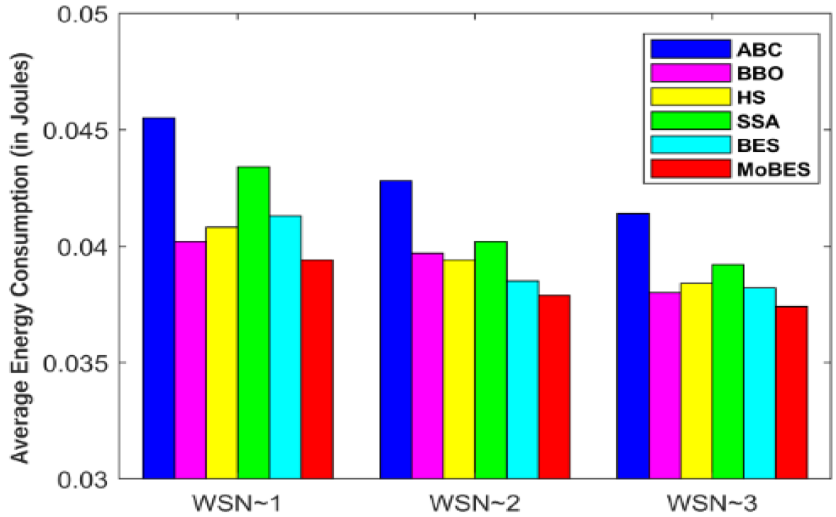

Fig.3 Comparison of MoBES with other techniques in terms of Average Energy Consumption

6.2.2 Comparison of Network's Residual Energy

The network's leftover energy is equal to the difference between how much energy was given at the beginning and how much energy the nodes used while sending, getting, and combining the data. The higher the amount of residual energy available, the longer the network will be able to function. As shown in Table 2, the proposed MoBES based technique has much more residual energy left as compared to ABC [25], BBO [18], HS [14], SSA [26], and BES [23] after the completion of 1,000 rounds.

Table 2

Comparative analysis of differences in terms of residual energy in Joules

Authors	Network Residual Energy		
	WSN~1	WSN~2	WSN~3
T. Ahmad et.al.(ABC)	83.2934	126.4710	169.7679
P. Lalwani et.al. (BBO)	83.1386	125.9098	168.3348
D. C. Hoang et al. (HS)	83.2665	126.2623	168.1766
S. Mirjalili et. al. (SSA)	83.4458	126.1647	168.8859
H. A. Alsattar et.al. (BES)	83.4927	126.8450	168.7455
Proposed Technique	83.6053	127.0416	170.1693

6.2.3 Comparison of Active Nodes

Table 3 compares the alive nodes of the five techniques with respect to the number of rounds. At the end of the $14{,}000^{th}$ round, the MoBES based technique has the maximum number of active nodes as compared to other techniques.

Table 3

Comparative analysis in terms of active nodes

Rounds	ABC	BBO	HS	SSA	BES	Proposed Technique
2000	98	100	100	100	99	100
4000	92	97	96	94	97	96
6000	90	93	95	91	91	95
8000	87	91	92	86	90	92
10000	84	88	89	81	85	91
12000	78	83	84	72	81	87
14000	71	67	73	61	69	83
16000	62	50	56	46	56	72
18000	43	40	46	22	45	52
20000	27	24	25	15	29	34

It can be concluded that the network lifespan has been increased in the proposed MoBES technique as compared to ABC [25], BBO [18], HS [14], SSA [26], BES [23] techniques. After completion of 20,000 rounds, MoBES based technique has 34 active nodes, whereas SSA has the lowest number of 15 active nodes, followed by BBO, HS, ABC, and BES which have 24, 25, 27, and 29 active nodes respectively.

6.2.4 Comparison of Dead Nodes

Table 4 specifies the count of dead nodes for five techniques versus the number of rounds. The performance of the proposed MoBES based technique in terms of dead nodes has been compared to ABC [25], BBO [18], HS [14], SSA [26], BES [23] techniques. In the proposed MoBES based technique, the number of dead nodes is less respective to number of rounds. At the end of 10,000 rounds, the proposed technique has only 9 dead nodes, whereas ABC [25], BBO [18], HS [14], SSA [26] have a maximum of 19 dead nodes, followed by ABC [25], which has 16 dead nodes and then BES [23], has 15 dead nodes at the end of 10,000 rounds.

Table 4

Comparative analysis in terms of dead nodes

Rounds	ABC	BBO	HS	SSA	BES	Proposed Technique
2000	2	0	0	0	1	0
4000	8	3	4	6	3	4
6000	10	7	5	9	9	5
8000	13	9	8	14	10	8
10000	16	12	11	19	15	9
12000	22	17	16	28	19	13
14000	29	33	27	39	31	17
16000	38	50	44	54	44	28
18000	57	60	54	78	55	48
20000	73	76	75	85	71	66

6.2.5 Comparison of Network Lifetime

Table 5 displays the estimated lifetime of the network based on the occurrences of the first node die and the half nodes die. The FND and HND of the proposed technique are at 2773 and 18287 rounds, respectively, which indicate that the network lasts longer in the proposed technique as compared to other techniques. Whereas in the cases of ABC [25], BBO [18], HS [14], SSA [26], BES [23], first node die at 1729, 2677, 2548, 2133, and 1995 round and half nodes die on 17080, 15796, 17763, 15618, and 16722 respectively. The proposed technique outshines the rest of the popular techniques in terms of network lifetime.

Table 5

Comparative analysis in terms of First Node Die (FND) and Half Nodes Die (HND)

Techniques	FND (Rounds)	HND (Rounds)
T. Ahmad et.al.(ABC)	1729	17080
P. Lalwani et.al. (BBO)	2677	15796
D. C. Hoang et al. (HS)	2548	17763
S. Mirjalili et. al. (SSA)	2133	15618
H. A. Alsattar et.al. (BES)	1995	16722
Proposed Technique	2773	18287

The proposed technique, which is based on a modified version of the Bald Eagle Search Algorithm (MoBES), is superior to the other techniques in terms of optimal clustering in WSN. This technique considers fitness function characteristics, intra-cluster distance, inter-cluster distance, and equipoise cluster formation using node degree. The suggested technique's performance is assessed using metrics, namely average energy consumption, residual energy, active nodes, dead nodes, and network lifetime. Therefore, it can be concluded that the suggested MoBES technique, when applied to the improvement of exploration in current BES, has enhanced the overall performance and may be employed for clustering in WSN.

7. Conclusion and Future Scope

In order to increase the lifetime of a WSN network, a modified bald eagle search technique is introduced using a replacement strategy for enhancing the exploration phase and to avoid local optima stagnation for clustering. In order to choose the best nodes as cluster heads from the WSN network, the MoBES based technique objective function takes into account intra-cluster distance, inter-cluster distance, and equipoise cluster formation using node degree. On the basis of network lifetime, dead nodes, alive nodes, residual energy, and average energy usage, the simulation results of the MoBES based technique are compared with those of ABC, BBO, HS, SSA, and BES. An analysis of the results demonstrates that the MoBES based technique performs better by delaying the first node die and half nodes die in the WSN network at 2773 and 18287 rounds and therefore gets an extended lifetime in comparison to other state-of-the-art techniques. This study proposes a MoBES based technique for optimal clustering to prolong the lifetime of the WSN network by optimizing its efficacy with regard to the number of active nodes. The MoBES based technique is deemed suitable for a network that requires a longer lifetime. MoBES based technique results show that it performs better than the existing state-of-the art techniques. It achieves maximum life expectancy and minimum energy dissipation among existing techniques. This presented MoBES based technique is compared with various state-of-the art techniques such as ABC, BBO, HS, SSA, and BES based average energy consumption, residual energy of the network, active node, dead node, and network lifetime. This suggested technique outperforms previous well-known techniques. In future, the proposed meta-heuristic technique can be extended to networks with mobile nodes and for the development of a robust routing algorithm.

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