EAI Endorsed Transactions
on Scalable Information Systems

Research Article EAI.EU

A Technique for Cluster Head Selection in Wireless Sensor Networks Using African Vultures Optimization Algorithm

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Abstract

INTRODUCTION: Wireless Sensor Network (WSN) has caught the interest of researchers due to the rising popularity of Internet of things(IOT) based smart products and services. In challenging environmental conditions, WSN employs a large number of nodes with limited battery power to sense and transmit data to the base station(BS). Direct data transmission to the BS uses a lot of energy in these circumstances. Selecting the CH in a clustered WSN is considered to be an NP-hard problem.
OBJECTIVES: The objective of this work to provide an effective cluster head selection method that minimize the overall network energy consumption, improved throughput with the main goal of enhanced network lifetime.
METHODS: In this work, a meta heuristic based cluster head selection technique is proposed that has shown an edge over the other state of the art techniques. Cluster compactness, intra-cluster distance, and residual energy are taken into account while choosing CH using multi-objective function. Once the CHs have been identified, data transfer from the CHs to the base station begins. The residual energy of the nodes is finally updated during the data transmission begins.
RESULTS: An analysis of the results has been performed based on average energy consumption, total energy consumption, network lifetime and throughput using two different WSN scenarios. Also, a comparison of the performance has been made other techniques namely Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Atom Search Optimization (ASO), Gorilla Troop Optimization (GTO), Harmony Search (HS), Wild Horse Optimization (WHO), Particle Swarm Optimization (PSO), Firefly Algorithm (FA) and Biogeography Based Optimization (BBO). The findings show that AVOA's first node dies at round 1391 in Scenario-1 and round 1342 in Scenario-2 which is due to lower energy consumption by the sensor nodes thus increasing lifespan of the WSN network.
CONCLUSION: As per the findings, the proposed technique outperforms ABC, ACO, ASO, GTO, HS, WHO, PSO, FA, and BBO in terms of performance evaluation parameters and boosting the reliability of networks over the other state of art techniques.

Keywords: Wireless Sensor Network (WSN), Cluster Head Selection, Network Lifetime.

Received on 09 September 2022, accepted on 22 December 2022, published on 11 January 2023

doi: 10.4108/eetsis.v10i3.2680

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1. Introduction

WSNs are self-configured and infrastructure-free wireless networks that monitor physical or environmental conditions such as temperature, sound, vibration, pressure, motion, or pollution and collectively transfer their data via the network to a central point or sink where the data may be examined and analyzed [1]. A variety of physical and environmental characteristics can be monitored using these sensors [2].

Sensor node has several obstacles in terms of hardware, communication method, battery life and computational cost. The battery powers processors, transmitters, and receivers in sensor nodes, but its limited life can collapse the network [3]. One of the primary limitations of the WSN is energy utilization of sensor nodes, which limits its computation, communication, and storage capabilities [4]. Other limitations of sensor nodes are node failure and network failure [5]. WSNs are hypersensitive and their lifetime is vulnerable to energy depletion of sensor nodes [6]. Optimal energy consumption in WSN is necessary to increase lifetime and performance. It can be achieved by performing clustering which decreases the energy consumption and increases the scalability of the network.

Clustering divides a network into equal or unequal clusters. Each cluster has a Cluster head (CH). CHs gather local data from cluster member sensor nodes, aggregate it, and transfer it to a distant base station (BS) directly or through other CHs [7, 8]. The BS is linked to the Internet. Figure 1. represents the architecture of the WSN.

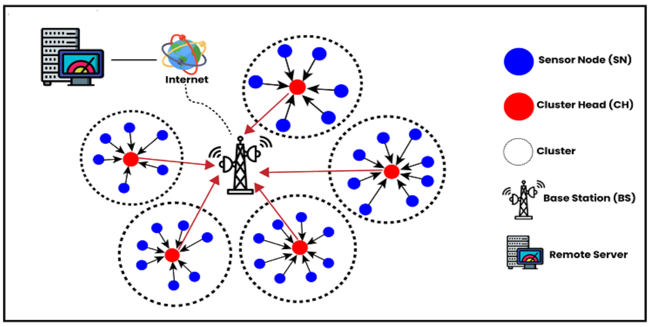

Figure 1. A WSN Architecture

In clustering, the selection of CHs is critical for improving the network durability since it affects member sensor nodes energy. As discussed in [9], CH-selection is an NP-hard optimization issue. As a result, the procedure of selecting the CHs is to be carried out with the utmost care.

The rest of the paper is divided into the following sections. The related work is presented in Section 2. Section 3 defines the network and energy model. Section 4 describes the proposed cluster head selection technique using AVOA. Section 5 discusses the nine meta heuristic techniques used for comparison with the proposed technique. Section 6 shows the simulation results and finally, section 7 concludes the paper.

2. Related Work

The essential contributions of researchers in the field of energy efficient clustering techniques have been discussed in this section. Many studies have been conducted by the researchers in the field of energy efficient cluster heads selection using conventional techniques as well as evolutionary techniques. These techniques are discussed here:

In the year 2000, Heinzelman et al. [10] proposed a technique called Low-energy adaptive clustering hierarchy (LEACH) which was a probabilistic technique that randomly selects CH in each round. LEACH attained a large energy consumption while lengthening lifetime of the network compared to static clustering method. In the year 2002, Lindsey et al. [11] proposed PEGASIS which was termed as Power-Efficient Gathering In Sensor Information Systems refers to an approach that was chain-based. PEGASIS arranged the sensor nodes (SNs) so that they formed a chain, with each SN communicating only with its immediate neighbours. In the year 2011, Liu et al. [12] proposed Genetic Algorithm based LEACH in which cluster head was selected based on optimal value of cluster head probability using Genetic-Algorithm. It gave optimal probability of nodes which could be selected as cluster heads with minimum energy consumption.

In the year 2014, Sharawi et al. [13] proposed a technique based on Bat Swarm Optimization algorithm to select optimized cluster heads by minimizing the intra-cluster compactness with minimum distance between nodes in same cluster. In the year 2015, Gupta and Sharma [14] proposed a clustering algorithm based on modified Ant Colony Optimization using residual energy as a parameter. Comparative analysis was performed taking average energy of network, number of live nodes respect to number of rounds as performance evaluation metrics. In the year 2016, Rao et al. [15] proposed an energy efficient Particle Swarm Optimization (PSO) based cluster head selection protocol. Parameters such as intra-cluster distance, residual energy and sink distance of all the CHs were used in the fitness function. In the year 2017, Sengottuvelan and Prasath [16] proposed an improved Breeding Artificial Fish Swarm Algorithm for optimal selection of Cluster head in the network. The multi objective function was based on end to end delay and energy was formulated. In the same year, an energy-efficient clustering scheme called New Chemical Reaction Optimization, proposed by Rao and Banka [17], was based on a recent variable population-based chemo-inspired approach (nCRO). It considerably increased the network's lifetime. However, CHs connect directly with the BS, which could be impractical in a large-scale network.

In the year 2018, Yogarajan and Revathi [18] presented Ant Lion Optimization for Clustering (ALOC), a technique to improve the energy efficiency of the network. The fitness function that was utilized in the ALOC took into account the residual energy, the number of nodes that were close to each node, the distance that separated the nodes from one another and the distance that separated each node from the BS. In the year 2019, Ahmad et al. [19] presented an approach for CHS based on an optimization technique called Artificial Bee Colony (ABC) method. The ABC's fitness function was evaluated on the basis of three parameters intra cluster distance, sink distance and residual energy. In the same year, Dattatraya and Rao [20] introduced a CH selection scheme using Glow worm Swarm Optimization (GSO) and Fruit Fly Optimization Algorithm (FFOA) to select the best CH in WSNs. Fitness Function was designed considering energy, distance, delay and QoS as important parameters. In the same year, an energy-efficient clustering scheme called New Chemical Reaction Optimization, proposed by Rao and Banka [17], was based on a recent variable population-based chemo-inspired approach (nCRO). In the year 2020, Prahadeeshwaran and Priscilla proposed a hybrid elephant optimization algorithm called NIUS-HEHOA [21] to extend the lifespan of the network by selection energy balanced cluster heads. In the year 2021, Arunachalam et al. [22] introduced Squirrel Search Optimization-based Cluster Head Selection Technique (SSO-CHST) was presented for enhancing sensor network lifetime by using a gliding factor to determine cluster head selection during data aggregation and dissemination. The sensor node with the lowest fitness value was the cluster member. High-fitness sensor nodes were the possible cluster head.

From the literature, it has been deduced that choosing CHs for large-scale WSN is an NP-Hard problem, but that it can be addressed using optimization methods. Several methods for energy-aware sensor node clustering have been discussed in the literature as a result of the fact that energy efficiency plays an essential role in the WSN. It is generally agreed that one of the most essential aspects of a WSN is its ability to minimize the amount of energy that sensor nodes consumes. The researchers have focused the attention on the clustering and cluster head selection methods. Considering this as a motivation, in this work, we propose a cluster head selection technique using meta heuristic based African Vultures Optimization Algorithm (AVOA) to reduce the energy consumption of nodes in the network. The main contributions of this paper are given below:

- A cluster head selection technique based on African Vultures Optimization Algorithm is proposed.
- Various set of parameters are incorporated in this paper to evaluate a fitness function.
- Comparison of proposed cluster head selection technique using AVOA with 09 state-of-the-art techniques in terms of average energy consumption, total energy consumption, network lifetime and throughput.

3. Preliminaries

In this section, network model and energy model, which are used in this paper, are discussed.

3.1. Network Model

The following are the characteristics of the WSN scenario considered in this paper. The sensors are distributed at random across the sensing field, and a node. The same methodology was used in the literature by [23]. As a result, no location-finding equipment, such as GPS, is required. After deployment, all sensor nodes are presumed to be stationary, and nodes can operate in cluster head and conventional sensor modes. Each node executes sensing on a regular basis and always has data to communicate to its CH or BS. The number of sensors exceeds the number of CHs. The sensor nodes are homogeneous and have identical processing and communication capabilities. Wireless, symmetric communication links are created between nodes when they are within transmission range of each other.

3.2. Energy Model

In this research, the classic Low-energy adaptive clustering hierarchy (LEACH) energy model [10, 24] is used to calculate network energy consumption and exhausted energy for all network nodes. The same first order wireless communication model was used by [25]. Following assumptions have been made:

- Initialize all the nodes with their attributes and establish their initial energies based on the first order radio energy model.
- Node are transferring message with k bits via a distance d on symmetrical communication channels, and hence consume energy is expressed by equation (1) and equation (2). Based on the distance d between the sender and receiver, the energy can be computed as follows:

$$E_{Tx}(k,d) = E_{Tx_{elec}}(k) + E_{Tx_{amp}}(k,d) \qquad (1)$$

$$E_{Tx}(k,d) = \begin{cases} E_{elec} \times k + E_{amp\_fs} \times k \times d^2 \; if \; d < d_0 \\ E_{elec} \times k + E_{amp\_mp} \times k \times d^4 \; if \; d > d_0 \end{cases} \qquad (2)$$

$$d_0 = \sqrt{\frac{E_{amp\_fs}}{E_{amp\_mp}}} \qquad (3)$$

where $E_{Tx}(k,d)$ is the transmission energy consumption k bits data to a node, d is the distance between sender and receiver nodes, E_{elec} is the energy dissipation per bit used to run the transmitter or receiver circuitry, E_{amp_fs} is the amplifier parameter of transmission corresponding to the free space, E_{amp_mp} is the amplifier parameter of transmission corresponding to the two ray model, d_0 is the transmission distance threshold which is expressed by equation (3).

On other hand, the reception dissipation energy for message of k bits for any node is expressed by the equation (4) due to running the receiver circuitry $E_{Rx}(k)$.

$$E_{Rx}(k) = E_{Rx_{elec}}(k) = E_{Rx_{elec}} \times k \qquad (4)$$

$E_{Rx}(k)$ is the energy consumption in receiving k bits of data.

4. Proposed African Vulture Optimization Algorithm (AVOA) Based Cluster Head Selection Technique

In 2021, Abdollahzadeh et al. [26] proposed the AVOA meta-heuristic algorithm, which has since been used in a number of real-world engineering applications. Simulations and models based on the foraging behaviours and living habits of African vultures were used to develop the AVOA. The following factors are taken into consideration in order to carry out the simulation that is known as AVOA, which recreates the living patterns and foraging tactics of African vultures.

(i) The African vulture population consists of N vultures, and the algorithm user determines the size of N based on the current circumstances. Each vulture's position space has a D-dimensional grid, with the size of D varying depending on the problem's dimension.
(ii) The population of African vultures is classified into three categories based on their living habits. Using the fitness value of the viable solution to measure vulture quality, the first group finds the best feasible solution. The second group contends that the workable solution is the second-best option out of all of the possibilities. The remaining vultures form the third group.
(iii) The vulture forages in groups across the population. As a result, various sorts of vultures serve distinct functions in the population.
(iv) Similarly, if the fitness value of the population's viable solution may be taken to represent the benefits and drawbacks of vultures, the weakest and most ravenous vultures correspond to the worst vultures at the present. Conversely, the best vulture right now is the strongest and most abundant vulture. In AOVA, vultures aim to be near the best and avoid the worst.

According to the aforementioned four norms, AOVA's problem-solving process may be broken down into five phases that mimic the actions of different vultures during the foraging phase.

Phase One: Identifying the best vulture in any group

After the formation of the initial population, the fitness of each solution is calculated, and the top and bottom performers are selected as vultures for the first and second groups, respectively. Populations are analysed comprehensively at each fitness iteration.

$$R(i) = \begin{cases} Best\ Vulture_1\ if\ PR_i = B_1 \\ Best\ Vulture_2\ if\ PR_i = B_2 \end{cases} \tag{5}$$

In equation (5), the chance that the chosen vultures will lead the others to one of the better solutions in each group is determined using B_1 and B_2.

Phase Two: Vulture Hunger Rate

They have high energy levels when they are full, so they can travel vast distances in quest of food, but when they're hungry, their energy levels are low and they can't walk as far as when they are full, so they become more aggressive. In order to model this phenomenon mathematically, equation (7) was applied in the process. For this reason, the rate at which vultures become full or hungry is taken into consideration while deciding whether or not to move from exploration to extraction. equation (7) has been used to describe the decline in the rate at which people become satiated.

$$T_1 = H_1 \times \left(sin^w\left(\frac{\pi}{2} \times \frac{itr}{\max\_itr}\right) + cos\left(\frac{\pi}{2} \times \frac{itr}{\max\_itr}\right) - 1\right) \tag{6}$$

$$V_f = (2 \times rnd_1 + 1) \times y \times \left(1 - \frac{itr}{\max\_itr}\right) + T_1 \tag{7}$$

Vultures full (V_f), iteration number (itr), maximum number of iterations (max_ itr), and a random value (y) between -1 and 1 (which changes with each iteration) are all symbols used in equations (6) and (7). h ranges from-2 to 2. rnd_1 is a random value between 0 and 1. When y is below 1, the vulture is starving; when it's 0, it's full.

Phase Three: Exploration

This stage examines AVOA's exploration phase. Vultures have excellent vision and can detect food and dying animals. Vultures meticulously inspect their surroundings and travel far to get food. In the AVOA, vultures can explore random areas using two distinct methodologies, and a parameter selects one. This option must be set between 0 and 1 before the search operation to determine which strategy is selected. A random integer between 0 and 1 is created when selecting a strategy in the exploration phase. Equation (9) is selected if the number is more or equal to the parameter . However, if number is smaller equation (11) is used. It is shown in equation (8).

$$Q(i+1) = \begin{cases} Equation\ (9)\ \ if\ Q_1 \geq rnd_{Q1} \\ Equation\ (11)\ if\ Q_1 \leq rnd_{Q1} \end{cases} \tag{8}$$

$$Q(i+1) = R(i) - D(i) \times V_f \tag{9}$$

$$D(i) = |X \times R(i) - Q(i)| \tag{10}$$

$$Q(i+1) = R(i) - V_f + rnd_2 \times \left((UB - LB) \times rnd_3 + LB\right) \tag{11}$$

A vulture's position vector in the following iteration is denoted by $Q(i+1)$, and its satiation rate in the present iteration is denoted by V_f which is obtained using equation (7). $R(i)$ is one of the best vultures selected by equation (5) in equation (10). Vultures move randomly in X to guard food from other vultures. The formula $X = 2 \times rnd$, where rnd is a randomly generated number between 0 and 1, is used to create X, which is then utilised as a coefficient vector to increase the random motion, which shifts with each iteration. The vulture's Q_i is the vector position. LB and UB show the variable bounds. rnd_3 boosts randomness. If rnd_3 is near to 1, similar solutions are distributed, adding a random motion to the LB.

Phase Four: Exploitation Stage-1

At this stage, the AVOA's efficiency stage is looked into. If the value $|V_f|$ is less than 1, the AVOA moves on to the exploitation phase. This phase also has two parts, each of which uses a different strategy. Two parameters Q_2 and Q_3, determine how likely it is that each strategy will be chosen in each internal phase. Parameter Q_2 selects first phase tactics, whereas Q_3 selects second phase strategies. Before running the search operation, both parameters must be set to 0 and 1.

$|V_f|$between 1 and 0.5 begins the exploitation phase. During the first phase, two distinct rotational flight and siege-fight strategies are employed. Q_2 determines each strategy's choosing, which should be between 0 and 1 before searching operation performed. At the start of this phase, rnd_{Q2} is formed. If this number is larger than or equal to Q_2, Siege-fight is implemented slowly. If the random number is less than Q_2, rotating flight strategy is used. This procedure is shown in equation (12).

$$Q(i+1) = \begin{cases} Equation\ (10)\ if\ Q_2 \geq rnd_{Q2} \\ Equation\ (13) if\ Q_2 < rnd_{Q2} \end{cases} \tag{12}$$

$$Q(i+1) = D(i) \times (V_f + rnd_4 - d(t)) \tag{13}$$

where,

$$d(t) = R(i) - P(i) \tag{14}$$

$D(i)$ is computed using equation (10), and V_f is the vulture satiation rate, which is derived using equation (7). rnd_4 is a number generated at random between 0 and 1.

Rotating Flight of Vultures

The model rotating flight pattern known as the spiral motion model is utilised frequently by vultures. With this strategy, a spiral equation is formed including every vulture and the top performer among the two. Equation (16) is used to describe the circular flight, and (17).

$$S_1 = R(i) \times \left(\frac{rnd_5 \times Q(i)}{2\pi}\right) \times cos\big(Q(i)\big) \tag{15}$$

$$S_2 = R(i) \times \left(\frac{rnd_6 \times Q(i)}{2\pi}\right) \times sin\big(Q(i)\big) \tag{16}$$

$$Q(i+1) = R(i) - (S_1 + S_2) \tag{17}$$

In (16) and (17), $R(i)$ represents position vector of the two best vultures in the current iteration. rnd_5 and rnd_6 are random between 0 and 1. Equations (15) and (16) computes S_1 and S_2. As a last step, the vultures' locations are revised using equation (17).

Phase Four: Exploitation Stage-2

The motions of the two vultures during the second stage of exploitation draw many vulture species to the food source, where siege and fierce competition for food occur. This phase is initiated when the $|V_f|$ value is less than 0.5. rnd_{Q3}, a value between (0,1) is generated during this stage. If rnd_{Q3} is more than or equal to Q_3, numerous vulture species ought to congregate over the food supply. Alternately, the aggressive siege-fight strategy suggested in equation (18) is used if the generated value is lower than Q_3.

$$Q(i+1) = \begin{cases} Equation\ (16)\ if\ Q_3 \geq rnd_{Q3} \\ Equation\ (17) if\ Q_3 < rnd_{Q3} \end{cases} \tag{18}$$

$$A_1 = BestVulture_1(i) - \frac{BestVulture_1(i) \times Q(i)}{BestVulture_1(i) - Q(i)^2} \times V_f$$

$$A_2 = BestVulture_2(i) - \frac{BestVulture_2(i) \times Q(i)}{BestVulture_2(i) - Q(i)^2} \times V_f \tag{19}$$

Finally, all vultures are aggregated using equation (20), where $A_1$and A_2 are from equation (19) and $Q(i+1)$ is the upcoming iteration's vulture vector. The top vultures in the first and second groups of the current iteration are respectively known as $BestVulture_1(i)$ and $BestVulture_2(i)$. The vector position of a vulture at any given moment is denoted by the symbol $Q(i)$, and the rate at which vultures become satisfied can be calculated using the equation (7).

$$Q(i+1) = \frac{A_1 + A_2}{2} \tag{20}$$

When $|V_f|$ is more than 0.5, the head vultures become starved, and they lack the strength necessary to contend with the other vultures. In order to model this motion, equation (21) is applied.

$$Q(i+1) = R(i) - |d(t)| \times V_f \times Levy(d) \tag{21}$$

where $d(t)$ reflects the vulture's distance from one of the two best vultures using equation (14).

4.1. Initialization and Solution Vector

To determine the ideal position of CH's in the network, a solution vector is employed to create an initial solution, which is processed using AVOA. The solution vector is composed of K nodes (African Vultures) chosen at random as CHs from a total number of N sensor nodes. The position of each node is randomly assigned a node-ID from the total number of nodes i.e. N.

The dimensionality dim of each node agent is directly proportional to the number of CHs in the network. Assume that AV_i denotes the ith node in the network, and that the position of each node $AV_{i,dim}$ is randomly assigned a node-ID between 1 to N. Solution encoding used for CH selection using AVOA optimization technique is illustrated in the figure below.

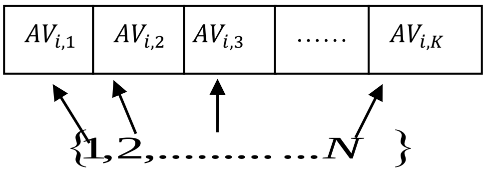

Figure 2. Solution encoding for CH selection using AVOA

4.2. Fitness Function

The primary objective of proposed technique is to select energy efficient cluster heads using three parameters Intra Cluster Distance, Residual Energy, Cluster Compactness. Since the three objectives are minimization problem in nature, so the ultimate fitness function F may be defined as a linear combination of f_1, f_2 and $f_3$which is formulated as equation (22) :

$$F = \varphi_1 f_1 + \varphi_2 f_2 + \varphi_3 f_3 \tag{22}$$

where, φ_1, φ_2 *and* φ_3 are the weighted coefficients such that, $\varphi_1 + \varphi_2 + \varphi_3 = 1$. The weight given are φ_1=0.4, $\varphi_2 = 0.3$ and $\varphi_3 = 0.3$ respectively; f_1 is Intra Cluster Distance, f_2 is Residual Energy and f_3 is Cluster Compactness.

Intra Cluster Distance:

The intra-cluster distance, or the distance that separates all of the sensor nodes in a cluster from the CH, is the first parameter that is evaluated for the objective function. Nodes depletes there energy when they communicate thus we must limit intra cluster distance. It means that CH may be selected to be closest to all cluster nodes. Thus, it is necessary to minimize the individual objective function f_1 which is shown below in equation (23) :

$$f_1 = \sum_{i=1}^{N} D_{s_i}^{ch^k} \tag{23}$$

This function gives total distance for N number of sensor nodes for k^{th} cluster heads. $D_{s_i}^{ch^k}$ is the distance between cluster head and sensor nodes.

Residual Energy:

Residual energy of the cluster head is taken into consideration. The goal is to make the most use of all of the WSN's remaining energy of the sensor nodes. Since, the objective function is a minimization problem, so it is expressed as in equation (24) below:

$$f_2 = \sum_{i=1}^{k} \frac{1}{Res_{ch^k}} \tag{24}$$

This function gives total residual energy of all the k cluster heads.

Cluster Compactness:

Cluster Compactness represents measure of closer proximity among the normal nodes and CHs. It is third essential parameter that aids in generating clusters which comparably spend less energy. Cluster compactness of a node is determined as node degree divided by sum of distance to neighbour nodes. High cluster compactness value implies that the node can form compact clusters and lowest intra cluster communication cost is incurred. Hence, a node with high cluster compactness score has greater probability of getting elected as CH. It is expressed as in equation below :

$$f_3 = \frac{ND^{(i)}}{\sum_{j \in Nbr_i} dist(i,j)} \tag{25}$$

where, $Nbr^{(i)}$ represents set of nodes at one hop distance from i^{th} node. ND is node degree.

4.3. Evaluation of Fitness Function

In this stage, the formed fitness function is assessed for each location of the sensor nodes by inputting the values that are related with the solution vector (decision variable). The fitness function value for the solution vector is then represented in equation (26).

$$fit_{eval} = \begin{bmatrix} fit(\mathrm{AV}_{(1,1)}, \mathrm{AV}_{(1,2)}, \dots \dots \dots \dots .. \mathrm{AV}_{(1,d)}) \\ fit(\mathrm{AV}_{(2,1)}, \mathrm{AV}_{(2,2)}, \dots \dots \dots \dots .. \mathrm{AV}_{(2,d)}) \\ \dots \dots .. \\ \dots \dots .. \\ fit(\mathrm{AV}_{(n,1)}, \mathrm{AV}_{(n,2)}, \dots \dots \dots \dots .. \mathrm{AV}_{(n,d)}) \end{bmatrix}$$

(26)

In this scenario, the fitness value of each sensor node depending on its position depicts how well they perform in terms of energy and minimal distances taken into account during the construction of the fitness function.

According to the solution vector, each sensor node in the network calculates its fitness value and arranges it in ascending order. The sensor node with the lowest fitness score will be selected as the network's cluster head. The cluster head in the following round may be chosen from among the remaining sensor nodes. This cluster head selection procedure, however, is reliant on the sensor nodes having enough energy because they must gather and transmit the data to the BS.

5. Meta-heuristic Techniques For Comparison

Meta heuristic algorithm, a method for solving optimization issues, begin by creating random response(s) and then advance to optimizing based on their operators and through modifying the generated random answers. In general, all meta heuristic algorithms use the similar approach to discover the optimal answer [27]. In the majority of these algorithms, the search process begins by producing one or more random solutions in a range of variables that is suitable. The primary generated solution in the population based algorithms is termed population, colony or group. and also each of solutions is named chromosome, particle, ant, and etc. [28] Then, utilizing operators and other methods of merging primary solutions, new solutions are formed. The new solution will also be selected from the pool of prior ones, and this process will carry on until the stop requirement is satisfied.

In this work, different meta heuristic techniques are used for comparative analysis with the proposed technique for CH selection i.e. based on African Vulture Optimization Algorithm. Meta-heuristic techniques used in this work are Artificial Bee Colony Optimization (ABC) [29], Ant Colony Optimization (ACO) [30], Atom Search Optimization (ASO) [31], Wild Horse Optimization (WHO) [32], Harmony Search Optimization (HS) [33], Gorilla Troops Optimization (GTO) [34], Firefly Algorithm (FA) [35], Particle Swarm Optimization (PSO) [36], Biogeography Based Optimization (BBO) [37]. Simulation parameters, average energy consumption, total energy consumption, network lifetime and throughput are used in this work for performance evaluation of the above mentioned techniques.

6. Result and Discussions

In this paper, we have proposed an energy-efficient CH selection technique based on African Vultures Optimization Algorithm (AVOA) and a fitness function considering intra-cluster distance, residual energy, and cluster compactness for the algorithm's energy efficiency. The algorithm compromises of two different scenarios namely WSN Scenario-1 for 100 nodes and WSN Scenario-2 for 200 nodes while considering same network area of $100m \times 100\,m$.

This section compares the performance of the techniques namely ABC, ACO, ASO, WHO, HS, GTO, FA, PSO and BBO based on the simulation parameters average energy consumption, total energy consumption, network lifetime and throughput. The simulation was run for 6000 rounds. However, 1000 rounds are used to evaluate the performance parameters of these techniques.

6.1. Simulation Setup

The adopted CH selection models have been implemented in MATLAB-2018b using the platform running under Windows 10 Professional with Intel Core i7 Processor @ 3.1 GHz frequency along with 8 GB RAM. Table 1 describes the parameters with their related values for modelling CHs in WSN. Accordingly, the proposed technique has been compared with the other techniques namely ABC [29], ACO [30], ASO [31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37].

6.2. Simulation Parameters

Simulation parameters used for performance evaluation of the proposed cluster head selection technique are as follows:

a) Average Energy consumption: It calculates the average energy difference between each node's original level and its remaining level [38].On a per-round basis, it is the amount of energy spent by a node to transmit the data in the WSN network.
b) Total Energy Consumption: Network energy dissipation per round is a measure of how much power is used by the network's nodes [15].
c) Network Lifetime (FND): A WSN's life span is defined in this study as the number of rounds it goes through before its first node dies [39] .
d) Throughput: The term 'throughput' refers to the total number of data packets that are successfully transferred to the sink [40].

Table 1. Parameter description

Parameter	Value
Nodes in the network area	100 m $\times$ 100 m
Number of rounds	6000
Number of cluster heads	10% of the total number of nodes in the network area
Number of nodes	WSN Scenario 1 - 100 WSN Scenario 2 - 200
Base station position	(50,50)
Initial energy (E_0)	0.5 J
Receiving power (E_{Rx})	50×0.000000001nJ/bit/m^2
Transmission power (E_{Tx})	50×0.000000001nJ/bit/m^2
Data aggregation energy (E_{DA})	5×0.000000001nJ/bit/m^2

6.2.1. Average Energy Consumption Evaluation

Average energy consumption for WSN Scenario-1 with 100 numbers of nodes is shown in Figure 3. It is observed from the figure that the proposed technique with AVOA is able to achieve average energy consumption of 0.0407 joules which is lower than ABC [29], ACO [30], ASO [31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37] by 7.71% 6.22%, 0.97%, 7.29%, 4.68%, 3.78%, 3.33%,4.01% and 1.93% respectively.

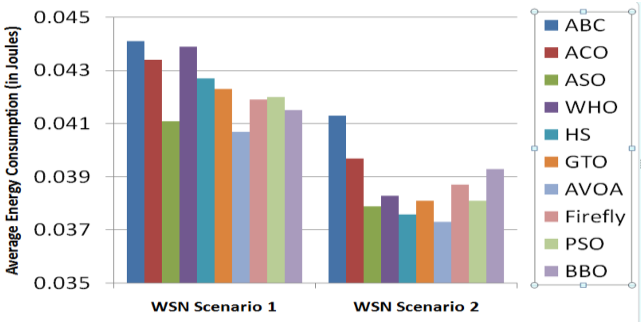

Figure 3. Comparative Analysis of Average Energy Consumption for WSN Scenario-1 & Scenario-2

However, In case of WSN Scenario-2 as the network node count increases from 100 to 200, the proposed approach reaches an average energy consumption of 0.0373 joules, which is less than ABC [29], ACO [30], ASO[31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37] by 9.69%, 6.05%, 1.58%, 2.61%, 0.80%, 2.10%, 4.11%, 2.09% and 5.09%. Therefore, it can be conclude from the table 2 that AVOA technique has minimum per node energy consumption compared to the rest of the techniques.

Table 2. Comparative analysis in terms of Average Energy Consumption (in joules) for WSN Scenario-1 and Scenario-2 at the end of simulation for 1000 rounds.

Name of Technique	WSN Scenario-1	WSN Scenario-2
ABC[29]	0.0441	0.0413
ACO[30]	0.0434	0.0397
ASO[31]	0.0411	0.0379
WHO[32]	0.0439	0.0383
HS[33]	0.0427	0.0376
GTO[34]	0.0423	0.0381
AVOA[26]	0.0407	0.0373
Firefly[35]	0.0421	0.0389
PSO[36]	0.0424	0.0381
BBO[37]	0.0415	0.0393

6.2.2. Total Energy Consumption Evaluation

As shown in Figure 4 and Figure 5, total energy consumption of the proposed technique with AVOA when compared with the rest of other techniques ABC [29], ACO [30], ASO [31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37] for 1000 rounds is the minimum. ABC technique consumes maximum energy while the proposed technique consumes lesser energy compared to rest of the techniques. Table 3 shows the comparative analysis in terms of total energy consumption.

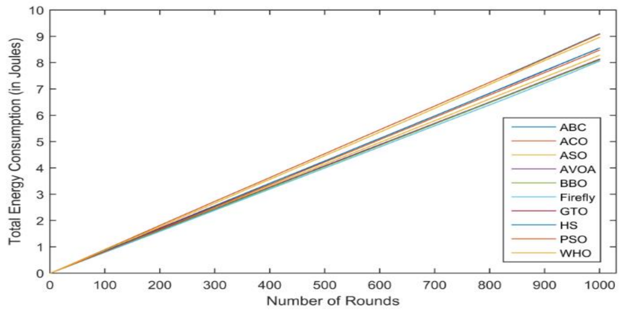

Figure 4. Comparative Analysis of Total Energy Consumption for WSN Scenario-1

When the number of nodes in the network is doubled from 100 to 200 while the number of simulation rounds is kept the same, the overall energy consumption of the proposed technique AVOA is lower than that of ABC [29], ACO [30], ASO [31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37].The maximum energy consumption is by the technique with ABC.

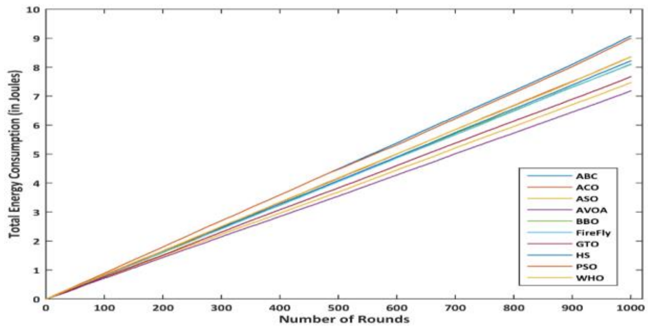

Figure 5. Comparative Analysis of Total Energy Consumption for WSN Scenario-2

Table 3. Comparative analysis in terms of Total Energy Consumption for WSN Scenario-1 and WSN Scenario-2 at the end of simulation for 1000 rounds

Name of Technique	WSN Scenario-1	WSN Scenario-2
ABC[29]	9.0943	9.0722
ACO[30]	9.0745	8.9840
ASO[31]	8.2760	7.4670
WHO[32]	8.9629	8.3489
HS[33]	8.5516	8.2147
GTO[34]	8.5493	7.6688
AVOA[26]	8.1334	7.1799
Firefly[35]	8.4158	8.1087
PSO[36]	8.4763	8.3542
BBO[37]	8.2994	8.0883

6.2.3. Network Lifetime (FND)

First Node Die (FND), which specifies the first node that depletes its available energy throughout the network, is the metric that is used to determine the network lifespan in WSN. The results of comparing the network lifespan of the proposed technique AVOA with the rest of techniques with ABC [29], ACO [30], ASO [31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37] are shown in Figure 6.

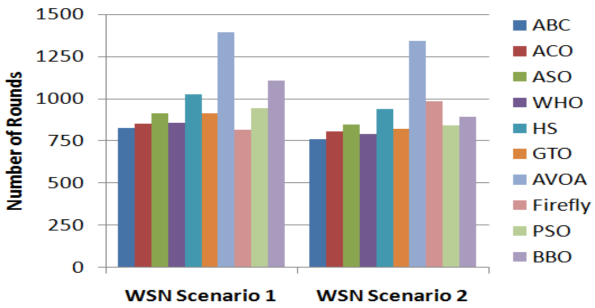

Figure 6. Comparative Analysis of Network Lifetime for WSN Scenario-1 and WSN Scenario-2

The AVOA has a FND of 1391 in Scenario-1 of the WSN and 1342 in Scenario-2 of the WSN, which is comparatively higher than the other techniques. It is shown that proposed technique has a higher network lifespan even if the nodes density increases from 100 to 200 nodes as compared with rest of the techniques.

6.2.4. Throughput

As shown in Table 4, throughput of the proposed technique with AVOA is maximum when compared with the rest of techniques with ABC [29], ACO [30], ASO [31], WHO [32], HS [33], GTO [34], FA [35], PSO [36], BBO [37]. It is observed that the proposed technique receives more data packets compare to the rest of the techniques. Also, when the node density is doubled, the proposed technique shows minimal decrease in throughput as compared with rest of the techniques.

Table 4. Comparative analysis in terms of Throughput for WSN Scenario-1 and WSN Scenario-2

Name of Technique	WSN Scenario-1	WSN Scenario-2
ABC[29]	8.22×10^4	7.57×10^4
ACO[30]	8.48×10^4	8.03×10^4
ASO[31]	9.12×10^4	8.46×10^4
WHO[32]	8.55×10^4	7.87×10^4
HS[33]	10.22×10^4	9.37×10^4
GTO[34]	9.13×10^4	8.17×10^4
AVOA[26]	13.91×10^4	13.42×10^4
Firefly[35]	8.16×10^4	9.85×10^4
PSO[36]	9.44×10^4	8.39×10^4
BBO[37]	11.08×10^4	8.91×10^4

7. Conclusion and Future Work

In conclusion, the lifespan of a network is an essential component of a WSN. Keeping track of how much energy is used is not an easy chore. We have proposed an energy-efficient CH selection technique based on AVOA and a fitness function considering intra-cluster distance, residual energy, and cluster compactness for the algorithm's energy efficiency. Our proposed technique findings have been compared to well known techniques namely ABC, ACO, ASO, WHO, HS, GTO, FA, PSO, and BBO. This technique has been thoroughly tested with two different WSN scenarios. According to the experimental results, the suggested technique outperforms the traditional technique on the basis of average energy consumption, total energy consumption, network lifetime, and throughput. The results demonstrate that taking into consideration the aforementioned factors lead to improvements in both the average amount of energy used and the lifespan of the network. As future work, other factors effect in parallel with residual energy such as sensor range and transmission energy can be studied and evaluated. Our future research will be to create a routing algorithm utilizing a meta heuristic method.

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