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Article

An Enhanced Energy Efficiency Routing for WSN based on Elephant Herding and Swarm Optimization Approaches

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Abstract: Energy utilization and inadequacy of sensor nodes are considered major drawbacks in wireless sensor networks (WSNs). This is because the sensor nodes use the battery for recharging energy. To overcome this issue WSN utilized a clustering-routing algorithm. This protocol divides the adjacent sensor nodes into separate clusters to choose a cluster head. Thus, the cluster head gathers information from all clusters and transmits it to the base station. In this article, the proposed method used cluster-based routing protocols to enhance energy efficiency and network lifetime. Moreover, this paper follows three stages to maximize energy efficiency. Initially, the clustering process is performed using dolphin swarm optimization (DSO), where a group of clusters is formed. Then the second stage is composed of cluster head selection among the group of clusters by elephant herding optimization (EHO) strategy. Finally, the collected data are necessary to forward to the base station for transferring the information. A specified path (routing) is selected by chicken swarm optimization (CSO). By using these algorithms, the network nodes support the balance of energy utilization. Experimental analysis proves when evaluated with existing methods the proposed technique has improved energy efficiency with an increase in network lifetime.

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1. Introduction

Wireless sensor networks (WSNs) compiled of wireless modules called sensor nodes. The primary work of these sensor nodes is to capture the surroundings and measure the sensed values from various sensor areas. Applications of WSN include agricultural, security systems, medical domain, disaster management, weather forecasting, and military applications. WSNs are utilized for data gathering with effective analysis of the surroundings [1]. The sensor nodes have components such as a micro sensor, memory, a battery, a microprocessor, and a trans-receiver to communicate with the remaining networks [2]. Due to the scheme

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and usage of WSNs, it faces primary difficulties because of the limited assets and restricted abilities of sensor hubs (nodes). For example, battery power, transmission capacity, storage, preparing, detection, and correspondence. Thus, energy is considered a serious issue for network researchers nowadays to transmit information. Hence, suitable algorithms and protocols are necessary to improve each sensor node's energy efficiency and lifetime to enhance the performance of the network. To overcome this issue several clustering and routing protocols have been developed [3]. In some clustering methods, the sensor nodes are joined to form a cluster whereas in other methods the cluster head is elected and is responsible for clustering the nodes. By using this criterion all other sensor nodes communicate only in intra-cluster strategy i.e., short distance communication where only less energy is consumed. However, a cluster head (CH) in a single hop communication sends information to the base station (BS) directly, whereas in multi-hop communication it makes use of relay nodes to transfer the information. The group heads screen and control the information stream across clusters for which impressive energy is devoured [4]. For effective communication between sensor nodes clustering technique is utilized for improving energy efficiency. The hierarchical clustering method has some advantages: (a) It lessens long reach correspondences and in general energy utilization, (b) It decreases channel conflict and packet collision (c) It brings about better throughput under high burden (d) It expands versatility (e) Efficient information accumulation and channel transfer speed are proficiently used [5]. The major issue behind clustering is non-uniform clustering and which causes heavy energy consumption among nodes and which leads to non-guaranteed connectivity of networks. The main aim of this proposed work is on hierarchical cluster-based routing schemes [6]. In WSN, routing [7] is required to develop data transfer communication between sensor nodes and BS. Consequently, routing is an intense assignment as the conventions relating to customary networks in WSN. Traditional routing strategy does not worry about the way rather it uses programmed rehashed solicitation, information connects innovation, or forward blunder checker [8]. Meanwhile, the most challenging assignment in routing is that the sensor nodes are deployed in remote ad-hoc networks in most of the research fields [9]. The main characteristics of routing are done by utilizing the selected number of nodes it performs successful probability in sending information to the BS with maximum success rate [10]. The routing challenges [11] include data processing, cross-layer design, high bandwidth, quality of service, compressing methods, and high energy utilization. Huge unpredictability is caused in securing WSN directing against assaults. Additionally, it is hard to locate the ideal arrangement other than ensuring the network. In this manner, a definitive objective of routing is to choose the right plan for directing information related to the best choice of sensor hubs [12].

Nowadays, nature-inspired algorithms are widely used to solve a range of optimization issues. In WSNs, clustering and routing are the two major issues that were well researched and developed using nature, bio-inspired algorithms. The most important intention is to elect suitable CHs among cluster nodes to minimize energy utilization of the network. A large portion of these strategies utilizes incorporated routing algorithms, due to the multifaceted nature of the execution of metaheuristic algorithms in disseminated conventions. The bio-inspired metaheuristic procedures can accomplish preferred execution over traditional methodologies

In this paper nature-inspired algorithm based on dolphin swarm optimization is used for clustering the sensor nodes. Once the nodes are clustered, data transmission will be much easy and it consumes less energy for transmitting data. Then, another nature-inspired algorithm named EHO is utilized for selecting the cluster head among the group of clusters. CH is chosen by the node's residual energy and the distance between the nodes. At last, the routing is done by chicken swarm optimization, for finding the best route to transfer data. Hence, the most important goal of the proposed technique is to improve energy efficiency with an increase in network lifespan. To discover quick and efficient arrangement, some neighborhood upgrades in the arrangement stage help these proposed algorithms to combine quicker contrasted and each of the basic algorithms. The principal involvement of the proposed method is described as below.

1. Developed a hybrid nature-inspired metaheuristic algorithm as dolphin swarm optimization and employed it for clustering the sensor nodes in WSNs.
2. Implemented an EHO algorithm with a fitness function, which can be tuned based on the requirements of the network.
3. Considering the parameters of residual energy, inter and intra-cluster distance, and distance between nodes to elect appropriate CH by EHO.
4. Introducing chicken swarm optimization as a routing protocol to transfer data to the base station in WSNs.
5. Finally, considering this nature and bio-inspired algorithms in various situations to exhibit its presentation against the current protocols, as far as energy utilization and network lifetime.

The workflow of the article is structured as Section 2 presents a discussion of the literature. The preliminaries of the proposed techniques are presented in Section 3. Section 4 describes the proposed system model. The proposed protocol is presented in Section 5. In Section 6 an analysis of the experimental results is explained. Finally, Section 7 Concludes the work.

2. Related work

Wireless sensor network (WSN) has numerous sensor nodes which are widely used for gathering information from various circumstances. The basic principle of WSN is to collect data from far-off spot regions, for example climate observation, military, transportation security, etc. In WSN the primary issue is the accessibility of restricted energy assets. So, improving energy productivity with a life expectancy of sensor hubs is a main concern and so, Bhola et al., [13] invented an energy effective routing protocol, low energy adaptive clustering hierarchy (LEACH) along with optimization genetic algorithm (GA). LEACH is one of the hierarchical protocols which elects the cluster head. The CH collects information from nodes and transmits it to the base station. A genetic algorithm is utilized to predict the route discovery path by its fitness value. Also, the exhibition of LEACH disintegrates strongly with expanding network size. WSN protocol is to broaden the network life expectancy while keeping up high adaptability. Ahmed et al., [14] presented an energy efficient clustering and hierarchical routing algorithm called Energy-Efficient Scalable Routing Algorithm (EESRA). The main objective of the protocol is to expand the life expectancy of the network despite in spite of an expansion in the network size. The protocol receives three-layer pecking order to limit the group heads heap to randomize the choice of CHs.

In wireless sensor networks, hubs are formulated together into clusters, predicting effective routing ways and regulating the clusters are the three primary factor that essentially improves the lifespan of the network. Hang et al., [15], suggested a chaotic genetic algorithm, a clustering routing protocol combined with these three features called CRCGA (clustering routing with a chaotic genetic algorithm). In CRCGA the turbulent hereditary protocol is utilized to elect the best cluster head. The optimal way for routing is carried forward by encrypting into a single chromosome. Nguyen et al., [16] implemented a new energy-efficient and secure clustering-based data transmission in pervasive wireless networks using the red deer algorithm (RDA) based clustering technique with blockchain (BC) enabled secured data transmission, named RDAC-BC. The RDAC-BC strategy follows an initialization process for clustering the nodes using the RDAC method. Afterward, CH is elected by the clustered method and cluster setup is processed. When the CHs are picked, blockchain empowered secure information transmission happens among group individuals just as CHs. The use of RDAC and blockchain innovation assists with accomplishing energy effectiveness and security.

PEGASIS is an alternation of LEACH (chain-based routing protocol). By using greedy algorithm sensor nodes are gathered to form a chain. In this protocol, each chain acts as a head chain, and all hub fuse the packet into packets. These packets are moved to the adjacent nodes until it reaches the leader chain. The leader chain consumes the packets and then transmits the data to the sink node directly. Moreover, by making use of this leader chain, the energy and network lifetime are minimized and as suggested by Rao et al., [17]. The main drawback of WSNs is the sensor nodes cannot be recharged and also it has only limited energy. So, regardless the only solution is to minimize the node's energy by making use of an efficient routing protocol. Sharma et al., [18] have enhanced the PEGASIS protocol following the rule of clustered sensor nodes which are densely employed in the area. Then the clusters themselves form a chain and by using this strategy the energy is minimized along with the decrease in delay in the PEGASIS protocol.

Clustering is one of the widely recognized procedures to adjust the energy utilization of all hubs while limiting traffic and overhead during the information transmission stages. Barzin et al., [19], introduced a multi-objective nature-inspired algorithm based on the shuffled frog-leaping algorithm and firefly algorithm (MOSFA). As an adaptive application-specific clustering-based multi-hop routing protocol for WSNs is utilized. By using MOSFA's, at each iteration in various scenarios, the CH is elected. Bhowmik et al., [20], proposed an improved particle swarm optimization (PSO) gravitational search algorithm (GSA) for clustering and routing in WSNs. The clustered protocol manages uniform distributed energy all over the network. The routed process identifies the optimal path to transfer information between the cluster head and the base station. This algorithm coordinates the investigation limit of GSA and the misuse capacity of PSO.

In WSNs unequal energy utilization in the path discovery process (routing) is considered a major problem. Shahbaz et al., [21] have explained network node clustering, way identification for CH, and managing the path in WSNs. Clustering is performed by the firefly algorithm and routing is done by fuzzy logic between CHs. Routing in CHs creates two paths: primary path and backup path. Kaur et al., [22] recommended a particle swarm optimization based dual sink mobility (PSODSM) technique to reduce the energy expenditure of sensor nodes. PSODSM has much attention on CH election based on the parameters like node degree, initial energy, node centrality, and so on. Hence, Sharma et al., [23] presented a variant Bat algorithm (BA) registers distance by computing the equality among the pulse transmitted by fake bat sound. This likewise centers on the pertinence of the variation of BA for identifying the ideal course in WSN.

Due to the presence of all the above-mentioned algorithms, the energy issue is still a challenging one. In, classical approaches do not consider proper rules for choosing the sensor nodes. Hence, metaheuristic-based nature and bio-inspired algorithms perform better than the classical approaches. The normal disadvantage of the approaches is that they are not application explicit as such, the controllable boundaries cannot be adaptively changed by the application prerequisites. Although these techniques may have satisfactory execution for certain applications, their presentation might be decreased for different applications. Moreover, to overcome this issue a CSO-EHO algorithm for efficient cluster-based routing protocol in WSN is introduced in this paper. In this proposed method we use Dolphin swarm optimization for clustering the nodes, and EHO is utilized for cluster head selection. Finally, the CSO strategy is utilized for path selection to reach the base station.

3. Preliminaries

In this section, we will discuss the algorithms utilized in this paper. Dolphin swarm algorithm by its echolocation functionalities identifies the prey easily and attacks. In elephant herding optimization, the elephant leaves their family with the herding behavior. Likewise, in chicken swarm optimization the function of the collective food searching mechanism it searches the food. A block diagram of the proposed method is shown in Figure 1.

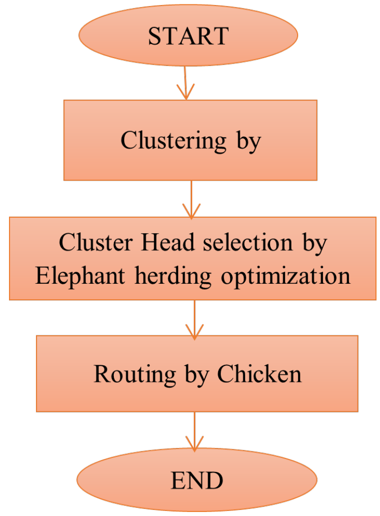

Figure 1. Block diagram of the proposed method.

3.1. Dolphin Swarm Optimization (DSO)

The DSO was proposed by Tian-qi et al., [24], as a productive worldwide inquiry technique for addressing various advancement issues. It is predominantly executed by reenacting the organic attributes and living propensities that appeared in the dolphin's genuine savage cycle. These include:

1. Echolocation: Naturally, Dolphin has good eye power, but in dim light, it has a slight variation in eyesight. Even though, dolphin uses an echolocation strategy to hunt for food. Echolocation is used by only very few creatures and dolphins are one of the most adept ones. By using this echo sound dolphins can predict the location, distance, and even the structure size of the prey due to the echo intensity. With the assistance of reverberation, the dolphin can even predict the general climate.
2. Cooperation and division of labor: As a rule, predatory conduct is not accomplished by a single dolphin. But, by the principle of cooperation and division of labor predatory is achieved by numerous dolphins. Even for encountering enormous prey, the attack conduct cannot accomplish by a single dolphin. In this scenario, the dolphin seeks the help of another dolphin for predation. Additionally, there is a particular division of work between the dolphins. However, they attack under the logic, the dolphin nearer to the prey are responsible for following the liable developments. The dolphins which are some distance from the prey structure, cover the prey.
3. Information exchanges: In the present examination it is to be noted that the dolphin's trade data. They can communicate various thoughts by utilizing their sound at various frequencies by using their language. In cooperation and division of labor process during predation the dolphins continuously call other dolphins for help to update the position of prey. By using this data exchange, the dolphins can predict more qualified moves, to make the prediction more viable.

The whole procedure of the DSO algorithm 1 follows three stages. Initially, the dolphins by using their sound system of echolocation find the position of the prey. Afterward, dolphins exchange their information with similar dolphins. Once the dolphins predict the position of prey, it seeks the help of other dolphins to follow the prey and some to encircle the prey for predation. Finally, the dolphin's predation process is done by attaching the prey for their need of food.

Algorithm 1: Dolphin Swarm Optimization Algorithm (DSO)

Input: m is the number of sounds, a is acceleration, n is the number of dolphins, e is radius reduction coefficient, C_i is the cluster notation
Output: Best fitness solution, K_i, Each dolphin calculates the distance D_{ij}

Initialization:
Randomly generate the initial dolphin swarm, $D = D_1, D_2 \dots D_n$.
Identify D_i based on i, (number of clusters)
D_i will make the cluster C_i with them.
Calculate the fitness for each dolphin, $F_k = F_{k1}, F_{k2} \dots F_{kn}$.
while condition is not satisfied **do**
    Search phase:
    Set maximum search time, t_1
    Search for a new solution that D_i gets its fitness (E_{ijt}).
    if $i = \min$ fitness(E_{ijt}) **then**
        Optimal solution $L_i(D_i)$ is determined
        if fitness(L_i) $<$ fitness(K_i) **then**
            Replace K_i as L_i
        else
            K_i does not change.
        end if
    end if
    Update their L_i and K_i.
    Call phase:
    Find better solution and its location then assign as centroids.
    Update transmission time matrix TS
    for K_i, K_j, and $TS(i.j)$ **do**
        if fitness(K_i) $>$ fitness(K_j) **then**
            Then update transmission time
        end if
    end for
    Reception phase:
    TS_{ij} reduces one unit time
    if $TS_{ij} = 0$ **then**
        Replace TS_{ij} by new transmission time t_2.
        if fitness(K_i) $>$ fitness(K_j) **then**
            Replace K_i as K_j
        else
            K_i does not change
        end if
    end if
    Predation phase:
    Calculate distance of individual optimal solution and neighbourhood optimal solution
    if individual optimal solution $<$ search radius **then**
        The encircling radius can be calculated
    else if (individual optimal solution $>$ search radius) **and** (distance of individual optimal solution $>$ neighbourhood optimal solution) **then**
        The encircling radius can be calculated, R_2 as new D_i
    else
        The encircling radius can be calculated, R_2
    end if
    D_i gets new position and formed as the clusters group.
end while
return its fitness.

3.2. Elephant Herding Optimization (EHO)

The proposed hybrid elephant herding is utilized for optimal cluster head selection in WSN. The EHO algorithm 2 with the herding behavior of elephants was developed by Wang et al., [25] Elephants, are social creatures that live with their families with females and calves. A group of the elephant has a head matriarch in their elephant clan. Here, the female elephants always like to live with their family members, whereas male elephants isolate from their families and live somewhere with another elephant group. They will progressively get autonomous of their families until they leave their families totally the accompanying suppositions are considered in EHO. Considering the EHO algorithm's basis on elephant behavior, the following key points are assumed:

1. The elephant group has some clans and, in each clan, there will be a particular number of elephants present.
2. At each generation, a particular number of male elephants will isolate themselves from their family.
3. The elephants can live together in each clan with their head matriarch.

Algorithm 2: Elephant Herding Optimization Algorithm (EHO)

Input: Generation limit count, total population size, function evaluations
Output: Calculate elephant's fitness for each individual

Initialization:
Initialize the population
Assign elephants as nodes and clans as clusters
Set generation counter $t = 1$, maximum generation $Maxitr$
Sort the population from most fit to least fit:
while $t < Maxitr$ **do**
  Sort all elephants according to their fitness
  Clan (cluster) Updating Operator:
  for $cidx = 1$ to $numClan$ for all clans (clusters) in elephant (nodes) population **do**
    for $j = 1$ to $newClanIndex$ for all elephants in clan **do**
      if $X_{cidx,j} = X_{best,ci}$ **then**
        Update old elephant (node) and generate new elephant (node)
      else
        Update old elephant and generate $X_{new,cidx,j}$ new elephant
      end if
    end for
  end for
  Separating Operator:
  for $cidx = 1$ to $numClan$ for all clans in elephant population **do**
    Replace the worst elephant (node) in clan (cluster)
  end for
  Calculate Fitness:
  Evaluate population by the newly updated positions
end while
return best solutions for all clans (clusters).

3.3. Chicken Swarm Optimization (CSO)

CSO is a recent swarm intelligence-based algorithm introduced by Meng et al., [26]. The hierarchal order with the effective food finding mechanism of the swarm is highlighted in the algorithm. Based on their fitness value the whole population of chickens is divided into roosters, hens, and chicks. The chickens with the most noteworthy food looking through capacity or fitness value are assigned as roosters. Similarly, chickens with less food finding capacity or fitness are considered chicks. Hence, chickens with intercommunication food searching capacity or fitness are considered hens. The mother–youngster relationship is additionally settled haphazardly. This hierarchal relation of mother-child is updated every G times. The birth behavior of a hen following the mate chicken and chicks following their mom in search of food is the logical behavior of the CSO algorithm 3. Likewise, the chickens would attempt to scratch the food found by other opposition chickens in the gathering. Every chicken is too easy to even consider cooperating. As a multitude, they form a group in search of food under explicit hierarchal request. This multitude of knowledge can be considered as a target issue in advance.

Algorithm 3: Chicken Swarm Optimization Algorithm (CSO)

```
Input: Generate initial population: n chickens x_i (i = 1, 2, ..., n), use the related parameter variables, t
       is number of iterations, G is number of generations
Output: Evaluate fitness value.
Initialize the population and parameters and assign chicks as a path.
while t < MaxGeneration do
    Rank the chicken fitness value.
    Establish a hierarchical order in the swarm.
    if t mod G == 0 then
        Split the swarm into different groups.
        Form the relationship between the chicks and mother hens in a group.
    end if
    for i = 1 to n do
        if i == rooster then
            Update the solution and location.
        else if i == hen then
            Update the solution and location.
        else if i == chick then
            Update the solution and position.
        end if
        Evaluate the new solution (best path).
        if the new solution (path) is better than its previous one then
            Replace current solution with new solution.
            Keep the best route to transfer the information.
        end if
    end for
end while
```

3.4. LEACH based approaches

The self-organization, nodes organize themselves into clusters are the potential characteristics LEACH protocol which turn conception [19]. In first stage based on threshold function defined with respect to tuning parameters like inter and intra-cluster distance, distance between nodes, and residual energy of the nodes, CHs are selected randomly. In the second stage communication between normal nodes and their corresponding CHs are used to establish clusters in self-adaptation manner. The data transmission is established in the final stage. The LEACH network model is shown in Figure 2.

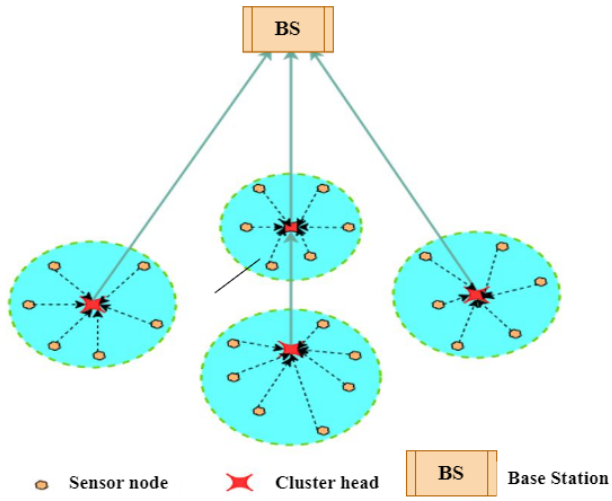

Figure 2. LEACH Network Model.

3.5. Fuzzy-based approaches

The selected parameters are utilized as the fuzzy inputs in these methods, but the fuzzy rule table is determined manually by an expert. The rule forming by expert is challenging and main limitation of these methods [27].

4. System model

In this section, the proposed method assumes that the network is a homogeneous structure with a sensor node densely deployed in an area. The sensor nodes transfer their data through the wireless link. In WSNs the data always send to the desired CH. The CH gathers data from the cluster members of the group through the wireless link by an available path the data is transmitted to the base station. The correspondences are over wireless connections. A wireless connection is set up between two hubs in particular on the off chance that they are inside the correspondence scope of one another. All hubs utilize similar communicating forces and accordingly, a hub can ascertain the distance to another hub dependent on the received signal strength.

4.1. LEACH protocol

Here in this method, for transmitting 1 bits of data, the two phases of energy are used as the energy at transmitter E_{trns}, the energy at the receiver E_{rec}. The distance between transmitter and receiver is given in Equation (1) as,

$$E_{trns}(l,d) = \begin{cases} lE_{elec} + lE_{fs}d^2) & d < d_0 \\ lE_{elec} + lE_{mp}d^4) & d \geq d_0 \end{cases} , \tag{1}$$

where l characterizes the quantity of bits and d indicates the distance between the node and the receiver. At the time of information communication, E_{elec} is the energy utilization of the electrical circuit. In free space and multipath, the amplification factor of the transmission amplifier is E_{fs} and E_{mp}. d_0 is the maximum transmission distance for every SN. Its value is equal to $\sqrt{\frac{E_{fs}}{E_{mp}}}$. The energy burned-through at the beneficiary side is determined in Equation (2) as

$$E_{rec}(l,d) = lE_{elec} \quad . \tag{2}$$

4.2. Performance measures

4.2.1. Residual Energy

The residual energy is an important performance measure to categorizing nodes because the less residual energy nodes is used as communication nodes, meanwhile more residual energy nodes is categorized CH. The nodes having less residual energy could be utilized as CH for diminishing packets loss.

4.2.2. Energy efficiency

The performance measure energy efficiency is used provide the clear impression that how much improvement has been achieved in energy efficiency in the proposed LEACH routing protocol as compared to the original LEACH routing protocol.

4.2.3. QoS parameters

The throughput, packet delivery ratio, delay, and energy consumption are considered as QoS parameters. The less QoS parameters valued node include malicious node in the route, so QoS parameters values should be optimized in order to avoid malicious node.

4.2.4. Live nodes

For achieving more data collection, transmission, and distribution, the number of live nodes must be improved by reducing the energy consumption amount because our existing system having limited energy resources.

5. Proposed protocol

The dolphin swarm optimization is used to cluster the network the sensor nodes in WSNs. In the setup phase, the base station uses the EHO algorithm to select the cluster heads based on the fitness values obtained with respect to the inter and intra-cluster distance, distance between nodes, and residual energy of the nodes, and uses the proposed chicken swarm optimization based routing algorithm to find the proper paths between each cluster head and the base station for transferring data to the base station in WSNs. In the stabilization phase, the members send the perceived data to the corresponding cluster head, and the cluster head sends the gathered data to the base station by using the proposed chicken swarm optimization-based routing algorithm. In this section, we first introduce how to use EHO to solve the problem of optimal cluster head selection, and then we elaborate on the chicken swarm optimization-based routing algorithm. Finally, CHs are selected based on balanced residual energy-LEACH (Proposed-LEACH) which is optimally searched with EHO algorithm with respect to inter and intra-cluster distance, distance between nodes, and residual energy of the nodes.

Here, we discuss the proposed protocol that has the following 3 phases: (1) the DSA clustering phase, (2) the EHO cluster head selection phase, (3) the CSO path selection phase. Figure 3 present the flow chart of the proposed method.

At first, the sensor centers are arranged in the network. Once, the hub energy is refreshed the network checks the protocol that it is cycle 1 or not. On the off chance that the condition gets satisfied clustering is handled in the network by utilizing CSO. Indeed, if it doesn't fulfill the condition, at that point the following round cluster head is chosen by using the EHO strategy. Subsequently, the CH chooses the briefest method to move data to the sink, this most limited way is chosen by utilizing CSO. Afterward, the network checks the condition that if the energy of the center is more noteworthy than the threshold, at that point the hub is alive, in any case the node is dead. From now on, the network revives the alive node in the

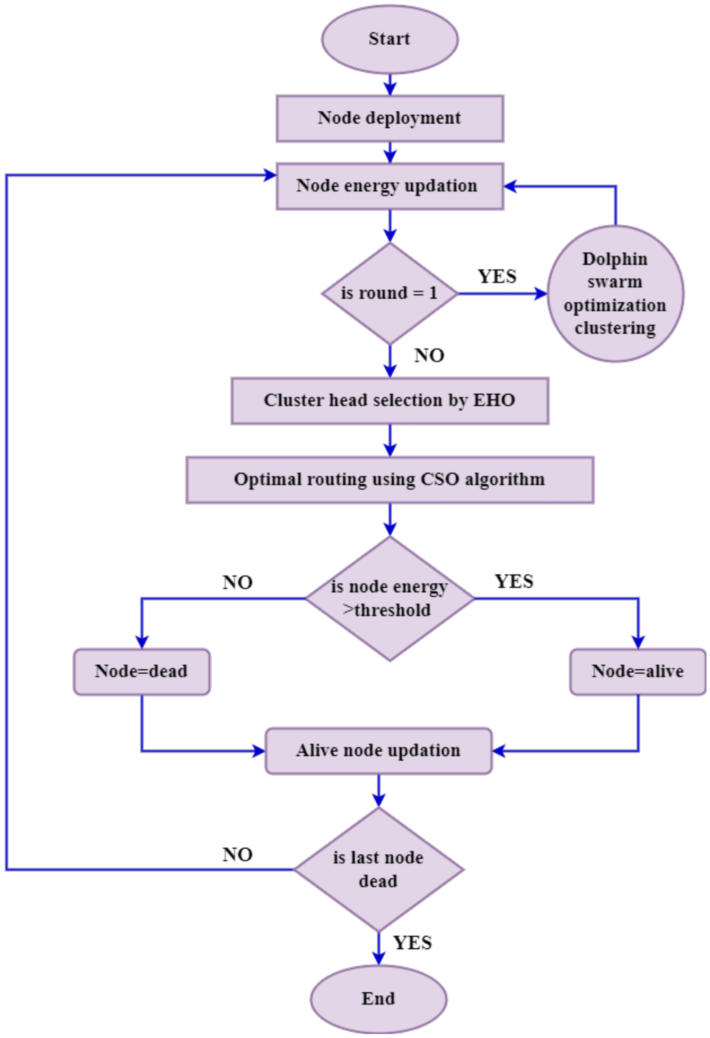

Figure 3. Flowchart of EHO-CSO algorithm.

accompanying round. At last, when the last node is dead then there will be no further adjustments will happen if not, till the node is dead the network constantly cycles.

5.1. DSO Clustering Phase

In the proposed method clustering of sensor nodes is done by a metaheuristic algorithm called the dolphin swarm algorithm and the natural characteristics are described above. Based on the behaviors of DSO clustering is carried out and they include echolocation, cooperation and division of labor, and information exchange. Dolphin predation on their prey through these behaviors.

In DSO, a swarm of N dolphins is placed. Dimensional D pursuit space of improvement issues, the dolphins are characterized as $ol_i = [x_1, x_2..., x_D]^T$, $(i = 1, 2, ..., N)$, where $x_j(j = 1, 2, ..., D)$ is a component. For each Dol_i, there are two related factors $L_i(j = 1, 2, ..., N)$ and $K_i(j = 1, 2, ..., N)$ where L_i indicates the optimal solution that Dol_i finds in a unique time and K_i represents the optimal solution of Dol_i gets from others. In DSO, three sorts of distances should be characterized, which are the distance among L_i and K_i, named DLK_i the distance between Dol_i and K_i, named DK_i and the distance between Dol_i and Dol_i , named $DD_{i,j}$.

5.1.1. Search phase

In the hunting stage, every dolphin looks through its close by territory making sounds V_i, V_j is the part of each measurement and the sound V_i that Dol_i makes all the time will look through another solution X_{ijt} with the greatest inquiry time T and it is communicated as $X_{ijt} = Dol_i + V_j * t$. The fitness value E_{ijt} for X_{ijt} is calculated by,

$$E_{ijt} = \text{fitness}(X_{ijt}) \ , \tag{3}$$

followed by the $Dol_i(i = 1, 2, ..., N)$ update, L_i and K_i dolphins get into the call stage.

5.1.2. Call stage

During the call stage, the dolphins generate sound to instruct similar dolphins regarding the outcomes in the search phase. Furthermore, the transmission time framework TS should be refreshed as follows: for K_i, K_j and $TS_{i,j}$ if

$$\text{fitness}(K_i) = \text{fitness}(K_j) \ , \tag{4}$$

$$TS_{i,j} > \left[\frac{DD_{i,j}}{A \cdot \text{speed}} \right] \ , \tag{5}$$

where A denotes acceleration, then $TS_{i,j}$ is updated in

$$TS_{i,j} = \left[\frac{DD_{i,j}}{A \cdot \text{speed}} \right] \ . \tag{6}$$

5.1.3. Reception phase

Here, $TS_{i,j}$ subtract one to indicate that the sounds spread a unit of time, then check all the variables $TS_{i,j}$, if $TS_{i,j} = 0$ then it means that the sound spreading from Dol_i to Dol_i can be received. Compare K_i with K_j. If it satisfies Equation (4), then replace K_i by K_j. Otherwise K_i does not change. Then set $TS_{i,j}$ as expressed in,

$$TS_{i,j} = \frac{\text{range}}{A \cdot \text{speed}} \ , \tag{7}$$

where the range is the length of the search space.

5.1.4. Predation stage

In the predation stage, every dolphin needs to get another situation as indicated by its known data and it very well may be examined in two cases. At first, if $DK_i \leq T \cdot \text{speed}$, Dol_i new position as new Dol_i is expressed by,

$$\text{new}Dol_i = K_i + w \times (Dol_i - K_i) \times (1 - 2/e) \ , \tag{8}$$

e is a steady worth it is more prominent than 2 and w is a self-assertive unit vector. At that point the following condition if $DK_i > T \cdot \text{speed}$. Now Dol_i new position as new Dol_1 is given by,

$$\text{new}Dol_i = K_i + w \times \left(1 - \frac{DK_i \times \frac{1}{\text{fitness }(K_i)} + (DK_i - DLK_i) \times \frac{1}{\text{fitness }(K_i)}}{e \times DK_i \times \frac{1}{\text{fitness }(K_i)}} \right) \times DK_i \ . \tag{9}$$

After all, the Dol_i get their new position newDol_i compare newDol_i with K_i in fitness as,

$$\text{fitness}\ (\text{new}Dol_i) < \ \text{fitness}\ (K_i)\ \ . \tag{10}$$

At that point supplant K_i by new Dol_i Otherwise K_i it does not change and the condition gets fulfilled, DSO enters the end stage. Something else, the DSO enters the inquiry stage again. Even though there are numerous boundaries utilized in DSO, a of clients are client indicated including the number of dolphins N, the number of sounds M, the speed of sounds speed, the maximum search time T, and the constant e utilized in the predation phase.

5.2. Cluster Head Selection by EHO

The flowchart of EHO is shown in Figure 4. The proposed Elephant Herding Optimization is utilized for CH determination with improved guidelines. The sensor nodes are considered as an elephant which fits to form a cluster called clans. It combines and where a matriarch as cluster head leads the team. The cluster (clan) considers a set of sensor nodes (elephants) that are eligible. In the proposed strategy, the clusters should have the same number of constant nodes. The refreshing activity of the location of the node in the cluster is accomplished by the relationship with the authority matriarch. The social affiliation is displayed dependent on a refreshing administrator. During this event, a set of sensor nodes go away from clusters for every single age, which is similar to the developed elephants. Hence, the refreshing cycle is displayed in EHO dependent on an isolating administrator. The cluster head (Matriarch elephant) in every cluster is the noteworthy potential sensor node. By evaluating the fitness function, the best and worst fitness function is determined significantly. The worst fitness sensor nodes go away from their family for having an autonomous existence.

The proposed method indicates the fitness function is very necessary to be classified among the group of clusters and it is determined based on the parameters of residual energy, the number of cluster heads, the cumulative distance between the cluster head and the base station, and cumulative intra-cluster distance of communication. The fitness function predicts maximum cumulative of intra-cluster separation of communication and minimum cumulative separation among the CH and the sink node, and that causes a smaller number of cluster head selections [28].

5.2.1. Clan updating operator

In each clan, there will be a head matriarch who lives with a group of elephants. The elephant in clan cm, its upcoming stage is denoted by matriarch cm. The elephant n in clan cm is expressed as,

$$E_{new,cm,n} = E_{cm,n} + \propto \times (E_{best,cm} - E_{cm,n}) \times r\ \ , \tag{11}$$

where $E_{new,cm,n}$ and $E_{cm,n}$ recently refreshed and old situation for elephant n in clan cm. $\propto \in [0,1]$ is a scale factor that decides the impact of matriarch cm on $E_{cm,n}$. $x_{best,cm}$ speaks to authority cm, which is the fittest elephant individual in the clan cm. In $r \in [0,1]$, uniform dissemination is utilized. It is distinguished at this point than $E_{cm,n} = E_{best,cm}$ which gathers that the potential sensor hubs in the group can't be refreshed dependent on Equation (11). To forestall this circumstance, the fittest sensor hub is refreshed dependent as,

$$E_{new,cm,n} = \beta \times E_{center,cm}\ \ , \tag{12}$$

where $\beta \in [0,1]$ speaks to a factor that decides the impact the $E_{center,ci}$ on $E_{new,cm,n} \cdot E_(new, cm, n)$ is the new individual. $E_{center,cm}$ is the center individual of clan cm. It is expressed in Equation (13). For the d-th dimension,

$$E_{new,cm,d} = \frac{1}{N_{cm}} \times \sum_{n=1}^{N_{cm}} E_{cm,n,d} \quad , \tag{13}$$

at this point, $1 \leq d \leq D$ depicts the measurement with N_{cm} and indicates the total number of sensor nodes in the network.

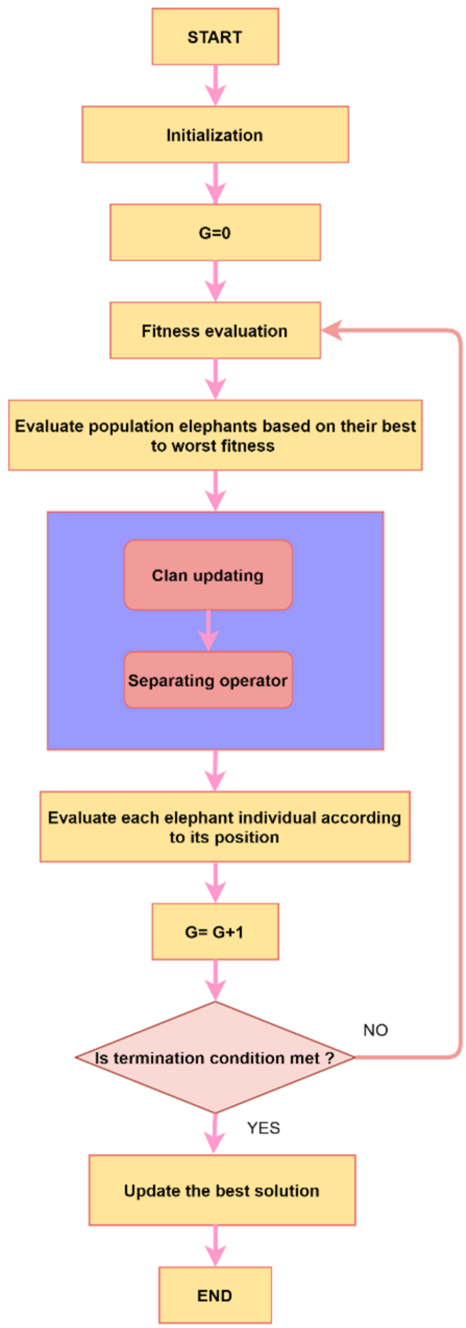

Figure 4. Flowchart of EHO.

5.2.2. Separating operator

The isolating cycle whereby male elephants leave their family gathering can be displayed in isolating administrators when tackling streamlining issues. The isolating administrator is executed by the elephant individual with the most noticeably awful wellness in every age, as appeared in,

$$E_{worst,cm} = E_m in + (E_m ax - E_m in + 1) \times \text{rand} \ , \tag{14}$$

where E_{max} shows the upper bound of the individual and E_{min} represents the lower bound of the individual. $E_{worst,cm}$ speaks the worst individual in clan cm. Rand [0,1] is a stochastic dispersion somewhere in the range of 0 and 1.

5.2.3. Fitness value evaluation

As an initial process, the best sensor hub is spared from the networks similarly the worst sensor hubs are supplanted by storing the best fitness sensor hubs toward the finish of the investigation cycle. At last, by calculating the fitness value the new position is identified, the predominant situation of the sensor hubs is spared, and there by a group head is chosen.

5.3. Routing by CSO

By the previous depiction of Chicken Swarm Optimization (CSO), we can create CSO numerically. The fitness estimations of the arbitrarily created starting populace of chicken are assessed, and a hierarchical request is set up dependent on this fitness esteem.

5.3.1. Initialization

During the initialization process, the population size and the variables of CSO are considered as (RN), number of Hens (HN), number of chicks (CN), number of mother hens (MN), and G is first defined. The fitness estimations of the arbitrarily created starting populace of chicken are assessed, and by its fitness value, the hierarchical order is determined. Hence, from the overall process, the best RN chickens are considered as roosters, and the worst CNs are assumed as chicks. Then the remaining are mentioned as hens. All N virtual chickens, portrayed by their positions as,

$$X_{i,j}^t (i \in [1, \ldots, N], j \in [1, \ldots, D]) \ , \tag{15}$$

in a D-dimensional space, step t search for food where, the optimization problems are minimal. The RN minimal fitness value is considered as a best RN chicken.

5.3.2. Movements of the chickens (Path selection strategy)

Path selection is based on its best CH (roosters). The roosters which have the enhanced fitness value have more priority in finding the food than the worst fitness ones. Similarly, in other words, it can be described as the rooster one which has high fitness value can search the food in a larger area whereas the least fitness ones have only a minimum area to search for food. This can be executed in Equation (16) as.

$$X_{i,j}^{t+1} = X_{i,j}^t \times (1 + \text{rand}(\ 0, \sigma^2)) \ \text{, where,} \tag{16}$$

$$\sigma^2 = \begin{cases} 1, \text{ if } f_i \le f_k \\ \exp\left(\frac{(f_k - f_i)}{|f_i| + \varepsilon}\right), \text{ otherwise} \end{cases} k \in [1, N], k \ne i \ \ . \tag{17}$$

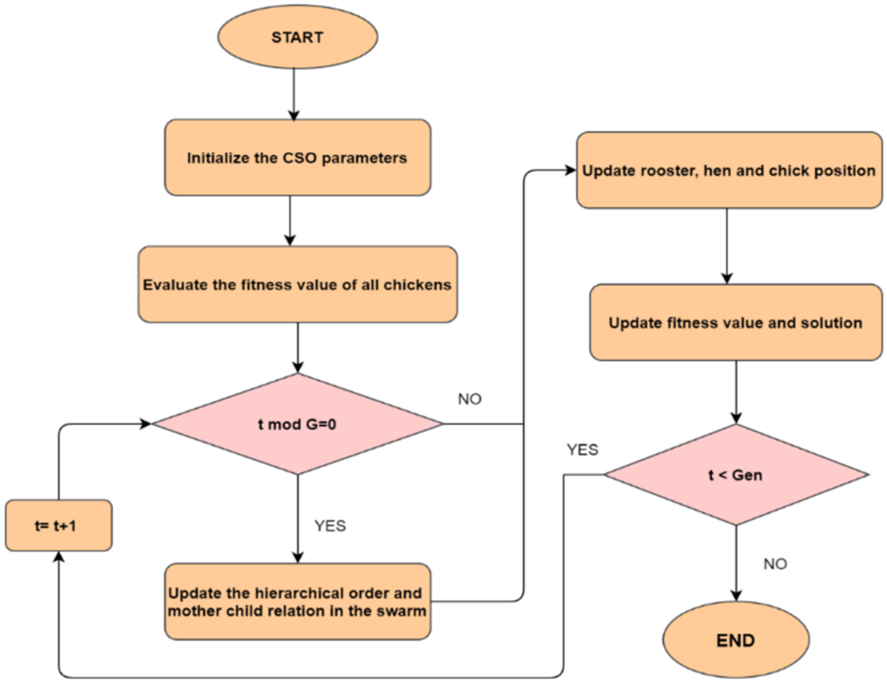

Figure 5. Flowchart of CSO.

Here, $\text{rand}(0, \sigma^2)$ is a Gaussian distribution with a mean 0 and the standard deviation σ^2. ε is the smallest constant used to avoid zero-division-error. k, a rooster's index, and f is the fitness value of the corresponding x.

In general, hens gather mate chickens as they continued looking for food. In addition, it is likewise to be noted that the chicken has the propensity to take food found by different chickens. The numerical portrayal of the updated recipe for hens (CH) is refreshed in Equation (18) as:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + \text{S1} \times \text{rand}\left(X_{r1,j}^{t} - X_{i,j}^{t}\right) + \text{ S2} \times \text{rand}\left(X_{r2,j}^{t} - X_{i,j}^{t}\right) \quad , \tag{18}$$

where $S1 = \exp((f_i - f_{r1})/(abs(f_i) + \varepsilon))$, $S2 = \exp((f_{r2} - f_i))$, and $r1, r2 \in [1, \ldots, N]$, $\text{r} \neq \; r2$, $r1$ is the index of a rooster, while $r2$ is a chicken from the swarm that can be a rooster or a hen, and a uniform random number is generated by rand.

5.3.3. Data communication

Naturally, the chicks follow their mother, and it is illustrated in,

$$X_{i,j}^{t+1} = X_{i,j}^{t} + FL \times (X_{m,j}^{t} - X_{i,j}^{t}) \quad , \tag{19}$$

where, $X_{m,j}^{t}$ indicates the location of i_{th} chick's mother. FL is denoted as a variable which means the chick follows its mother. FL is commonly picked somewhere in the range of 0 and 2. From Equation (18) the new best path will be identified from the available paths. The flow chart of CSO is shown in Figure 5.

Table 1. Simulation parameters of the whole network

Algorithm	Parameter	Values
Simulation parameters	Area	500m*500m
	Initial energy node	2J
	E_{elec}	50nJ/bit
	ε_{fs}	10pJ/bit/m^2
	ε_{mp}	0.0013pJ/bit/m^4
	Packet size	5000 bits
	Sink location	(250,500)
	Number of clusters	5
DSA	Maximum search time (t_1)	3
	Maximum transmission time (t_2)	1000
	Speed	0.1
	Node density	50-500
	Number of dolphin (n)	20
	Acceleration (a)	5
	No. of sounds (m)	2
EHO	Elitism	2
	Population size	No. of nodes in each cluster
	Dimension	No. of variables in each population
	Alpha	0.5
	Beta	0.1
CSO	Number of Generation	10
	Population size of Roosters	0.15
	Population size of Hens	0.7
	Population size of Mother hens	0.5
	Maximum iterations	100

6. Results and discussion

The implementation of the proposed nature-inspired algorithms for cluster-based routing protocol in WSNs is estimated by extensive simulations. The efficiency of the proposed algorithm is estimated by utilizing minimum energy with prolonging the network lifetime. This has been compared with the existing LEACH and Fuzzy logic techniques in the network. The simulation results predict that this proposed method has overcome the existing algorithms. This work has been implemented by using MATLAB 2018a simulation software.

6.1. Simulation Parameters

In this proposed work the nodes have been deployed over an area of 500m*500m with 5000 bits of packet size. The sink has been located on the axis of (250,500) with 500 sensor nodes. Additionally, the mobility model of random waypoint was utilized in the experiment by considering the number of nodes ranges between 100 – 500 nodes for the simulation process. The speed of mobility also varies from 0 to 20 m/s. Number of rounds experiments executed is 2250. Table 1 shows the simulation parameters of the network.

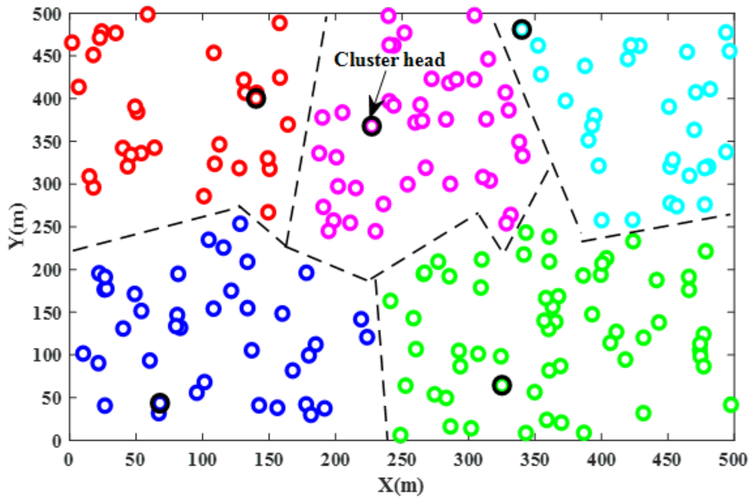

Figure 6. Network portioning by proposed method.

6.1.1. Performance measures

- Residual Energy: The residual energy is an important performance measure to categorizing nodes because the less residual energy nodes is used as communication nodes, meanwhile more residual energy nodes is categorized CH. The nodes having less residual energy could be utilized as CH for diminishing packets loss.
- Energy Efficiency: The performance measure energy efficiency is used provide the clear impression that how much improvement has been achieved in energy efficiency in the proposed LEACH routing protocol as compared to the original LEACH routing protocol.
- QoS parameters: The throughput, Packet Delivery Ratio, delay, and energy consumption are considered as QoS parameters. The less QoS parameters valued node include malicious node in the route, so QoS parameters values should be optimized in order to avoid malicious node.

6.2. Simulation Results

Figure 6 shows the results of clustering in the networks for 500 nodes. It is analyzed that the network has a good portioning, where the CHs are equally positioned over the network and placed at the center of each cluster. The existing protocols LEACH and Fuzzy position the CH in the uneven order in the sensor field. In this paper, the proposed Dolphin algorithm establishes a good clustering process due to the inherent characteristics of the swarm algorithm.

6.3. Residual Energy

The energy efficiency of the node's residual energy for an interval of 250 to 1000 rounds is obtained, in order to determine the cluster-based routing protocols. The difference between the residual energy for the proposed method and the existing techniques is shown in Figure 7. It predicts that the proposed algorithm has high residual energy than the LEACH and Fuzzy method. This is due to the use of cluster based routing protocols in this paper, which minimizes the number of packets sent to the BS. Through this process automatically the energy consumption level gets reduced.

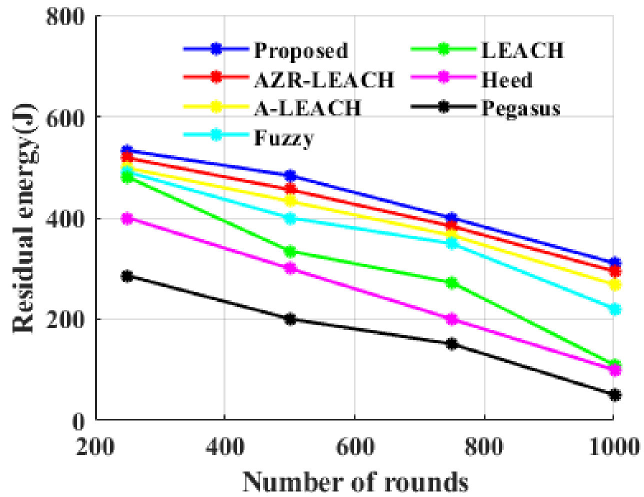

Figure 7. Residual energy vs rounds.

6.4. Energy Efficiency

Figure 8(a) shows the energy efficiency of the proposed method with that of the existing algorithms. The number of nodes changes from 100 to 500, and the energy efficiency of the proposed method is higher than the existing LEACH and Fuzzy method. The proposed method attains 98% energy efficiency Fuzzy has 89% and the LEACH method has 84% for node 100. At node 500 the proposed method has 90% of energy efficiency. The energy efficiency has a higher value in the proposed method because of the selection of the best CH by EHO. The CH selects the neighbouring nodes for data transfer and thereby the network lifespan gets increase.

6.5. Packet Delivery Ratio (PDR)

PDR is defined as the number of packets successfully transmitted by the transmitter to the number of packets received by the receiver to the sink node. Figure 8(b) shows the scalability of the proposed cluster-based routing protocol. In general, if the number of nodes gets an increase in the network the delay, and node's energy consumption gets increase but the delivery of packets gets decreased. Even though, in this paper, the proposed algorithm beats the other two existing algorithms, that even when the nodes get increased the packet delivery ratio increase than the existing protocols. This is processed because of the selection of CH, which selects the adjacent nodes for data transmission based on their length and residual energy. The packet delivery ratio of the proposed protocol is comparatively more when compared with traditional techniques. The delay in the packet delivery becomes decrease due to the traffic free transmission on the way to the base station by EHO cluster head selection and CSO routing protocol.

6.6. End to end transmission delay

Delay is explained as the time taken for data transmission to be received at the base station. The delay in this proposed paper is decreased due to the routing protocol of the CSO algorithm. The efficient path selection between the source and to destination for data transfer is an efficient strategy. Because of the selection of the perfect path, the traffic in the network gets reduced and packets can deliver to the BS quickly. In the proposed methods the delay is minimum when compared to the existing methods. For the number of rounds, the delay gets a higher value moreover than the existing algorithms. The cluster head nodes with higher energy levels are given priority to participate in the discovered path among CH to sink

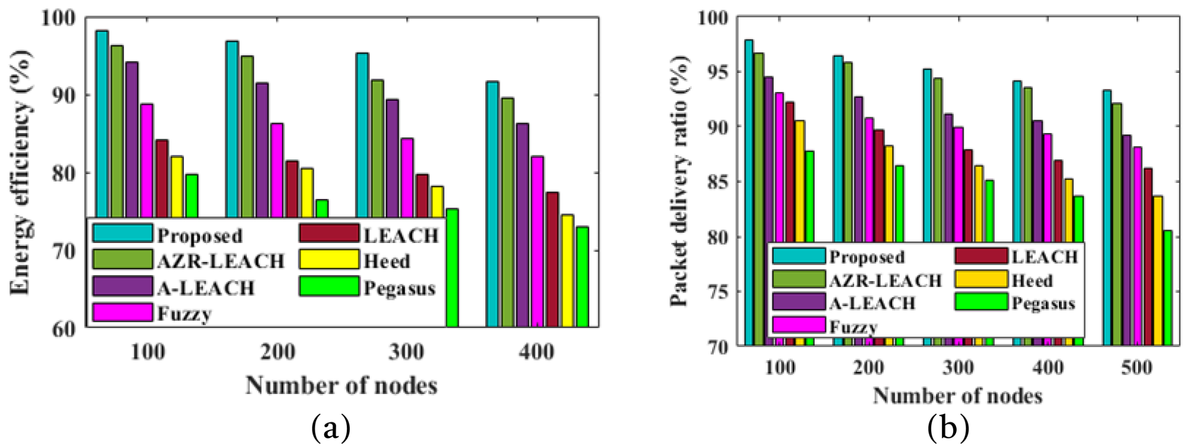

Figure 8. (a) Energy efficiency. (b)Packet delivery ratio.

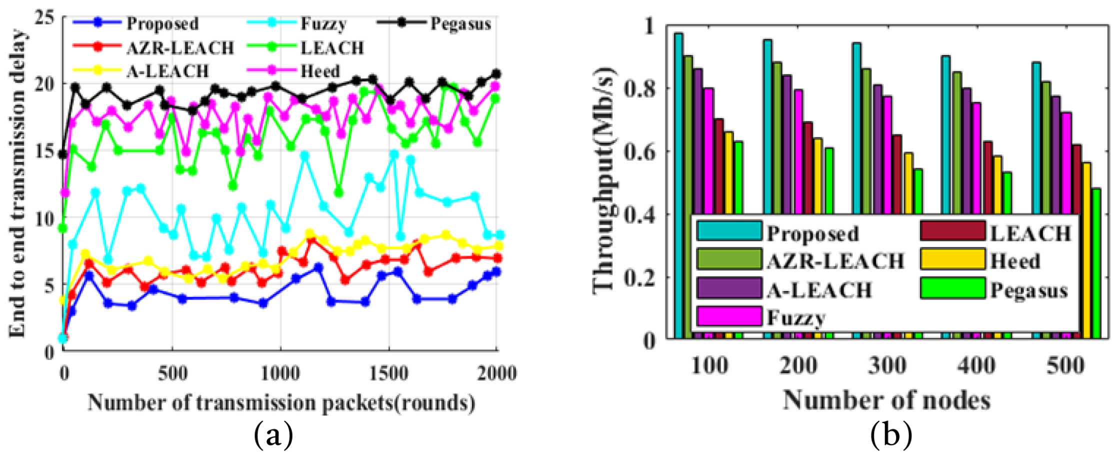

Figure 9. (a) End to end delay Vs Rounds. (b) throughput Vs Number of nodes.

node. Through this process, the delay gets a decrease in this proposed method as in Figure 9(a) end to end delay transmission.

6.7. Throughput

Throughput is defined as the number of data units the network can process in a certain period of time for the number of nodes. The proposed method has high throughput for efficient transmission of data than the existing methods. For node=100 the throughput attains a higher value of 0.98 mbps value whereas for node=500 it is 0.9 mbps value which is higher than the fuzzy and LEACH methods. This happens because the proposed method always picks the most feasible path for data transmission. The routing path is selected based on an accurate path that has a shorter distance to the sink or if they have a greater energy level than other routes. By applying these criteria, while selecting the path the data are sent with minimum packet drop. It can be analyzed that the throughput gets decrease with an increase in the number of nodes. Fuzzy gets decrease from 0.8 to 0.74 mbps and LEACH decrease from 0.7 to 0.62 mbps for node density increase from 100 to 500 nodes. The throughput with the number of nodes is shown in Figure 9(b).

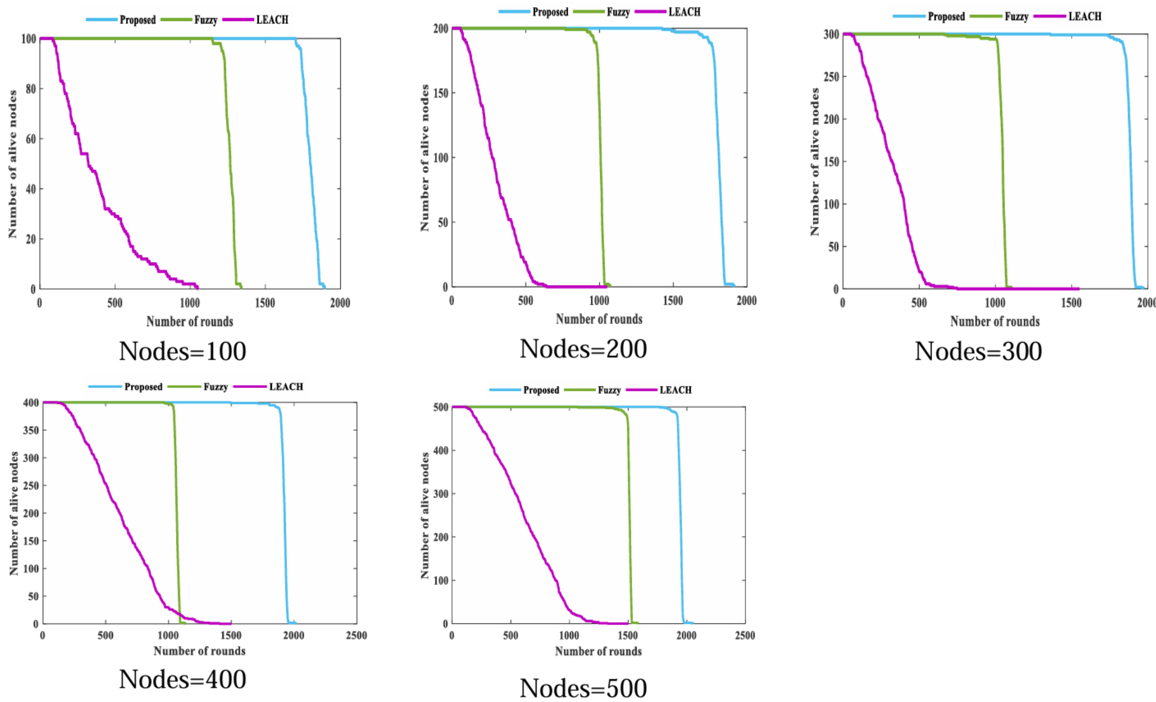

Figure 10. Number of alive nodes.

6.8. Number of Alive nodes

Figure 10 depicts the number of alive nodes between the proposed method with the existing fuzzy and LEACH method and simulated for 100 to 500 nodes. The parameter of the number of alive nodes is explained to notice the degree of stability of the protocol and the length of its durability of the sensor nodes. Therefore, the proposed method has a higher number of alive nodes for the maximum number of rounds. Based on its optimal routing path and cluster conservation. The cluster is preserved without any dead in the network until 1701 rounds for 100 nodes and 1848 rounds for 500 nodes. Consequently, the node which has the maximum energy is considered for CH selection. The alive nodes in the proposed method withstand till 2054 rounds, but the Fuzzy and LEACH withstand until 1580 and 1493 rounds. By the balancing energy consumption technique, the proposed method achieves more alive nodes. Therefore, selecting the shortest path for routing consumes balanced energy for data transmission.

6.9. Network Lifetime

To evaluate the lifetime of the network, here we consider the first node dead (FND), half node dead (HND), and last node dead (LND) value is tabulated in Table 2. It is clearly explained that the number of active nodes in the network by using the proposed routing algorithm has a greater number of FND, HND, and LND nodes when compared with the existing methods. The results predict that the nodes in the nearby area have the same data rate i.e., when the first node gets dead in the network does not affect the operation of networks but the quality of nodes becomes less. When half of the nodes get dead the quality of data gets poor however if the last node is dead, the network stops its operation. In this proposed work, the first node gets dead due to the lack of energy only after a longer period of time than the existing methods. This is done due to the energy balancing of CH by selecting the best node among the clusters by the EHO algorithm. During cluster formation, the sensor nodes which have more energy join the CH for efficient data transfer for a longer period of the lifetime.

Table 2. Comparison of FND, HND, and END with proposed and existing methods

	No. of nodes	Proposed	AZR-LEACH	A-LEACH	Fuzzy	LEACH	Heed	Pegasus
FND	Nodes=100	1701	1483	1213	1147	85	68	22
	Nodes=200	1445	1326	1169	930	66	53	16
	Nodes=300	1761	1579	1404	689	73	50	11
	Nodes=400	1838	1635	1028	982	171	96	51
	Nodes=500	1848	1742	1489	1382	156	112	95
HND	Nodes=100	948	816	746	671	525	453	383
	Nodes=200	957	759	647	536	526	438	388
	Nodes=300	986	826	734	554	776	612	485
	Nodes=400	1007	833	749	568	751	614	480
	Nodes=500	1027	876	803	790	747	634	545
END	Nodes=100	1896	1323	1211	1341	1050	501	426
	Nodes=200	1914	1289	1175	1073	1051	504	409
	Nodes=300	1972	1614	1256	1107	1551	734	587
	Nodes=400	2015	1238	1023	1136	1501	725	578
	Nodes=500	2054	1699	1334	1580	1493	756	599

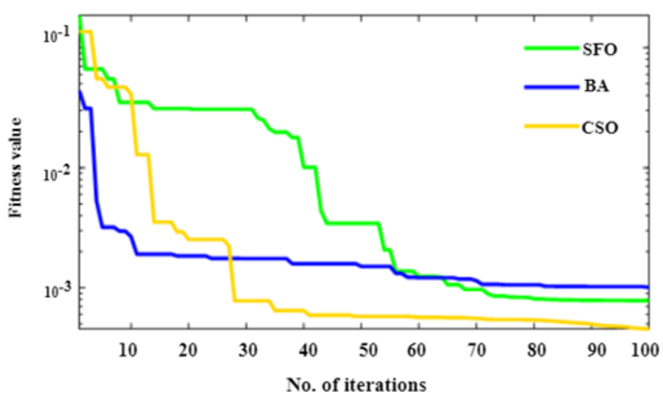

Figure 11. Number of alive nodes.

6.10. Fitness Function

Figure 11 plots the cost function of the proposed and existing methods. It illustrates that the proposed CSO method has a higher convergence speed than SFO (Sailfish optimizer) and BA (Bat algorithm) methods. The CSO algorithm achieves the best energy efficient technique based on the fitness function.

7. Conclusions

The main aim of this work is to reduce energy consumption and maximize the lifespan of the network. The selection of CH and routing generation are considered challenging tasks in WSNs. So, an energy efficient clustering routing protocol is executed in this article. Here, it undergoes three stages of network operation. Firstly, clustering the sensor nodes the DSO algorithm, second process is CH selection is done by the EHO algorithm. At last, an efficient routing path is identified for data transmission by the CSO algorithm. This nature-inspired algorithm has an efficient energy balancing technique for clustering and routing the sensor nodes for data transfer. The proposed method has been compared with existing optimization cluster-based routing protocols. On the other hand, this proposed technique sensor nodes lasted for about 2054 rounds for node 500, which is higher than traditional techniques. The proposed algorithm displays an enhancement in terms of quality-of-service parameters namely, the number of alive nodes, energy efficiency, throughput, FND, HND, LND, residual energy, end-to-end delay, and packet delivery ratio. The future improvement includes the execution of multi-hop routing among cluster head nodes to improve energy efficiency. Also in future the comparisons can be made with other evolutionary optimization methods.

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