An Energy-Aware Cluster Head Selection Protocol based on Multi-Objective Dolphin Swarm Optimization in Wireless Sensor Network

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Abstract: The Wireless Sensor Network (WSN) is spread widely in many applications due to its portable, cost-effective, and user-friendly approach. This needs to adopt routing schemes to forward the sensed information to the sink nodes or base station through minimum-cost links. The frequently utilized data accumulation approach is clustering which organizes the nodes into clutches to minimize the consumption of energy. Likewise, in clustering protocols, the additional load will be bear by the Cluster Head (CH) for organizing various deeds inside the cluster. As a result, appropriate CH selection and their power balance using efficient clustering protocol are significant features for the long-term operation of the Wireless Sensor Network (WSN). In this paper, An Energy-Aware Cluster Head Selection Protocol based on Multi-Objective Dolphin Swarm Optimization (EACHP-MODSO) is proposed to enrich the lifetime of Wireless Sensor Network (WSN). This proposed method considers six criteria to select effective Cluster Head like residual energy, inter cluster distance, intracluster distance, mobility, node density, and delay. The results of the proposed system show better enhancement of network lifetime compared to existing protocols.

Keywords: Base Station, Cluster Head, Multi-Objective Dolphin Swarm Optimization, Wireless Sensor Network

1. Introduction

WSN is a network that comprises sensor nodes spatially distributed to monitor the environmental or physical conditions [1]. These sensor devices are capable of data gathering, processing, and broadcasting. Furthermore, they are relatively small in size and low in cost. They can join together to form a sensor network with well-organized end-to-end data distribution [2]. This field is progressing with a lot of advancements and valid in important applications such as transportation, wildlife monitoring, healthcare, military surveillance, and air pollution monitoring. These nodes are installed in open spaces such as roads, industries, or commercial buildings. Furthermore, there are few limitations in sensor nodes such as limited memory, energy, and less processing power [3]. The consumption of the energy in WSN is because of three aspects they are sensing, processing, and communication. The batteries in sensor nodes are integrated with limited energy and replacing these batteries is practically viable [4]. Due to this fact, WSN expires when the battery power runs out. Therefore, network lifetime and energy consumption are the important constraints to be considered while developing a WSN [5]. Commonly the sensor nodes in WSN transmit the sensed info directly to the base station (BS). Due to the far distance of BS, the energy consumption is enormous [6]. Additionally, collision, congestion, traffic also consumes more energy. Then according to the application, every node will lose its energy

during the process of data transmission and reception [7]. To solve this above constraint there is an effective mechanism known as clustering. In this mechanism, the network is divided into several sub-sections known as clusters. Each cluster is grouped under a Cluster Head (CH). In cluster-based WSN sensor nodes forward the sensed info to CH and these CH nodes convey this info to the BS [8]. Designing an energy-efficient WSN is a challenging task. Generally, CH consumes more energy than member nodes. So, the effective selection of the CH leads the WSN to an increased lifetime. In recent years, there is a sizeable amount of research and development in the WSN field especially to enrich the efficiency of energy utilization and improving the network lifetime. In previous, Researchers used many evolutionary algorithms such as Genetic Algorithm, Artificial Bee Colony (ABC), Cuckoo Search Optimization (CSO), Particle Swarm Optimization (PSO), and others [9, 10, 11]. These are improper clustering methods that lead to high energy consumption and load distribution. Furthermore, because of multi-hop routes, the CH which are closer to sink nodes consume more energy and soon become dead [12]. The effective selection of CH is necessary to increase the network lifetime.

1.1 Motivation

To overcome all the above issues, we proposed an energy-aware clustering protocol integrated with a multi-objective Dolphin Swarm Optimization algorithm for enhancing the network lifetime. Also using multi-objective Dolphin Swarm Optimization we optimize the energy consumption through partitioning sensor nodes into clusters. This algorithm makes use of residual energy, intracluster distance, inter cluster distance, mobility, node density, and delay to select an effective cluster head. After clustering direct virtual backbone (DVB) rooted in the sink node is utilized for data routing.

The contribution of our work includes:

1. The newly adopted multi-objective Dolphin Swarm Optimization algorithm uses residual energy, intracluster distance, inter cluster distance, mobility, node density, and delay of the sensor nodes for the effective cluster head selection and the energy consumption is reduced.
2. Proposing a network model to increase the lifetime of the network by reducing the energy consumption of the sensor nodes.
3. Evaluating and comparing the proposed system with the existing techniques to show its effectiveness.

The systematic work is arranged as shown here: section 2 describes the related works in clustering of sensor nodes in WSN. Section 3 illustrates the, proposed methodology. Section 4 deals with the results and discussion about the proposed work and finally, section 5 describes the conclusion.

2. Related Work

In WSN, energy consumption is a great issue because low-power batteries are installed in the sensor nodes. The related works are summarized below, based on the clustering techniques. Darabkh et al. [13]

proposed energy-aware layer-based clustering and routing protocol (EA-CRP). Here, the network topology is modeled based on several layers. Each layer is composed of a group of sensor nodes that is a cluster. For each cluster, a sensor node of that cluster is considered as a cluster head. Other sensor nodes transmit the information to the cluster head. These cluster heads are selected based on the energy-aware head selection algorithm. At the beginning of each cluster formation, each node broadcast their id to other sensor nodes using CSMA (Carrier Sense Multiple Access). Using this the neighborhood table is updated. Thus, the nodes having more residual energy are selected as cluster head nodes and the other nodes as tentative nodes. This increases the network lifetime. Moreover, the relay nodes used in inter-cluster communication soon become dead because of the consideration of randomness in deciding factor.

Sharma D, Bhondekar AP [14] proposed a traffic and energy-aware routing method to enrich the stability period of the network. Here, it considers the nodes' traffic and also the levels of energy to select the cluster head. This scheme selects the node which is having high residual energy as CH. At the same time, it refuses to select the high traffic load nodes as the cluster head. The base station keeps tracking the network to evaluate the residual energy of the nodes in the network for every operation in all rounds. The performance of this scheme is better regarding the stability period. Moreover, the network lifetime is not increased.

Razzaq M et al. [15] proposed a k-mean clustering-based routing protocol. Here, the nodes in a particular sensing area are classified into cluster members and cluster heads. These CH's collect the information and transmit it to the base station. These cluster heads are selected based on the K-mean clustering protocol. This algorithm separates the data set into k cluster. Then it computes the distance between the sensor nodes and assigned the cluster center by computing the mean value. Here it assumes two weights to assume the cluster head they are distance and energy. It uses Rayleigh fading channel for transmitting the information to the base station. However, the reliability of the overall system is quite low.

Tabatabaei et al. [16] proposed an energy-aware clustering technique by utilizing Lion Pride Optimization (LPO) along with fuzzy logic. Here it categorizes the sensor nodes into clusters and optimizes the CH using LPO. Other nodes are member nodes and the CH nodes transfer the information to the Base station via sink node. Two weights are used for the optimization of CH they are battery level and distance from the sink. For data routing, they utilize Direct Virtual Backbone (DVB). The fuzzy membership function is applied to weigh the fitness function for each solution. After fuzzification, for data transfer, each cluster assumes the sink node as their parents. This method improves the reliability of packet delivery. Even though, the network stability is quite low.

Kong L et al. [17] introduced an energy-aware routing protocol using a genetic algorithm. Here, they develop a middle-oriented network layer. This layer is of numerous stations which act as an intermediate by collecting the data from the sensors and transfer it to the sink node. This design is of two phases they are selecting candidate middle layer and genetic algorithm phase. To obtain a good

number of stations genetic algorithm is used. They partitioned the network into four sections. Sampling is used to select the subset from the population and two sampling methods are adopted they are systematic and simple random sampling. The construction cost is quite high.

Zakariayi S, Babaie S [18] introduced a method Distributed energy-aware hexagon-based clustering algorithm. Here, it minimizes the mobility of the nodes and maintains the sleep mode in the overlapping areas. Three steps are involved in this scheme they are updating information, selecting the cluster heads, forming clusters, and covering the areas without holes. By adopting the Euclidean distance formula, the distance is calculated and the effective cluster head is selected. Further, member nodes for each cluster head are assigned. Re-clustering takes place once the lifetime of the cluster head is over. This scheme gives better coverage but the energy consumption of the network is high.

Sharma R et al. [19] introduced an energy-efficient clustering that is based on the nature-inspired algorithm. Particle swarm optimization is utilized for selecting the cluster head and the formation of the cluster. Here, the fitness is evaluated based on the energy dissipated in the intra and intercommunication of the network. Hybrid clustering based on the nature-inspired is performed for the formation of effective CH. The CH selection is done using fuzzy logic. The node will survive till the residual energy remains in the network. It works well regarding the network lifetime. Moreover, the network stability is quite low.

From the analysis of the existing works on energy-efficient clustering, we conclude that there are many issues in efficient CH selection. The proper fitness can efficiently balance the energy of the node and the network lifetime can be increased. Moreover, the schemes are shown in the literature review not able to provide an optimal solution for CH selection and routing. Also, the CH sends the information to BS and the energy of this CH dissipated and soon it becomes dead. So, the lifetime of the network will be reduced. In this research, both CH selection and routing establishment are considered simultaneously to objective an optimal clustering solution.

Table 1: Comparative analysis of previous works

Author	Method	Advantages	Disadvantages
Darabkh et al. [13]	EA-CRP	Increases network lifetime	relay nodes are soon become dead
Sharma D, Bhondekar AP [14]	traffic and energy-aware routing method	Better performance	Lifetime not increased
Razzaq M et al. [15]	Mean clustering-based routing protocol	Better performance	Low in reliability
Tabatabaei et al. [16]	energy aware clustering technique	Reliable	Low in stability
Kong L et al. [17]	energy aware routing protocol using genetic	Better in reliability	Cost is high

	algorithm		
Zakariayi S, Babaie S [18]	Distributed energy-aware hexagon-based clustering algorithm.	Better coverage	High energy consumption
Sharma R et al. [19]	Hybrid clustering-based on nature-inspired	Lifetime is moderate	No network stability

3. Proposed EACH-MODSO

In the proposed method, selecting an effective cluster head process took place in the central control system. The network model developed is a single-hop model in which the cluster heads communicate with the base station directly. In each iteration, the central station monitors the energy level of the network and also the positions of the nodes. Each of the nodes senses and collects the information around them for every iteration. Further, it processes the information and transmits it in the form of packets to the cluster heads. At that moment, each CH collects the information from its member nodes and forwards the information in the form of data packets to the BS in single-hop communication. The proposed method network model is shown in figure 1 given below,

Figure 1: Architecture of EACH-MODSO

3.1 Energy consumption

In this proposed protocol, n bit of data packet transmitting with the transmitting and receiving distanced, the consumed energy by a transmitting node is computed using the equation,

$$E_{Tx}(n, d) = n \left[E_{elec} + \varepsilon_{amp} d^2 \right] \quad (1)$$

Where, E_{elec} denotes the consumption of energy by an electronic device and ε_{amp} stands for the energy necessary to transmit signals. However, for receiving the n bit of data, the energy consumption

of a receiving node is computed as,

$$E_{Rx}(n) = n \times E_{elec} \quad (2)$$

3.2 Steps involved in the proposed system

This proposed clustering method includes three processes they are a selection of effective CH, cluster formation, and data transmission. This algorithm comprises of two phases: initially, the cluster formation phase which includes the selection of CH and creation of the cluster. Finally, the register phase which includes the scheduling program and data transmission. In this, the cluster head selected effectively by adopting Multi-objective Dolphin Swarm Optimization in the central station. Further, the connection establishment and registration are carried out. The flow diagram which represents the proposed protocol is portrayed in figure 2.

3.2.1 Cluster formation phase

In each iteration, the CH is selected effectively using the MO-DSO algorithm in the central station. The central station sends a message to the determined CH's to inform other nodes about its role as a CH in the current round. Then the CH shares the information about its role to other nodes in the network. For this above process, CH broadcasts an advertisement message in the entire network. The sensor nodes determine their CH based on minimum energy consumption for communication. That is, each member node assigns the closest CH as their administrator.

For the formation of the cluster, each non-CH node decides about which cluster should belong to for the current round. Each of the member nodes transmits the message Join-REQ to cluster heads. The cluster heads send the acknowledgment and the cluster forms. To avoid the collision during the data transmission CH creates TDMA scheduling according to the number of member nodes. Then all the CH's send the scheduling program to all their respective member nodes. So that, it can avoid the collision of messages inside the cluster. The essential condition is the radio elements of all the member nodes to be in sleep mode in all the processes except its process. So, energy consumption is reduced. The start-up phase is completed after all cluster nodes recognize the TDMA schedule. Now the register phase begins.

Figure 2: Flowchart of the proposed method

3.2.2 Register phase

This phase is partitioned into several time frames. In each time frame, all the nodes in the cluster transmit their data to the CH in the respective time frame. We consider all the nodes are synchronous to each other in the proposed scheme. For recognizing this occurrence central station transmits a synchronous pulse to all the nodes in the network. Likewise, for minimizing the energy consumption of each member node based on the advertisement signal received from CH, a power control method is adopted to regulate the power in the CH. However, except for their own frame time, the member nodes are in sleep mode. Subsequently, clusters are formed and scheduling based on TDMA determined, the data transmission process takes place. Here the member nodes transmit their sensed data to their appropriate CH in the allocated time. The member nodes collect the data using Carrier Sense Multiple Access (CSMA) and transmitted it to the corresponding CH using a distribution code. A unique distribution code is distributed to all the member nodes and using this they transmit the data. Further, CH filters all the received messages using distribution code. When a CH needs to transmit data, it listens to the network and checks whether any other nodes are transmitting by utilizing distribution

code. If yes it waits; otherwise, CH transmits the data to the central station using the code.

3.3 Cluster Head Selection

The process of selecting an effective cluster head using the multi-objective Dolphin Swarm Optimization is elaborated in this section. The Dolphin is a cleverest creature with interesting characteristics. Dolphins make use of their living behaviors for communication purposes and hunting of prey. This intelligence can be used for optimization and this algorithm is known as Dolphin Swarm Optimization Algorithm. The steps in DSO are echolocation, teamwork, and division of labor, information exchange. These are illustrated below,

Echolocation: Dolphin's eyesight is good but it does not help for predating. Henceforth, these dolphins use their special intelligence echolocation for searching prey. Using this echo, it estimates the size, location, and also distance of the prey.

Teamwork and division of labor: If the prey is huge, then it cannot be hunt by a single dolphin. So, it calls for other dolphins for help. Further, the predation is done by the joint effort of dolphins with cooperation and division of labor.

Information exchange: Dolphins use their sounds for communication with different frequencies. This process enriches the efforts taken by dolphins during the predation phase.

The terminologies of the DSO are discussed below,

- The predation process of the Dolphin helps to solve the optimization problem. The solution for a D dimension of the field defined as a dolphin, $Dolphin_i = [x_1, x_2, x_3, \dots, x_D]^T$ ($i = 1, 2, \dots, N$), Where N is the number of dolphins and x_j is the component of each dolphin to be optimized.
- Individual and neighborhood optimal solution are denoted as $Ibest_i$ and $Nbest_i$ which is associated with each dolphin $Dolphin_i (1, 2, \dots, N)$.
- Fitness is a function that is used to estimate the solution best or not. In DSO, if the solution is close to zero then the solution is best.

Distances are of three types they are,

Distance between two dolphins $Dolphin_i$ and $Dolphin_j$ which is given as $DDolphin_{i,j}$ and is computed as

$$DDolphin_{i,j} = \|Dolphin_i - Dolphin_j\|, i = 1, 2, \dots, n \quad (3)$$

The distance between the optimal solution $Nbest_i$ and the dolphin $Dolphin_i$ is given as

$DNbest_i$ and is computed as,

$$DNbest_i = \|Dolphin_i - Nbest_i\|, i = 1, 2, \dots, n \quad (4)$$

The distance between the global and individual optimal solution is given as $DINest_i$ computed as

$$DINest_i = \|Ibest_i - Nbest_i\|, i = 1, 2, \dots, n \quad (5)$$

The four processes in the DSO are the search process, call process, reception process, and predation process. These steps of these process are explained below,

- (1) Dolphins only search, attack, or prey on swarms in their search space.
- (2) Dolphins utilize their modes of swimming when they are preying on swarms.
- (3) Each dolphin emits ultrasonic to detect the position of the object by receiving the echo.
- (4) Process of searching is of three steps: detecting the locations of prey, tracking, and achieve the target.
- (5) The dolphin can dynamically change its swimming mode and can use different search strategies following its need.

3.3.1 Multi-objective DSO

The cluster head selection using multi-objective DSO is based on the factor's residual energy, intra-cluster distance, inter cluster distance, mobility, node density, and delay of the sensor nodes. The fitness function is used to select the optimum CH. These multi-objective factors are given as,

$$F = \frac{1}{2} \left[\frac{1}{3} (f_1 + f_3 + f_5) + \left(1 - \frac{1}{3} \times [f_2 + f_5 + f_6] \right) \right] \quad (6)$$

Where $f_1, f_2, f_3, f_4, f_5, f_6$ denotes energy, inter cluster distance, intracluster distance, mobility, node density, and delay.

3.3.1.1 Energy-based fitness

The overall energy of the cluster is the remaining energy in the CH and individual nodes. The residual energy of the node should be more so that the performance of the network is better. This increases the lifetime of the network.

$$f_1 = \frac{1}{2} \left[\frac{1}{X \star Y} \left(\sum_{j=1}^X \sum_{i=1}^Y \xi_{ji} \right) + \frac{1}{X} \sum_{j=1}^m \xi_j \right] \quad (7)$$

Where X and Y are the total number of CH and nodes in the cluster, ξ_{ji} denotes energy in the i th node of the j th cluster and ξ_j is the energy of the j th CH.

3.3.1.2. Intercluster distance fitness

This is the distance between the CH and the nodes in that particular cluster. The estimated fitness is

computed as,

$$f_2 = \frac{1}{x^* y} \left(\sum_{j=1}^x \sum_{i=1}^y \left\| \frac{S_j, S_i}{\mathcal{N}} \right\|^2 \right) \quad (8)$$

Where, S_j, S_i location of j th and i th CH. $\left\| \frac{S_j, S_i}{\mathcal{N}} \right\|$ denotes the distance between the j th CH and the i th node in the respective cluster. $\mathcal{N}$ is the normalization factor.

3.3.1.3 Intracluster distance fitness

This is the distance between two clusters. The estimated fitness is computed as,

$$f_3 = \frac{1}{x^* x} \left(\sum_{j=1}^x \sum_{i=1}^x \left\| \frac{S_j, S_i}{\mathcal{N}} \right\|^2 \right) \quad (9)$$

3.3.1.4 Mobility based fitness

The mobility of the node is evaluated based on the mobility of the j th cluster in the previous and current iteration. This is computed as,

$$f_4 = \frac{1}{x} \sum_{j=1}^m \frac{\left\| S_j^t, S_j^{t-1} \right\|}{\mathcal{N}} \quad (10)$$

3.3.1.5 Fitness based on node density

Node density is the number of nodes at the one-hop transmission distance to node j . It can be computed as,

$$f_5 = Nbr^j \quad (11)$$

Where Nbr^j is the one-hop transmission distance from node j .

3.3.1.6 Fitness based on delay

The total number of nodes in the j th CH should be low for delay less transmission. This is given as,

$$f_6 = \frac{1}{x} \cdot \sum_{j=1}^x |CH_j| \quad (12)$$

Where $|CH_j|$ is the total number of node in the j th cluster.

The dolphins initially perform a random search, then it predicts the distance of the prey. In DSO, the initial stage is the exploration phase and the second investigation phase is performed. This method is very much flexible and feasible. The nodes are considered to be the dolphins and the optimal prey is the CH. This algorithm well suits for multiple fitness factors. The main advantage of this MO-DSOA

is convergence to the global optimal solution is not parameter-dependent and optimization is computationally efficient. The dimensional search of the MO-DSOA is computed as follows,

$$S_i(t+1) = S_i(t) + \alpha_{1i}(Ibest_i - X_i(t)) + \alpha_{2i}(Nbest_i - X_i(t)) \quad (13)$$

$$S_i(t+1) = S_i(t) + \alpha_{1i}Ibest_i - \alpha_{1i}X_i(t) + \alpha_{2i}Nbest_i - \alpha_{2i}X_i(t) \quad (14)$$

$$S_i(t+1) = S_i(t) + \alpha_{1i}Ibest_i + \alpha_{2i}Nbest_i - (\alpha_{2i} - \alpha_{1i})X_i(t) \quad (15)$$

Where, $S_i(t+1)$ and $S_i(t)$ are the search space dimension of the i th dolphin in $(t+1)$ th iteration and t th iteration. α_{1i} and α_{2i} are the random numbers of the i th dolphin in the interval $[0,1]$. $Ibest_i$ and $Nbest_i$ are the individual best position and global best position of the dolphin. Then the updated position of the dolphin is,

$$X_i(t+1) = X_i(t) + S_i(t+1) \quad (16)$$

Further, by substituting Eqn (16) and Eqn (15) we get the updated rule of the MO-DSOA as,

$$X_i(t+1) = X_i(t) + S_i(t) + \alpha_{1i}B_i + \alpha_{2i}V - (\alpha_{2i} + \alpha_{1i})S_i(t) \quad (17)$$

3.4 Algorithmic steps involved in the MO-DSOA

The steps in the MO-DSOA to select the optimal CH is as follows,

1. Initialization: Generate the dolphins that are cluster nodes randomly in the search space of the individual location of dolphins. The initialization is given as,

$$Ibest_i(t+1) \text{ and } Nbest_i(t+1); i = 1, 2, \dots, n \quad (18)$$

2. Predefined probability computation: The convergence varies based on predefined probability in the optimization process and is given as,

$$\rho(L_i) = \rho + (1 - \rho_1) \times \frac{L_i^{pc} - 1}{(L_z)^{pc} - 1} \quad (19)$$

Where, ρ denotes predefined probability, ρ_1 is the convergence factor of the first iteration. The number of current loops is denoted as L_i and pc is the power of the convergence curve.

3. Estimation of Fitness of Individual dolphin: The fitness of the dolphin of individual location is given as,

$$Y_i = \text{fitness}(X_i) \quad (20)$$

Where, $fitness(X_i)$ is the fitness of individual nodes calculated from Eqn (6).

4. Computation of accumulative fitness based on dolphin rules: The fitness based on dolphin rules updated for every iteration and is given as,

$$Z_{(E+t)h} = \frac{1}{R} * (R - |t|) fitness(X_i) + Z_{(E+t)h} \quad (21)$$

Where, $Z_{(E+t)h}$ is the accumulative fitness and R denotes effective radius which should not exceed

$\frac{1}{4}$ of the search space.

5. Initializing individual best position and global solution of the dolphins: The individual best of the dolphin $Ibest_i$ and the global best solution $Nbest_i$ is initialized as $Ibest_{i0} = x_i$ and

$$Nbest_i = \min(Ibest_{i0}); i = 1, 2, 3, \dots, n. \quad (22)$$

6. Updation of search space of dolphin: The search phase of the dolphin is updated using dynamic inertia weight and is computed as,

$$\omega_t = \left[\omega(0) - \omega(Z_{pc}) \right] \frac{(Z_{pc} - t)}{Z_{pc}} + \omega(Z_{pc}) \quad (23)$$

Where, Z_{pc} is the maximum number of iterations, Z_{pc} is the initial inertia weight and Z_{pc} is the final inertia weight. The search space dimension denoted as,

$$S_i(t+1) = \begin{cases} S_i(t+1); & \text{if } S(t+1) < \partial_{\max} \\ \partial_{\max}; & \text{if } S_i(t+1) \geq \partial_{\max} \end{cases} \quad (24)$$

The position of the dolphin gets updated using Eqn (22). Where, $S_i(t+1)$ is the search space dimension.

7. Updation of individual best position and global solution using new fitness: The best position of both the individual and global is given as,

$$Y_{i,new} = fitness(X_i), Ibest_i = Y_{i,new}, \text{ and } Nbest_i = \min(Ibest_i) \quad (25)$$

8. Ending Conditions: If the ending condition is met the best solution is returned otherwise the fitness computation steps are repeated. The global best is elected as the Cluster Head.

After the successful selection of CH, the transmission of data takes place between the CH and base station. This facilitates less energy consumption and extends the network lifetime. The iteration is repeated by updating the remaining energy in the nodes. This iteration ends when the ending criteria

are met.

Algorithm of MO-DSOA

Step 1: Initialization

Generate dolphins $Ibest_i(t+1)$ and $Nbest_i(t+1); i = 1, 2, \dots, n$

Step 2: Predefined probability computation

$$\rho(L_i) = \rho + (1 - \rho_1) \times \frac{L_i^{pc} - 1}{(L_z)^{pc} - 1}$$

Step 3: Estimation of Fitness of Individual dolphin

The fitness is estimated by $Y_i = \text{fitness}(X_i)$

Step 4: Computation of accumulative fitness based on dolphin rules

$$Z_{(E+t)h} = \frac{1}{R} * (R - |t|) \text{fitness}(X_i) + Z_{(E+t)h}$$

Step 5: Initializing individual best position and global solution of the dolphins

$Ibest_{i0} = x_i$ and $Nbest_i = \min(Ibest_{i0}); i = 1, 2, 3, \dots, n$.

Step 6: Updation of search space of dolphin

$$S_i(t+1) = \begin{cases} S_i(t+1); & \text{if } S(t+1) < \partial_{\max} \\ \partial_{\max}; & \text{if } S_i(t+1) \geq \partial_{\max} \end{cases}$$

Step 7: Updation of individual best position and global solution using a new fitness

$Y_{i,new} = \text{fitness}(X_i)$, $Ibest_i = Y_{i,new}$, and $Nbest_i = \min(Ibest_i)$

Step 8: Ending Conditions

4. Results and Discussion:

The results of the An Energy-Aware Cluster Head Selection Protocol based on Multi-Objective Dolphin Swarm Optimization is discussed below,

4.1 Simulation and parameters

The simulation is carried out in the NS-2. The parameters taken in the simulation are shown in table 2.

Table: 2 Parameters

Parameter	value
Network size	60m x 120m
BS location	X=30, Y=-90
Number of nodes	100 nodes
Data message size	6400 bits

Control message size	200 bits
Initial energy	0.5 J

4.2 Performance Metrics

The metrics used to analyze the performance of the proposed system is stated below,

Network lifetime: To examine the robustness and efficiency of the proposed protocol three definitions are taken in to account they are,

- Death of First Node: The time when the first node dies measured in rounds.
- Death of Middle Node: The time when half of the node die measured in rounds.
- Death of the Last Node: The time when the Last node die measured in rounds.

4.3 Simulation Results

To show the importance of our contribution we compare the proposed work with the UCR(20), COCA(21), and EA-CRP(13). The simulation results of the proposed EACH –MODSO is deliberated below,

4.3.1 Evaluation based on Number of alive nodes with a number of rounds

From the result, it can be seen that the results are in the decreasing order that is when the rounds increase the nodes lose their energy and soon become dead. So, the total count of alive nodes decreased. For every round, sensor nodes lose their energy to transmit their data on their allocated TDMA schedule time slots. In Figure 3 we observe that the proposed EACH-MODSO performs well than all other existing protocols that are it remains about 517 rounds while the UCR (20), COCA (21), and EA-CRP (13) remains active for 322, 254, and 431 rounds respectively.

Figure 3: No. of alive node Vs number of rounds comparing our proposed with existing COCA, UCR, EA-CR

If we choose the network dimension of 60m x 180m the COCA has better performance than UCR. It is observed from figure 4 that the proposed system outperforms well compared to the existing methods.

Figure 4: No.of alive node vs number of rounds for network dimension 60m x 80m

4.3.2 Network lifetime vs initial energy of node

Figure 5 shows the effect of changing the initial energy on the exhibition of our proposed protocol and UCR, COCA, EAR protocols, from the point of view of network lifetime. It is unmistakably seen that our proposed protocol despite everything performs superior to different plans. Also, it is very fascinating to see the quick increment in the number of rounds over the other proposed conventions as the underlying energy increments. This can be legitimized as managing the most noteworthy energy effectiveness among the others.

Figure 5: Network lifetime vs initial energy of each node

The alive node analysis of the proposed system with state of art methods is depicted in table 2.

Table: 3 Alive node analysis

Method	No. of rounds till the last node dies
UCR (20)	322
COCA (21)	254
EA-CR (13)	431
EACH-MODSO (Proposed)	517

5. Conclusion

Energy management is the foremost concern in the research of clustering protocols of WSN. In this, an Energy-Aware Cluster Head Selection Protocol based on Multi-Objective Dolphin Swarm Optimization (EACHP-MODSO) is proposed. The CH is selected using Multi-objective dolphin swarm optimization based on the criteria like energy, inter cluster distance, intra-cluster distance, mobility, node density, and delay. The sensors with low energy are not selected as CH. This increases the network lifetime of the WSN by reducing the energy consumption of the nodes. The effective cluster head selection that is the low residual energy nodes are not assumed as CH which improves the lifetime of the network. The performance was evaluated based on the metrics of network lifetime and network utilization. The proposed protocol outperforms well compared to existing protocols in terms of the above-mentioned metrics. Further, this work can be extended for mobile sensor nodes.

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