A WOA Based Energy Efficient Clustering in Energy Harvesting Wireless Sensor Networks

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***Abstract*— In this paper, we propose various effective clustering methods for increasing the lifespan of Wireless Sensor Networks (WSNs), i.e., the period until a given proportion of the nodes die due to recent advances in WSNs. In particular, an optimization method for maximizing the lifespan of a single-cluster network was developed, followed by an expansion to handle multi-cluster networks. Then, by adding energy-harvesting (EH) nodes, we investigate the combined issue of extending network lifespan. EH nodes act as specialized relay nodes for cluster heads, and a method for optimizing network lifespan is suggested. The suggested algorithms may easily produce optimum or suboptimal solutions, according to theoretical analysis and comprehensive simulation findings, the enhancement of 76.7%, 66.25%, and 28.09% of network lifetime of WOA-BC against the remaining protocols GA, ACO, and PSO respectively, and therefore serve as valuable benchmarks for different centralized and distributed clustering scheme designs.**

Keywords*—*WOA-BC, energy harvesting, remaining energy, clustering, WSNs

I. INTRODUCTION

WSNs are made up of a limited number of sensor nodes that are dispersed across the environment. Wireless network development has been utilized for a variety of applications in the last decade, including medication monitoring, environmental sensing, picture tracking, underground mines, security surveillance, military field, and many more [1]. WSNs are made up of a large number of low-cost, low-power sensor nodes. The processor unit, transceiver unit, loading unit, and sensing unit are the four main components of the sensor node. Sensor nodes are randomly placed in the field or in inaccessible locations such as hills, thick forests, and disaster areas in WSNs [2]. Sensor data is also sent to the base station (BS) in a single-hop or multi-hop manner. A significant difficulty is that sensor nodes are widely distributed over a large area, making data exchange between sensor and sink nodes inefficient in energy consumption. Moreover, the clustering technique was used to show the study on node energy conservation for WSN network life [3].

Sensor nodes continue to be combined into various clusters, in the clustering technique, and the cluster head (CH) is the coordinator for each cluster, while the other sensor nodes in the cluster are known as cluster members (CMs) [4]. Every cluster head collects data from its own sensor nodes across all clusters. A multi-hop routing method gathers and sends individual CH information to the sink node [5]. A data aggregation procedure is a well-known clustering protocol method for reducing energy usage and duplicating data. The goal of the clustering technique is to reduce energy usage while increasing the sensor network's lifespan. Furthermore, sensor node deployment methods in distant locations are another difficult problem for WSNs to charge the sensor node batteries [6]. Subsequently, Fig. 1 demonstrates the clustering mechanism in detail.

Sensor nodes (SNs) are tiny and have limited energy capabilities. They are experiencing communication difficulties due to their restricted-energy capabilities. As a result, new techniques for decreasing the consumption of energy and increasing network lifespan in EH-WSNs are required. Clustering is a well-known technique of conserving energy during the WSN data transmission stages; clustering lowers traffic and overhead by balancing energy use in all SNs. CHs are chosen in the clustering-based method, and SNs transmit data to the closest cluster head. A significant amount of data gathering and compression is performed by CHs [7] [8].

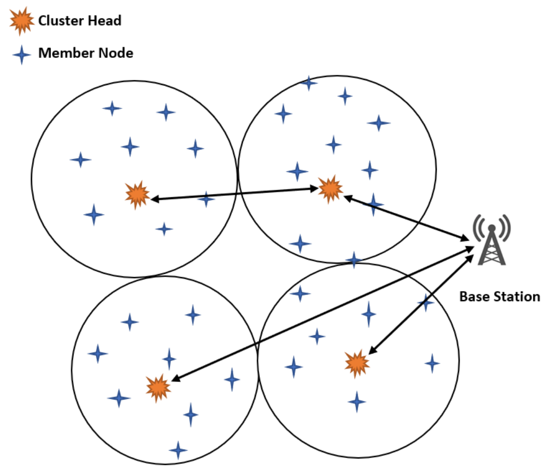

Fig. 1 Clustering mechanism in WSN

More responsibilities for CHs will need greater energy consumption to analyse and transmit data from each cluster, resulting in network depletion that is both premature and irregular [9-10]. The dissipated energy and network lifespan are not determined and optimized generically. There are many ways to improve one feature and to raise energy usage in others. In addition, the measurable calculation of energy practice for the whole network does not take account of current methods [11-12], [27].

The proposed whale optimization algorithm-based clustering (WOA-BC) for EH-WSNs as a future advancement [9], [28], [34]. The following are the paper's major contributions:

- Each cluster contains an SN that monitors and saves residual energy data for every CM and CH in real-time. Based on the monitoring results during the selection stage for the CH, the suggested SN chooses a corresponding CM as substitute CH, reduce the load on the CH and enables more energy to be utilized for data transmission.
- The proposed approach shows cutting-edge research by dynamically selecting energy-efficient clusters with efficiency cluster heads using the proposed WOA optimization algorithm.

The remainder of the paper is laid out as follows: Section 2 examines the literature work. The proposed method of WOA-BC is discussed in section 3. Section 4 provides the suggested algorithm's performance assessment, followed by section 5 conclusions and future development.

II. Literature Review

Cluster-based routing methods rely heavily on the selection of certain nodes as CHs. Several CH selection methods have been used to improve the performance of cluster-based routing protocols throughout the years. LEACH is one of the most well-recognized clustering algorithms, and has been shown to be effective in increasing network lifespan. For an effective uneven clustering procedure, distributed unequal clustering (DUCF) was utilised, using a fuzzy method [13]. The sensor network's energy distribution was balanced using this technique, and CH was chosen using a fuzzy approach. The multi-objective immune method was subjected to an uneven clustering mechanism (UCM) [14]. According to the energy consumption in the sensor network, this model was updated via intra-clustering and inter-clustering techniques. In [15], they suggest balanced flow routing (FBR) to increase the power efficiency of the network while still maintaining coverage. The FBR technique made advantage of multi-hop routing to extend the network's lifespan. A prediction model such as EWMA, which builds upon the EH centralized clustering protocol, describes the discrete particle space optimization technique for EH-WSNs to prolong the network life of the sensor nodes [16].

Zhang et al. [18] recommended a routing system that is both efficient and effective. To determine the optimum number of clusters, the clustering method is used. In EH-WSNs, Darabakh et al. [19] offer a new clustering and routing method. Using a multi-layer design, this method attempts to reduce energy usage. This method lowers the range of communication while simultaneously lowering the communication overhead. This article also offers a multi-hop routing method that considers two variables: total distance and RN energy.

Lin et al. [20] developed an energy-efficient WSN clustering technique that selects a CH node from each cluster's specified center area. Other researchers with different perspectives proposed other successful CH selection techniques for WSNs. According to Shalini and Vasudevan [21], irrational cluster head selection leads to overlapping coverage and uneven energy usage within the cluster communication. They suggested a new dynamic cluster head selection technique to minimize overlapping coverage and imbalanced energy usage in cluster communication. Priyadarshi et al. [22] chose two CHs for each cluster while tackling a similar issue. For energy-constrained heterogeneous fog-supported WSNs, Naranjo et al. [23] used two heterogeneous nodes. The CHs for both the normal and advanced nodes are chosen using weighted probability and specified energy criteria. Certain scholars have suggested artificial bee colonies [24], fireflies [25], and particle swarm optimization [20], and chemical reaction optimization algorithms [26] as CH selection algorithms based on nature-inspired methods. On the other hand, all of these algorithms are intended for non-rechargeable battery-powered WSNs and cannot be used in EH-WSNs directly. Furthermore, except for the nature-inspired techniques, picking new CHs is usually started and completed by existing CHs in the algorithms mentioned earlier, and the energy needed for selecting new CHs is not considered [17],[38-39].

Mirjalili et al. [8,9] recommended a WOA method that is implemented as a new dynamically impacted metaheuristic optimization technique among swimming intelligent systems. Humpback whales form a diminishing team around prey, producing characteristic bubbles along a spiral-shaped trail [10]. Sahoo et al. [26] designed and implemented a hierarchical hybrid method for distributed clustering in WSNs.

III. The Proposed Whale Optimization Algorithm Based Clustering (WOA-BC) in EH-WSN

Clustering techniques offer several major benefits. Clustering improves energy efficiency and scalability in EH-WSNs by lowering the energy consumption of SNs. Clustering lowers network traffic and overhead.

During communication, clustering prevents duplicate messages from being sent. Clustering allows CHs to conduct data compression and aggregation, resulting in lower network energy usage. In the clustering process, the transmission range among SNs also decreases. In the clustering process, only CHs have high-range data transmission. The selection of CHs is one of the most challenging problems in the clustering process since they play such an important part in the clustering mechanism. Traditional optimization techniques fail to provide a satisfactory solution in a reasonable period of time. To find the optimum answer to these optimization issues, meta-heuristic techniques are often employed.

A. *Objective Function:*

To develop a mathematical model that is usually maximised or minimised, the performance of the objective function may be combined with fitness features. The specific part is about two different factors determining an individual's fitness. The following are the exercise settings that were applied to the goal:

- Objective1 (Maximizes the minimum energy):

$$Obj_1 = \max_n \left(\min_m (E_{R_i}) \right) \qquad (1)$$

Where the residual energy of the ith node, as indicated in equation (1), is denoted byE_{R_i}.

- Objective 2 (Maximizes the average energy):

$$Obj_2 = \max_n \left(\frac{1}{N} \sum_{i=1}^{N} E_{R_i} \right) \qquad (2)$$

Where N is the total number of nodes in the system and $E_{R_i}$is the residual energy of the ith node in the system, as shown in equation (2).

Following the single expression is a representation of the objective function, which is represented by the following equation (11):

$$Objective\ Function = [(\gamma * Obj_1) + (\theta * Obj_2)] \qquad (3)$$

Where, γ, and θ are the constant values and $\gamma + \theta = 1$

Mirjalili and Lewi proposed the whale optimization method in 2016 to solve numerical problems [9]. The program mimics humpback whale intelligence hunting behaviour. Encircling prey during the hunting approach is a foraging behaviour that is only seen in humpback whales. While surrounding prey during hunting, the whales create the usual bubbles along a group road. To allow for optimization, the following is the general phrase for surrounding prey and searching for prey:

$$\vec{D} = |\vec{C}.\overrightarrow{X_a}(t) - \vec{X}(t)| \qquad (4)$$

$$\vec{X}(t+1) = \overrightarrow{X_a}(t) - \vec{A}.\vec{D} \qquad (5)$$

Where, $\overrightarrow{X_a}$ indicated the prey's location vector and t denoted the current iteration in the aforementioned equations (1) and (2). The location vectors of each agent are indicated by $\vec{X}$ and coefficient vectors are $\vec{A}$ and $\vec{C}$.

The coefficient vectors $\vec{A}$ and $\vec{C}$ are evaluated as

$$\vec{A} = 2.\vec{a}.\overrightarrow{r_1} - \vec{a} \qquad (6)$$

$$\vec{C} = 2.\overrightarrow{r_2} \qquad (7)$$

$$\vec{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}| \qquad (8)$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \qquad (9)$$

In equations (6) and (7), $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are the arbitrary vectors with values between 0 and 1, and the element an is decreased progressively from 2 to 0 over iterations; in equations (8) and (9), $\overrightarrow{X_{rand}}$ is the random vector produced as a result of |A| > 1 and |A| < 1.

The complete process of whale optimization algorithm active in the proposed work has been introduced into the Algorithm which is considered to be follows:

Algorithm 1: Proposed Whale Optimization Algorithm

1: **Input:** Initialize the whale population, X_i, i = 1, 2,. . , n, $\vec{A}$, $\vec{C}$, $\vec{a}$, and p
2: **Output:** final position of best whale
3: Find the objective function
   \\ Using equation (3)
4: **while** (round <= max_iteration) do
5: **for** each whale do
6: Update $\vec{A}$, $\vec{C}$, $\vec{a}$, p
7: **if** (p < 0.5) **then**
8: **if** | A |< 1 **then**
9: Search agent update
10: **else** | A |≥ 1 **then**
11: Select random search agent
12: update the position of whale
13: **end if**
14: **else if** (p ≥ 0.5) **then**
15: Update the current positions of whale
16: **end if**
17: **end for**
18: t = t + 1
19: **end while**
20: Return best optimized solution
21: **end**

IV. SIMULATION AND RESULT ANALYSIS

We used MATLAB to simulate the suggested method and various outcome parameters in this part. We did, however, compare the WOA-BC to other protocols like GA, ACO and PSO. A run-time instance of the WOA-BC algorithm, network lifespan, network stability period vs network instability period, and a cumulative data packet delivered are all included in the WOA-BC algorithm testing. The wireless sensor network has 100 nodes and is set up in a 200m x 200m area.

Table 1 Simulation parameters.

WOA-BC Parameters	Values
Size of Networks	200 ×200 m^2
Total Nodes (N)	100
Sink node	1
Node energy (in Joules) (E_o)	0.5
E_{elec}	50nJ/bit
Threshold distance (d_o)	87m
(E_{efs})	10pJ/bit/m^2
Inertia weight	0.7
Size of data packets	2000bits
Number of total particles	30
C_1	2
C_2	2
Simulation run	20

The efficacy of comparing the suggested WOA-BC protocol to current state-of-the-art algorithms is examined in order to determine if the recommended work is superior. We are now evaluating current procedures such as GA, ACO, and PSO protocols for assessment purposes, and the outcomes are measured using various metrics such as stability period, network remaining energy, and throughput.

Figure 2 depicts the first node dead (FND), half node dead (HND), and final node dead (LND) in each network cycle. However, according to the GA, ACO, and PSO algorithms, WOA-BC outperforms them, according to our methodology. According to Fig.2, the First Node Dead (FND) in WOA-BC occurs after 1204 rounds, whereas FND occurs after 589, 678, and 823 rounds in GA, ACO, and PSO, respectively, and Half Nodes Dead (HND) occurs after 2100 rounds in WOA-BC, but only after 1188, 1323, and 1675 rounds in the GA, ACO, and PSO algorithms, respectively.

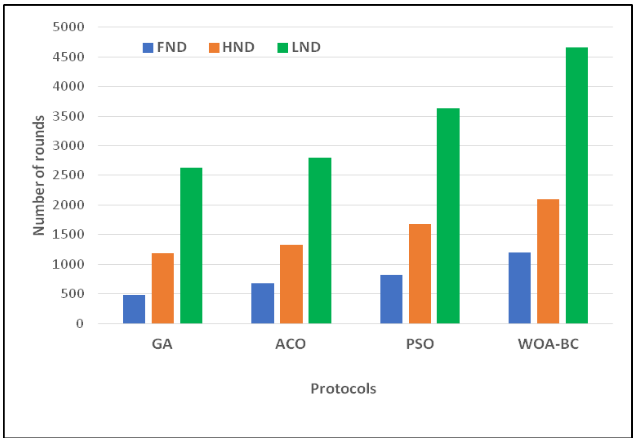

Fig. 2 Comparative analysis of the dead nodes in EH-WSN

The given figure 3 shows that WOA-BC is completed at 4655 rounds while the network lifetime compared to ACO and PSO algorithms have been seen on 2624, 2800, and 3634 rounds, respectively. According to the investigation, WOA-BC covers 2031, 1855, and 1021 more cycles than the GA, ACO, and PSO algorithms, as shown in Figure 3.

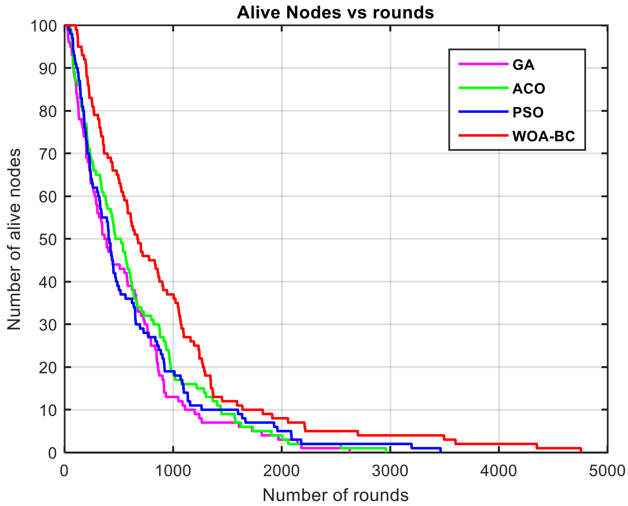

Fig. 3 Comparison analysis of the protocols in EH-WSN

According to Figure 4, the First Node Dead (FND) in WOA-BC occurs after 1204 rounds, whereas FND occurs after 589, 678, and 823 rounds in GA, ACO, and PSO, respectively; after 2100 rounds, Half Nodes Dead (HND) in WOA-BC occurs after 1188, 1323, and 1675 rounds; and after 4655 rounds, Last Nodes Dead (LND) in WOA-BC occurs after 2031, 2800, and 3634.

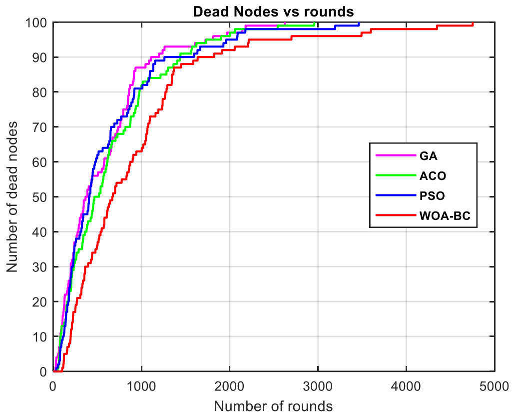

Fig. 4 Comparison analysis of the protocols in EH-WSN

In the given figure 5 has shown that in WOA-BC to be increased as the effective transmission of 26074 data packets while, GA, ACO and PSO sent 13546, 30346, and 16197 packets of information, separately.

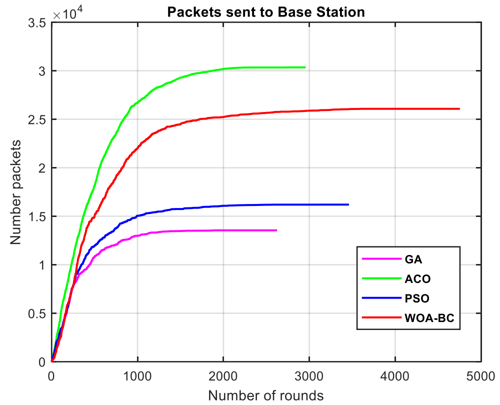

Fig. 5 Comparative analysis of Throughput WOA-BC with existing algorithms

Figure 6 shows that the suggested work has more rounds for the given rounds. Compared to the planned work, the protocols GA, AOC, and PSO cover less rounds. This parameter is a measure that depicts the pattern of energy consumption by sensor nodes. The sensor nodes' energy, which is 70 Joules, is progressively depleted as the rounds proceed.

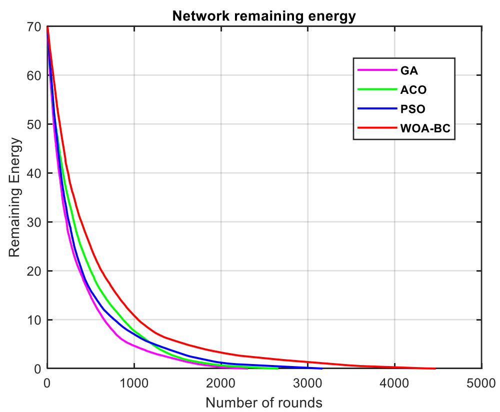

Fig. 6 Remaining energy analysis of the protocols in EH-WSN

In nutshell, the summary enhancement by WOA-BC in term of network lifetime, half node dead, stability period, and throughput are given in table 2.

Table 2 Lifetime and throughput of the sensor node at the different round in the EH-WSN.

Protocols	**Stability Period**	**Half Node Dead**	**Network Lifetime**	**Throughput (packets)**
GA	589	1188	2624	13546
ACO	678	1323	2800	30346
PSO	823	1675	3634	16197
WOA-BC	**1204**	**2100**	**4655**	**26074**

V. CONCLUSION

The clustering protocol's primary goal is to decrease the energy consumption of the network in WSNs. In addition, a lot of effort has gone into improving the clustering routing protocol of WSNs in order to extend the network lifespan. A novel clustering method known as the WOA-BC algorithm was developed in response to the aforementioned energy-intensive issue. Because solar energy is used, the suggested approach differs from previous clustering methods. Solar energy improved the sensor network's lifespan and outperformed alternative clustering protocols. There is the enhancement of 104%, 77.5%, and 46.29% of stability period of WOA-BC against the remaining protocols GA, ACO, and PSO correspondingly and the enhancement of 76.7%, 66.25%, and 28.09% of network lifetime of WOA-BC against the remaining protocols GA, ACO, and PSO respectively. In addition, the adoption of an effective harvesting mechanism in future EH-WSNs may extend this field of study.

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