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VIRTUAL REALITY OPERA SPACE: ENERGY-EFFICIENT CLUSTERING PROTOCOL BASED ON CLUSTER CENTERS FOR WIRELESS SENSOR NETWORKS

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Abstract. Energy efficiency presents a notable challenge in wireless sensor networks (WSNs) as the sensor nodes, which are responsible for collecting and transmitting data, operate under limited energy capacity. The sensor nodes must generate as much power as possible to make the network last longer. Generally, every sensor node in a WSN has batteries with limited capacities. It can be challenging to replace this little battery at times due to its vast number and numerous environmental issues. Therefore, it is believed that energy-efficient communication is essential for prolonging the lifespan of a sensor node. This work suggests a brand-new routing protocol clustering method that is energy efficient. Initially, the bamboo growth optimizer novel metaheuristic method was built on differential equations of bamboo growth and the Gaussian mixture model (BFGO). Secondly, a Cluster Centered Cluster Head Selection Algorithm (C3HA) of a routing protocol (BFGO-C3HA) is presented, with the encoding method and fitness function being revised. This algorithm is based on the BFGO technique. It can reduce transmission distance and increase energy efficiency. The results of simulations show that applying BFGO-C3HA can efficiently lessen the sensor network's energy consumption while increasing the amount of information transmitted to extend the network's lifetime.

Key words: wireless sensor networks; energy-efficient clustering mechanism; bamboo forest growth optimizer, Cluster Centered Cluster Head Selection

1. Introduction. Wireless sensor networks are made up of numerous sensor nodes placed throughout an area and collect data from the observed region. It connects the physical and digital worlds, making it a crucial component of the Internet of Things. WSNs are currently used in various applications, including monitoring the ecological environment, military operations, medical care, travel, and urban land use [23, 4, 21]. WSNs are widely used, which has drawn the interest of numerous academics in recent years. In WSNs, the sensor nodes cooperatively perceive, transmit, and gather data. There will be some energy used in this procedure.

Nevertheless, the battery-powered sensor nodes could only carry a certain quantity of power. The distribution of collected information will be somewhat hampered once the batteries run out and the power source cannot be replaced or augmented in time; even the entire sensor network may become paralyzed [8, 3]. Hence, a bottleneck issue in real-world sensor network applications is the need to be as energy efficient as appropriate in a situation of limited power to prolong the lifespan of the complete sensor network.

In real-time applications, batteries with a reduced capability are used to power the wireless sensor nodes. The wireless sensor network is installed in unsupervised outdoor or hazardous environments with a competitive field. The observation area is unregulated and powered by a charge, which makes it difficult to deliver power to or change the batteries in the sensor nodes. The most efficient method for extending a sensor network's lifespan is to reduce sensor nodes' energy consumption [1]. This will ensure that WSNs can operate continuously. To some extent, numerous specialists and academics have carried out studies to optimize the energy consumption of sensor nodes [25, 22, 17, 7, 25].

In addition, the WSN sensor node's sleep and idle listening phases resemble game mechanics. Sensor nodes will employ various tactics, resulting in multiple functionalities of sensor networks with varying advantages and results. The energy consumption of sensor nodes can be reduced by allowing them to sleep [14], although they will still use energy when changing between the active and sleep states [26]. During the state, the sensor nodes' energy use will grow if the energy is used because of the excessive transition. Either way, sensor nodes will use some power when just sitting around and observing. Long listening periods when idle sensor nodes result in significant energy waste. In all other terms, the phases of idle listening and sleep interact with one another and together define the lifespan of the wireless sensor network.

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The main Contribution of the proposed method is given below:

1. The novelty of this work is that the proposed method works in Heterogenous Wireless Sensor Network (WSN) using a Gaussian mixture model (BFGO) based Cluster Centered Cluster Head Selection Algorithm (C3HA).
2. In a WSN, a few heterogeneous nodes can typically be utilized to increase network longevity and stability, and various node types have variable starting energy requirements and energy usage rates.
3. In the two-level heterogeneous WSN under study, energy heterogeneity is considered, and the sensor nodes are separated into advanced and ordinary nodes.
4. The proposed method minimizes energy usage and reduces the node communication transmission distance.

1.1. Motivation. The motivation behind this research is to address the significant challenge of energy efficiency in wireless sensor networks (WSNs). WSNs rely on sensor nodes to gather and transmit data, but the limited energy capacity of these nodes poses a significant obstacle to network longevity. Given that every sensor node in a WSN has batteries with limited capacities, it can be difficult to replace them due to their vast number and various environmental issues.

The researchers aim to demonstrate that applying BFGO-C3HA can efficiently reduce the sensor network's energy consumption while increasing the amount of information transmitted, thereby extending the network's lifetime. Ultimately, the motivation behind this research is to improve the energy efficiency of WSNs, which can help overcome the challenge of limited battery life and enhance the overall performance and longevity of these networks.

The rest of our research article is written as follows: Section 2 discusses the related work on Wireless Sensor Networks, the Internet of Things, and Clustering Methods. Section 3 shows the proposed work's algorithm process and general working methodology. Section 4 evaluates the implementation and results of the proposed method. Section 5 concludes the work and discusses the result evaluation.

2. Related works. WSNs are utilized in many industries because of the Internet of Things' fast growth. Numerous specialists and academics have undertaken multiple studies on energy efficiency because of the growing attention given to the energy issue in WSNs. Maximizing the network's lifespan is becoming a major topic in current conversation because of the constrained energy of sensor nodes. In [6], they employed two levels—corresponding to two steps, i.e., the creation and functioning of the cluster—to optimize the formation of groups and the selection of cluster heads (CHs). A new clustering optimization technique was put forth to accommodate wireless sensor networks with multilayer power variability.

Modern mathematics has a new subfield called game theory. It focuses mainly on the advantages and tactics of competitors, and it researches their optimization tactics. Currently, game theory is increasingly being applied in WSNs, primarily in data collection, voltage regulation, power efficiency, and security mechanisms [6, 2, 5, 12]. The use of game theory in recent years to improve WSN energy efficiency has produced some impressive outcomes. For instance, a power management game framework was established to balance energy usage and data packet signal quality [16]. To balance the consequences of its actions and network lifetime, this paper's first step was to define the trade-off using a multivariable optimization model.

No precise scientific hypothesis supports the algorithm's computational formula, and it's not intimately tied to the fundamentals of everything. We looked for formula derivations concerning the biological development concept of bamboo forests to create a meta-heuristic optimization with great results and a tight relationship to the reality of things. This research suggests a new meta-heuristic optimization technique called the bamboo forest growth optimizer (BFGO) and shows how the efficiency of the method's optimization ability is proved on the CEC test sets and through combinatorial optimization. The technique is built around the differential model of bamboo growth and the Gaussian mixture models [20].

The base station (sink) and the CH should be adequately installed for proper communication in clustered WSNs [9, 11, 15, 18]. Spatial variations enable efficient data flow on the network and a longer network lifespan. The current state-of-the-art problem of determining the correct placements of the sensors in the network has enabled the development of several algorithms in the literature. These studies generally concentrate on optimization methods [24, 19, 10, 13]. Based on this research, CHs were chosen randomly and may be close to one

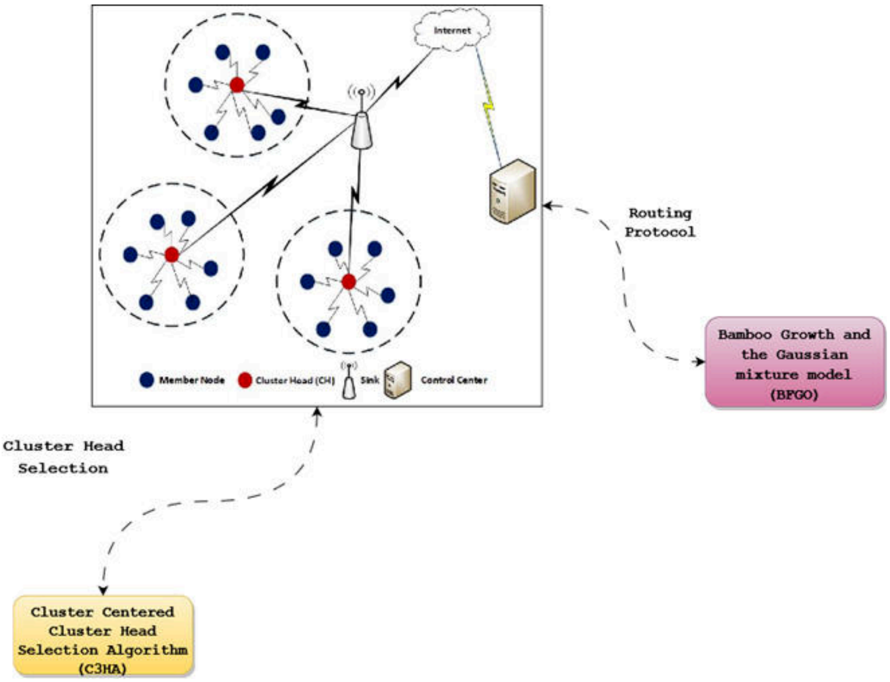

Fig. 3.1: Architecture of Proposed Method

another. This problem results in a rise in power usage. The selected CH in these clustering techniques may be far from the cluster.

The problem that was identified in previous study is the lack of standardized and universally accepted algorithms for optimizing network lifespan and energy efficiency. While many studies have been conducted on these topics, there is still a need for further research to develop more efficient and reliable algorithms. Additionally, some of the optimization techniques proposed in the literature may be highly dependent on specific network conditions, making them difficult to generalize across different WSN applications.

3. Proposed Bamboo-gaussian Cluster Head Selection Methodology. The Energy-Efficient clustering protocol minimizes the energy consumption taken during transmission sensor nodes in WSN. The use of bamboo growth is a novel approach to optimize the network performance, while the Gaussian mixture model is used to cluster the sensor nodes effectively. Additionally, the proposed method also includes a comprehensive system, network, and energy consumption model that can be used to evaluate the performance of the network accurately. Finally, the architecture of the proposed method, as shown in Figure 3.1, is also unique and can provide an efficient framework for implementing the proposed algorithm in real-world applications.

3.1. System Model. There are both advanced and standard nodes in the heterogeneous network, which has two levels [4]. This means that there are n nodes, m advanced nodes make up a certain percentage of all nodes, and each advanced node has an energy (EN) four times greater than a typical node. If EN_0 is assumed to be the starting energy for normal nodes, then EN_0 $(1 + \alpha)$ represents the starting energy for advanced nodes. Hence, the total HWSN's total node energy is:

$$EN_{total} = n * (1 - m) * EN_0 + n * m * (1 + \alpha) * EN_0 = n * EN_0 * (1 + \alpha * m) \tag{3.1}$$

To gather data, N nodes randomly and uniformly install a WSN. In the simulated environment, the following fundamental presumptions are created:

1. Nodes are fixed. The network's base station node is distinctive and strategically placed.
2. Every node has a distinct identification number.

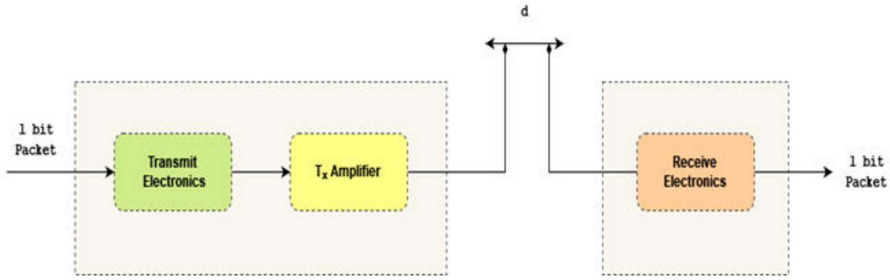

Fig. 3.2: Energy Consumption Model

3. Data fusion is carried out by the CH node, which also sends the merged information to the base station.
4. Sensor nodes' energy supply is constrained. They can no longer use the network after they pass away.
5. Nodes may compute, store information, calculate their remaining energy, and determine their location from other nodes.
6. The only node heterogeneity considered is their energy heterogeneity; additional node heterogeneity features are not considered.
7. The sink node has a reliable power source and does not go out.

3.2. Network Model. A WSN is a network assembled randomly from a specific number of sensor nodes, and each one forms a cluster with a cluster head node and several cluster members (CMs). Each CM evaluates its membership in a group considering its matching location. Also, each CM has a specific sensing range that each node can use to gather data from the monitored object and deliver it to the associated CH, which further transmits the information to the sink node.

3.3. Energy Consumption Model. The network's primary source of energy use is wireless transmission among nodes. The energy usage of nodes in this research is calculated using the energy loss formula in accordance with the first-order radio concept. Figure 3.2 displays the model diagram. The components of the sensor node that are responsible for sending and receiving information are identified and described. Specifically, there are two main components involved: a transmitter and a receiver. The transmitter is situated on the left module of the sensor node, while the receiver is located on the right module.

Furthermore, the amount of data that the sensor node can send or receive is measured in bits and denoted as "l". This means that the sensor node has a fixed capacity for transmitting or receiving data, which is determined by the number of bits it can handle at a time.

Lastly, the distance between the transmitter and receiver is referred to as the "separation" and is measured in units of length (e.g., meters, feet, etc.). This distance is critical because it determines how far the signal can travel before it weakens or becomes distorted, which can affect the accuracy of the data that is being transmitted or received.

The transmitting electronics provide the data to the amplifier, as seen in Figure 3.2, through a signal. They are wirelessly transmitted d metres to the receiving electronics. The node's total energy consumption during data transmission comes from the energy used by the amplifier circuit as well as the electrons that are transferring. The following equation depicts the routing protocol's estimation of transmitting volume based on BFGO-C3HA 3.2.

$$EN_{tx}(l,d) = \begin{cases} EN_{elec} \times l + \epsilon_{fs} \times l \times d^2, d < d_0 \\ EN_{elec} \times l + \epsilon_{mp} \times l \times d^2, \ else \end{cases} \tag{3.2}$$

Here, ϵ_{fs} and ϵ_{mp} are the power amplifier factors for the free spaces and multi-path fading models, respectively, and EN_{elec} stands for the energy used by the receiver and transmitter. Equation 3 illustrates that d_0 is the distance threshold between the transmitter and receiver.

$$d_0 = \sqrt[2]{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \tag{3.3}$$

A multipath fading model is present if d > d_0; otherwise, a free space approach is present. Equation displays the received values for energy consumption, EN_{rx} 3.4.

$$EN_{rx}\left(l\right) = EN_{elec} \times l \tag{3.4}$$

In Equation 5 illustrates the data fusion's energy requirements.

$$EN_{m}\left(l\right) = EN_{DA} \times l \times \left(1+n\right) \tag{3.5}$$

Here EN_{DA} stands for the data fusion's unit energy usage.

3.4. Proposed Bamboo Growth and the Gaussian mixture model (BFGO) based Cluster Centered Cluster Head Selection Algorithm (C3HA). The proposed method works in the Heterogenous Wireless Sensor Network environment for energy efficient data transmission between sensor nodes. It uses Cluster Centered Cluster Head Selection Algorithm (C3HA) for CH selection. Then the bamboo growth and the Gaussian mixture model (BFGO) protocol is used for providing an optimal routing between sensor nodes.

3.4.1. Bamboo Growth and the Gaussian mixture model (BFGO). An herbaceous plant called bamboo can grow quickly to the length of a tree. Its shoot stage is when it experiences this quick growth. According to the "bamboo rule," bamboo only grows 3 cm in the first four years and then 30 cm each day from the fifth year on, growing to 15 m in under six weeks. The bamboo shoot is a brief phase of rapid development that takes place while the bamboo expands its roots several hundred metres into the soil. As a result, there are two phases to the establishment of a bamboo forest: (a) the underground extension of the bamboo whips, and (b) the development of the bamboo shoot.

While the meta-heuristic optimization method looks for possibilities, the two stages of bamboo forest growth may relate to global exploration, local exploitation, etc. As a result, by combining the mathematical problem of bamboo forest growth, a bamboo forest growth optimizer (BFGO) method can be created.

Three variables affect the trajectory of the underground bamboo whip expansion: the directives for the group cognitive items, the bamboo whip memory, and the bamboo forest center. This indicates that the worldwide optimal solution, the intra-group optimum, and the position of the central solution all influence the course of solution exploration. Equations 3.6–3.8 provide the formula for the development path.

$$cos_{\alpha} = \frac{\overrightarrow{X}_t . \overrightarrow{X}_G}{|\overrightarrow{X}_t| \times |\overrightarrow{X}_G|} \tag{3.6}$$

$$cos_{\beta} = \frac{\overrightarrow{X}_t . \overrightarrow{X}_{P(k)}}{|\overrightarrow{X}_t| \times |\overrightarrow{X}_{P(k)}|} \tag{3.7}$$

$$cos_{\gamma} = \frac{\overrightarrow{X}_t . \overrightarrow{C}_{(k)}}{|\overrightarrow{X}_t| \times |\overrightarrow{C}_{(k)}|} \tag{3.8}$$

Here $\overrightarrow{X}_t$ is the location of the current method, and $\overrightarrow{X}_G$ is the location of the person who is performing at the highest level globally. On the k-th bamboo whip, $\overrightarrow{X}_{P(k)}$ and $\overrightarrow{C}_{(k)}$ represent the central solution and intra-group optimal solution, respectively. The current person's expansion directions on $\overrightarrow{X}_G$, $\overrightarrow{X}_{P(k)}$, and $\overrightarrow{C}_{(k)}$ are represented by α, β and γ.

In the initialization step, the Gaussian mixture model leads people to a globally optimal outcome. The probability of the method entering local optimization grows with the number of iterations. Make it more probable that individuals will gravitate towards a centralised approach for preventing the algorithm from getting stuck in local optima. In doing so, the method's ability to locate the best solution is improved, and the distribution of options during the iteration phase is more diversified.

3.4.2. Cluster Centered–Cluster Head Selection Algorithm (C3HA). As a fresh clustering approach for WSNs, the C3HA was suggested. C3HA was created for sensor clusters. The K-means technique was used to identify the network's clusters. A new CH selection (CHS) method called the suggested C3HA was created to increase network longevity and optimise energy usage. This method requires two-fold clustering, in contrast to the methods described in the literature. Thus, a specific subset of the nodes that make up a cluster is initially identified for every cluster after the network has been grouped using k-means.

The nodes in this unique subset, known as CC (Cluster Centered), are given precedence during CH selection. OCC (Out of Cluster Centered) refers to the set of nodes outside of CC, also known as the complement of CC. Nodes inside this set are able to join CH once all the nodes inside CC have died. Next, we'll go into the specifics of how CC and OCC are determined. By giving the centre nodes more weight using the new method C3HA has proposed, CH selection will be more effective. Let's break down the suggested approach in terms of math Eq 9-12.

$$Cl_k = \frac{1}{n_i}\sum_{j=1}^{n_j} x_i \tag{3.9}$$

$$d_l^k = \sqrt{(x_r^k - x_c^k)^2 + (y_r^k - y_c^k)^2} \tag{3.10}$$

$$r_k = \frac{1}{n_i}\sum_{i=1}^{n_j} d_i \tag{3.11}$$

$$OCC_k = CC_k^{'} = (x_i, y_i) \in U_k|(x_i, y_i)| \notin CC_k \tag{3.12}$$

The CC border is a circle with radius r k that corresponds to the mean Euclidean distance from all sensors to the centre of the kth cluster, as provided in Eq 3.12. The final piece of set CC_k is called OCC_k. Included in it are the sensors from the KTH cluster that are not listed in CC_k according to Eq 3.12. The routing protocol uses the following as its implementation of BFGO-C3HA pseudo-code for Algorithm 1.

Algorithm 1 BFGO-C3HA

Input: CHs, dead normal nodes N_a, survival state N_s, maximum rounds R_m, current running rounds R_c

Output: Optimal path

Step 1: Initialize the deployment of the nodes in the WSN, the energy of the nodes in the HWSN, and the node information.

Step 2: while ($R_c \leq R_m$) do

Step 3: if N_s==false then

Step 4: end

Step 5: end if

Step 6: for j = 1; j $\leq$ N ; j + + do

Step 7: if energy $\leq$ 0 then

Step 8: N_a++;

Step 9: N_n++;

Step 10: end if

Step 11: end for

Step 12: Cluster Head Selection CH

Step 13: Initialize the nodes

Step 14: Random distributions of node to area

Step 15: Select Cluster Head using eq 9-12

Step 16: End

Step 17: Estimate the number of cluster heads (N_{ch})

Step 18: for i = 1; j ≤ N ; j + + do
Step 19: if Node(i)==cluster head; then
Step 20: Transmitting Data
Step 21: Evaluate consumed energy, remaining energy, and transfer volume using.
Equations 2-5
Step 22: else Send data to cluster head
Step 23: end if
Step 24: end for
Step 25: end while

The algorithm is for optimizing energy consumption in a wireless sensor network while maintaining network connectivity. It involves initializing the network nodes, selecting cluster heads, and transmitting data to the base station or nearest cluster head. The algorithm iterates over the network nodes, checking their energy levels, and counting the number of dead nodes. The number of cluster heads is estimated, and data is transmitted to the base station or nearest cluster head. The output of the algorithm is the optimal path that minimizes energy consumption while maintaining network connectivity.

The algorithm starts by initializing the network nodes, their deployment, energy levels, and other relevant information. It then sets up a loop that will continue iterating until the current running rounds are less than or equal to the maximum rounds. Inside the loop, the algorithm checks the survival state of the network to see if it is still able to operate. If the network is not able to operate, the loop terminates. Otherwise, the algorithm iterates over all the nodes in the network, checking their energy levels and counting the number of dead nodes.

The next step is to select the cluster heads, which are responsible for collecting data from the sensor nodes and transmitting it to the base station. The algorithm randomly distributes the nodes across the network area and selects cluster heads based on a formula that takes into account the distance between nodes and their remaining energy levels.

Once the cluster heads are selected, the algorithm initializes the nodes and estimates the number of cluster heads in the network. The algorithm then iterates over all the nodes in the network and checks if a node is a cluster head. If a node is a cluster head, it transmits the data collected from its associated sensor nodes to the base station. The algorithm evaluates the consumed energy, remaining energy, and transfer volume using equations 2-5.

If a node is not a cluster head, it sends its data to the nearest cluster head. The algorithm continues iterating over all the nodes in the network, evaluating their energy levels and transferring data to the base station or nearest cluster head. Finally, when the current running rounds are greater than the maximum rounds, the algorithm outputs the optimal path that minimizes energy consumption while maintaining network connectivity.

3.5. Result Analysis. In this work, MATLAB was employed to evaluate the proposed method (BFGO-C3HA) and compare it with the low-energy adaptive clustering hierarchy (LEACH) [23], the distributed energy efficient clustering (DEEC) [23], and the enhanced LEACH-centralized (LEACH-C) [23]. The benefits of heterogenous WSN sensor nodes are then assessed regarding node survival state, node longevity, and data transfer. In this study, 100 sensor nodes were placed at random inside a 100-square-foot space, and the sink node was set to (50*50). Energy was no longer provided after the sensor nodes were set up. The precise parameter parameters used during the simulation are shown in Table 3.1.

The proposed method evaluates the lifetime of the network, remaining energy, volume of data transmission and throughput. The proposed method BFGO-C3HA is compared with the existing methods such as LEACH, DEEC and LEACH-C.

The lifespan of the network is measured by the number of rounds until the final node dies. Figure 3.3 displays the modifications in the remaining nodes of the LEACH, DEEC, LEACH-C, and BFGO-C3HA protocols together with the total number of rounds. Figure 3.3 shows the survival trend for the four clustering procedures (LEACH, DEEC, and LEACH-C) as well as the protocol based on BFGO-C3HA. The power used by nodes for transmission of data and processing increases as the network operates. Many nodes run out of power and die after several operation rounds. The graph shows that the network survives slightly longer and the nodes of the BFGO-C3HA method die slightly slower than the previous three protocols.

Table 3.1: Simulation Parameter

Parameters Used	**Values**
Network Area	100*100 m^2
Total Number of Nodes Used N	100
Position of BS	(50,50)
Packet Size (J)	4000 bits
Initial Energy of Node	0.5 J
Total Number of Iterations	20
Fitness function Weight	4
Transmitter Amplifier	0.0013 nJ/bit/m^4
Energy Cost	5 nJ/bit

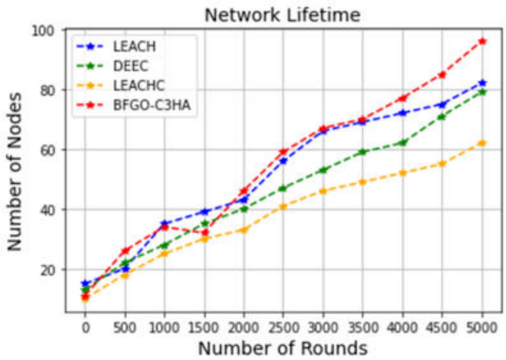

Fig. 3.3: Network Lifetime

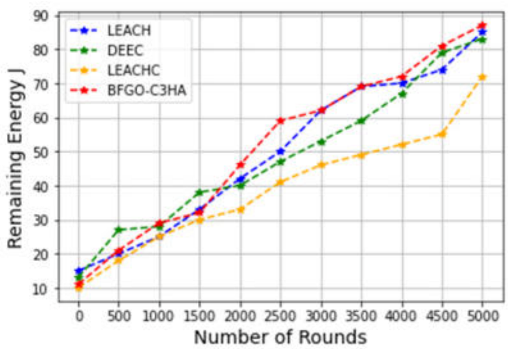

Fig. 3.4: Remaining Energy

The amount of energy used while a network is in use reflects how well it is working. Less energy usage and improved network performance are shown by more energy that remains. Figure 3.4 displays the fluctuation of remaining energy with the total number of rounds for the LEACH, DEEC, LEACH-C, and BFGO-C3HA protocol operating in the networks, while Figure 3.4's pattern in energy consumption reveals that the BFGO-C3HA treatment has more energy left over than the LEACH, DEEC, and LEACH-C protocols.

Each round, the network's surviving node transmits an incoming packet to the CH nodes, who subsequently send it to the base station, which records the amount of data packets received. The entire number of packets sent makes up the data transmission rate, which measures the network's throughput. Figure 3.5 displays the

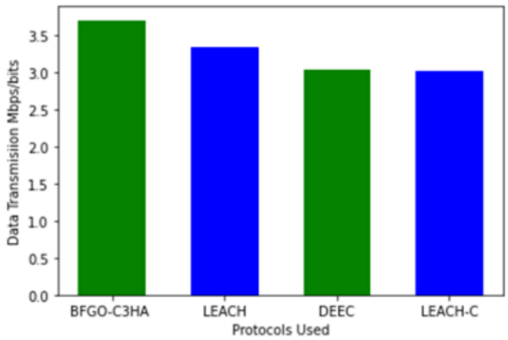

Fig. 3.5: Data Transmission between CH nodes

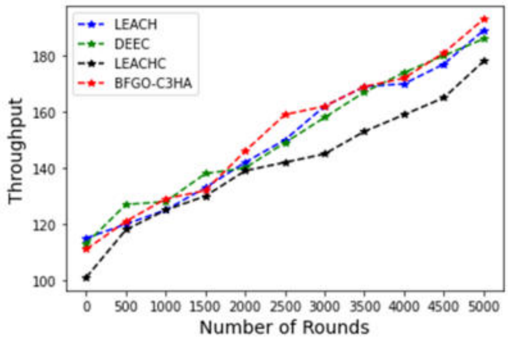

Fig. 3.6: Throughput

data transmission volume for the four protocols.

In Figure 3.6 depicts the variation in throughput that occurs when varying numbers of sensor nodes are implemented across a single network cross-section 3.10. The BFGO-C3HA algorithm used in this work greatly exceeded the other four algorithms as the number of deployed sensor nodes, or throughput, increased.

3.6. Summary. This work finds the optimal path for wireless sensor networks (WSN) by deploying nodes and selecting cluster heads (CHs) based on energy and survival state. The algorithm takes inputs of CHs, dead normal nodes Na, survival state Ns, maximum rounds Rm, and current running rounds Rc, and outputs the optimal path. The algorithm initializes the deployment of nodes, energy of nodes, and node information. It selects CHs using equations 9-12 and estimates the number of CHs (Nch). The algorithm then transmits data and evaluates consumed energy, remaining energy, and transfer volume using equations 2-5. The process is repeated until Rc reaches Rm. At each round data transmission rate, energy consumption, throughputs are measured and output are drawn. From all the outcome it is proved that proposed obtains better performance.

4. Conclusion. In this study, we present a BFGO-C3HA-based clustering technique for the routing protocol for heterogeneous WSNs. Using the BFGO-C3HA method's optimising capabilities, it aims to pick the best cluster heads, identify the best CH nodes, ensure the fairness of cluster allocation, and maximise network performance. An intelligent bionic optimization technique is initially developed for the optimization problem based on the development characteristics of a bamboo forest. This paper proposes a brand-new energy-efficient clustering technique for the routing protocol. At first, a brand-new metaheuristic technique called the bamboo growth optimizer was developed using the Gaussian mixture model and difference equations for bamboo development (BFGO). Second, a routing protocol (BFGO-C3HA) with a cluster-centered cluster head selection algorithm (C3HA) is described, with updates to the fitness function and encoding scheme. The BFGO method is the foundation of this algorithm. Both the transmission distance and energy efficiency can be decreased. The simulation results show that the BFGO-C3HA application can effectively reduce the energy consumption of the sensor network while increasing the amount of information transmitted, thereby extending the network lifetime. The proposed method efficiently overcomes the existing method and works in Heterogenous environment and enhances the data transmission between the nodes.

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