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Hybrid Leader Artificial Ecosystem Based Optimization Mechanism for CH Selection and Routing

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Abstract

Wireless Sensor Networks (WSNs) are gaining importance due to the applicability in various domains of modern research. Nevertheless, energy-constrained nodes pose the biggest challenge in WSNs. The optimization of energy usage and stability within WSNs has consistently been a focal point in research endeavors. This paper presents a hybrid mechanism, Hybrid Leader Artificial Ecosystem based Optimization (HLAEO) algorithm as an effective strategy to address the dual challenges of cluster head selection and routing in WSNs. It combines two powerful mechanisms namely Hybrid Leader-Based Optimization (HLBO) and Artificial Eco-based Optimisation (AEO). HLAEO uses leader-based optimization for cluster selection. Here channel probabilities are adjusted based on network performance metrics and thus making nodes to efficiently navigate available channels. This would certainly enhance the spectral efficiency and reducing interference. For routing, the algorithm uses an efficient optimization approach to discover and maintain optimal paths between the sensor nodes. The proposed HLAEO algorithm continuously refines routing paths, adapting to the changes in the network conditions and topology dynamics. Performance of the proposed HLAEO is validated through simulations. Results show that the proposed HLAEO perform well with respect to energy utilization. HLAEO provides several benefits including real-time adaptation to environmental changes and enhanced energy efficiency by minimizing redundant transmissions and extending the lifespan of a network.

Keywords: Clustering, Leader-based Optimization, Artificial Eco-based System Optimization, Wireless Sensor Network.

1 Introduction

WSNs are becoming popular due to its applicability to various applications. It is a network of several sensors that communicate with one another in a large area. The nodes are connected using a mesh topology or a star topology with each node interconnected to other nodes (Keliwar et al., 2023). The nodes collect information from the sensor and send them to other nodes in an aggregated form. WSN includes a user, sensor nodes, and an interconnected backbone (Ahmad Ali et al., 2017). A sensor node

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collects sensed information, performs some processing, and interact with other nodes in WSNs (Yang et al., 2020; Albakri et al., 2019; Suguna et al., 2024; Kiruba et al., 2023). However, the limited computing and energy capacity of the gadget pose the challenge on its usage (Mohammed et al., 2020). Energy efficient data transmission is therefore a critical component of WSN performance. From several studies, it can be concluded that the routing protocol plays an important role in energy conservation at nodes. (Li et al., 2019). Clustered routing protocols (Fawzy et al., 2017; Zareei et al., 2019; Vincentelli & Schaumont, 2025; Abolqasem et al., 2015) are proved to be advantageous in terms of energy conservation, resource sharing, and scalability.

Since data transmission and reception are the primary causes of energy drain (Yan et al., 2016), the typical routing method focuses primarily on finding the shortest way to expedite data movement from the source node to the sink. Another potential source of network congestion is the "many-to-one" data transfer method. For instance, in case of a major event, congestion may arise because the nodes must send lot of information to the destination. The reliability of data transmission can be decreased by congestion due to discarding a substantial quantity of data packets. According to some studies on congestion, when congestion is detected, specific steps are usually taken to control the data rate of the influx. (Sergiou & Vassiliou, 2010). However, to avoid congestion, the upstream node may find it difficult to control the downstream node's data rate.

Using layered topologies helps lowering network energy usage, especially in large WSNs (Daanoune et al., 2021; Shahraki et al., 2020). Clustering is a popular kind of layered architecture. Discrete clusters of nodes are formed, and the Cluster Head (CH) node in each cluster is responsible for gathering data from the other cluster members. Since data gathered by nodes in the same cluster is comparable, CHs aggregate the data before transmitting it to the Base Station (BS). Clustering techniques reduce network load and increase network lifetime by aggregating data (Ennajari et al., 2017; Singh, 2015; Prakash & Prakash, 2023), nevertheless, selecting the right CH is very important (Sivakumar et al., 2024). Many different literary works provide the CH selection scheme. In order to increase the network's resilience and energy efficiency, some papers select the CH based on artificial neural network back propagation technology (Mehmood et al., 2017). However, these processes are complex, and choosing a CH candidate takes time.

Following are the major contributions of this study:

- Designing an energy model for WSN.
- Provide a unique hybrid algorithm for selecting CHs in HLAEO that uses less energy throughout the network lifespan.
- Checking the scalability and network longevity of the method implementation by testing it under various situations with varying sets of sensor nodes.
- Compare the suggested algorithm's energy consumption and number of alive nodes in the network to those of the prior algorithms.

The rest of the paper is organized as follows. Section II presents an overview of the literature in this area. Section III details the proposed HLAEO algorithm and finally, results are presented and analyzed Section IV and Section V gives the conclusion.

2 Literature Survey

Numerous researchers have proposed a range of clustering approaches that can greatly extend network lifetime and lower network energy usage (Fanian et al., 2019; Wang et al., 2012). Clustering routing systems offer several benefits, including increased robustness, reduced load, lower energy usage, and scalability (Xuxun Liu et al., 2012). One of the popular and earlier algorithms for clustering was the Low-Energy Adaptive Clustering Hierarchy (LEACH) (Heinzelman et al., 2002). In LEACH, each node was assigned a random number between 0 and 1 for each round, and based on the random number and the predefined threshold, CH is selected. The selected CH then advises its identity, after which other nodes respond create clusters. Nevertheless, it did not take energy into account while choosing CHs, which led to the selection of some nodes with lower energy as CHs which may lead to early deaths of nodes. Different methods were utilized to determine the probability becoming CHs in Distributed Energy-Efficient Clustering (DEEC), and two distinct classes of nodes are set based on residual energy (Qing et al., 2006).

Clustering routing offers the benefit of high robustness, minimal energy utilization, minimal load, data aggregation/fusion, high scalability, and so on (Xuxun Liu, 2012; Amit Kelotra & Pandey, 2019; Amit Sarkar & Murugan, 2019). WSN routing technique is accountable for maintaining the data communication route in the network layer. The packets are transmitted to the sink node from the source node through multiple hops along the route. The network survival time and the amount of energy utilized during data transmission from the sensor node are determined based on the routing technique (De-ga Zhang et al., 2015). The majority of routing techniques in WSNs do not take energy utilization into account resulting in the temporary unavailability of either portion or the entire network. Most of these approaches determine the routes considering minimal delay or hop count (Yi et al., 2005).

In (Weiguo Zhao et al., 2020), a novel meta-heuristic algorithm called AEO was put out. It is inspired by the energy flow in an ecosystem on Earth. The production, consumption, and decomposition processes of biological creatures are mimicked by AEO. HLBO's primary concept is to use a hybrid leader to direct the algorithm population. Two phases of exploration and exploitation are used to mathematically model the processes of HLBO (Mohammad Dehghani & Pavel Trojovský, 2022). Glow-Worm Swarm Optimisation is used in conjunction with the Firefly Algorithm to choose CHs efficiently and identify the best routes (Bharathiraja et al., 2023). An enhanced Grey Wolf Optimization algorithm has been proposed for CH selection, focusing on energy efficiency. Algorithm incorporating an improved fitness function to select CHs that minimize energy consumption was proposed in (Yuxiang Hou et al., 2022). The Artificial Bee Colony method has been used to create an energy-efficient routing protocol that extends the lifetime of WSNs. The multi-threshold segmentation technique is used to improve cluster formation and CH selection. This would optimize routing paths by considering energy usage and thus increasing the total energy of the network (Xiuqin Pan et al., 2024; Yin-Di Yao et al., 2022).

3 Proposed HlAEO Algorithm

Network Model

The following characteristics of WSN are considered:

- Every node is fixed and distributed randomly in the network region.
- Data transmission between clusters can occur in a single hop, and data transmission within clusters can occur in multiple hops.

A node is aware of its remaining energy, but it is unsure of its location.

- Each node is unique and has the potential to be a CH.
- In the WSN, there is only one BS and it is fixed and other nodes are dynamic.

Adaptation of the transmission power to the receiver's distance can be achieved. A receiver can determine how far away from the sender they are by comparing the strength of the signals they transmit and receive. The purpose of data aggregation is to reduce energy usage.

Proposed Model

Energy conservation at nodes can be achieved though careful CH selection and efficient routing. The cluster nodes should be relatively closer to the CH, when choosing a location. The CH, which serves as a link between the node members and the BS, ought to have a high residual energy. The routing path needs to be created after the CH has been chosen using the HLAEO algorithm. Here, routing is done by building the routing tree and applying the HLAEO algorithm.

Energy Model

Consider all nodes in the network with an initial energy E_0 in the initial stage and it is assumed that the nodes cannot be re-energized (Kumar & Kumar, 2016). Whenever data is transmitted from the p^{th} node to the q^{th} CH, energy dissipation occurs depending on the node type (CH or normal) and distance. When the p^{th} node transmits data having S bytes, then the energy dissipated is formulated as given in (1) and (2),

$$E_{dis}\left(C_N^p\right)=\begin{cases} E_{ele}*s+\varepsilon_{mp}*s*\left\|C_N^p-C_{ch}^q\right\|^4; & \left\|C_N^p-C_{ch}^q\right\|\geq d_0 \\ E_{ele}*s+\varepsilon_{fs}*s*\left\|C_N^p-C_{ch}^q\right\|^2; & \left\|C_N^p-C_{ch}^q\right\|< d_0 \end{cases} \tag{1}$$

$$d_0=\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{2}$$

Where ε_{mp} shows the energy connected to the transmitter's power amplifier, ε_{fs} indicates the free space energy, and $\|C_N^p - C_{ch}^q\|$ characterizes the distance among the q^{th} CH and p^{th}node, E_{ele} specifies the electronic energy and formulated as presented in (3),

$$E_{ele}=E_{tx}+E_{aggr} \tag{3}$$

Here, E_{tx} represents the transmission energy, and E_{aggr} specifies the data aggregation energy.

The energy used while CH is receiving B byte of information is formulated as given by (4),

$$E_{dis}\left(C_{ch}^q\right)=E_{ele}\times B \tag{4}$$

The energy of all nodes is computed every time when a transmission or reception of data is performed and this is accomplished based on equations (5) and (6) as given below.

$$E_{z+1}\left(C_N^p\right)=E_Z\left(C_N^p\right)-E_{dis}\left(C_N^p\right) \tag{5}$$

$$E_{z+1}\left(C_{ch}^q\right)=E_Z\left(C_{ch}^q\right)-E_{dis}\left(C_{ch}^q\right) \tag{6}$$

Data is transferred until all nodes' energy is exhausted and they are no longer functional.

Link Life Time (LLT) Model

The LLT (Mamtha Balachandra et al., 2014) in a WSN is computed at all hops throughout the path navigation of the route request packet. All nodes compute the LLT of the link ahead of it and the prior hop. When a node is the previous hop for a node, then the movement details and location are appended to the route request packet. Equation (7) is used to determine LLT,

$$LLT = \frac{-(cd+ef)+\sqrt{(c^2+e^2)\gamma^2-(cf-de)^2}}{(c^2+e^2)} \tag{7}$$

Here, $c = M_{G_1} \cos \emptyset_{G_1} - M_{G_2} \cos \emptyset_{G_2}$, $d = X_{G_1} - X_{G_2}$, $e = M_{G_1} \sin \emptyset_{G_1} - M_{G_2} \sin \emptyset_{G_2}$, $f = Y_{G_1} - Y_{G_2}$ and γ represents the range of transmission, M_{G_1}, $\left(X_{G_1}, Y_{G_1}\right)$ and $\emptyset_{G_1}$ specifies the mobility speed, coordinates and orientation of the motion of the node G_1 and M_{G_2}, $\left(X_{G_2}, Y_{G_2}\right)$ and $\emptyset_{G_2}$ specifies the mobility speed, coordinates and orientation of the motion of the node G_2.

4 CH Selection

Since sensor nodes in WSNs have limited energy, choosing a right CH is crucial since transmitting data directly from far nodes to the BS causes a significant energy loss and thus reducing the network's lifespan. This can be effectively prevented by clustering the nodes and designating one node as the CH. CH is typically a cluster node with the highest fitness. Selecting CH optimally ensures minimal energy use, and the HLAEO algorithm is used in this work to select CHs. Here, the HLAEO algorithm is produced by combining the HLBO and AEO algorithms. The following is an explanation of the CH selection process proposed in this work:

Solution Encoding

Solution encoding describes the representation used for the optimization algorithm's solutions. Any optimization method will modify the candidate solutions through many steps, and the encoding process enables a comparison of solutions to determine which one is the best. Since the HLAEO algorithm determines the CH in this instance, the replies indicate the CH. Figure. 1 illustrates the solution encoding that the HLAEO algorithm utilizes to carry out CH selection.

Figure 1: Solution Encoding for CH Selection

Fitness Function

A variety of factors, including delay, distance, energy, and LLT, are taken into account while choosing the CH. In general, the CH node is chosen based on its maximum LLT, minimum distance to other nodes, minimum delay, and highest residual energy. The fitness function is developed with the following factors as given in (8):

$$Fit = \frac{1}{4}\sum_{p-1}^{a}\left(E + \left(1 - dt_{pq}\right)\left(1 - \delta_{pq}\right) + LLT_p\right) \tag{8}$$

Here, E refers to the residual energy of the p^{th} node, δ_p is the delay parameter, dt_p presents distance, and LLT_p is the LLT associated with the p^{th} node. dt_{pq} refers to the distance between the p^{th} and the q^{th} CH and is formulated as in (9),

$$dt_{pq} = \left\| C_N^p - C_{ch}^q \right\| \quad (9)$$

Further, the delay δ_{pq} refers to the time incurred for a data packet to reach the q^{th} CH from p^{th} node, and is given as in (10)

$$\delta_{pq} = \frac{1}{a}\sum_{q-1}^{a}(m_q) \quad (10)$$

Where a indicates the total number of nodes in the network and m_q refers to the number of nodes in the cluster.

HLAEO Algorithm for CH Selection

The HLAEO algorithm, which combines the HLBO and AEO algorithms, is used in this instance to choose the CH. The AEO algorithm mimics the three different behaviors of living things and is designed on the energy flow of the natural ecosystem. Any ecosystem depends on biotic (living) and abiotic (non-living) components to maintain its energy and nutritional balance. The three categories of biotic components—producers, consumers, and decomposers—are taken into consideration when the AEO algorithm explores and uses the search area. Organisms that produce their food and energy without the aid of other energy sources are known as producers. Conversely, the consumers are classified as herbivores, carnivores, or omnivores and obtain their energy from outside sources. Decomposers break down dead and decaying organisms into an absorbable form that may be utilized by producers, ensuring the energy flow being maintained.

The AEO method has a strong convergence rate and is effective in handling real-time issues, however, its computing capacity varies depending on the complexity of the task. Conversely, the HLBO (Mohammad Dehghani & Pavel Trojovský, 2022) method is a stochastic optimization process in which each member of the population is updated and guided by a single hybrid leader. In this case, the hybrid leader is created taking into account three different people: the best, an arbitrary, and corresponding members. High global convergence can be achieved with the help of the HLBO algorithm. Thus, the suggested HLAEO algorithm delivers the optimal solution with a high convergence rate by integrating the HLBO algorithm into the AEO algorithm. The algorithmic process of implementing the HLAEO algorithm is described in detail in the following phases.

a. Initialization: The primary step in the realization of the HLAEO algorithm is an initialization of individuals in the ecosystem, H as shown in (11).

$$H = \{H_1, H_2, \dots\dots, H_l, \dots\dots H_r\} \quad (11)$$

Wherein, r indicates the total count of individuals in the ecosystem and H_l presents an individual.

b. Fitness calculation: Following the population's initialization, each person is assessed for fitness, where the optimal solution is indicated by maximal fitness. The population's members are ranked according to their level of fitness; the most fit member is considered the producer, or worst individual, while the least fit member is considered as decomposer, or best member. The rest members are considered consumers.

c. Production: The producer, which is in charge of producing energy in the natural ecosystem, needs to be informed about the decomposer and the upper and lower bounds of the search space in this algorithm, since it directs the other population members to search in different regions. The producer operator permits the algorithm to arbitrarily generate a member to replace the random member H_{rand} in (14) and the optimal member H_r in the search space. Equations (12) and (13) give the mathematical model of the producer operator,

$$H_l(s+1) = (1-\lambda)\, H_r(s) + \lambda H_{rand}(s) \tag{12}$$

Wherein,

$$\lambda = \left(1 - {}^{s}/_{S}\right) u_l \tag{13}$$

$$H_{rand} = u(up - low) + low \tag{14}$$

Here, r denotes the size of the population, in (13) λ represents the weight coefficient used to drift a member linearly from the randomly generated position towards the optimal solution, s and S label the number of iterations thus far and the total number, up and low represent the upper and lower bounds of the search area, u and u_l show random numbers ranging in $[0, 1]$.

d. Consumption: The customers carry out the consumption operation when the production operation is finished. The consumers obtain energy by consuming the producer, another low-energy consumer, or both. Typically, the Levy Flight operator is used to mimic the food searching behaviors of animals, resulting in a high degree of exploratory abilities. However, due to its complexity and the need for several adjustments, the Levy flight operator uses a consumption factor to solve this problem. The consumption factor is provided as given in (15) and (16).

$$D = \frac{1x_1}{2|x_2|} \tag{15}$$

$$x_1 \sim N(0,1)\,, x_2 \sim N(0,1) \tag{16}$$

Wherein N (0,1) indicates a normal distribution with mean=0 and variance=1.

Herbivores: These are the consumers produced randomly, they feed on the producers alone and this conduct is formulated using (17),

$$H_l\,(s+1) = H_l(s) D.\left(H_l(s) - H_1(s)\right), \quad l \epsilon [2, \dots, r] \tag{17}$$

ii) Carnivore: The consumers who consume another consumer with higher energy will be selected as carnivore and this behavior is represented as (18),

$$H_l\,(s+1) = H_l(s) + D.\left(H_l(s) - H_y(s)\right), \quad l \epsilon [2, \dots, r] \tag{18}$$

Here $y = randi([2i - 1])$

Equation (18) can be rephrased as,

$$H_l(s+1) = H_l(s)(1 + D) - D.H_y(s) \tag{19}$$

By incorporating the HLBO algorithm into the AEO algorithm, the individuals' standing within the population can be improved as shown in (19). The member position can be adjusted using the HLBO algorithm as shown in (20).

$$\begin{cases} H_l(s) + v(K_l + P.H_l(s)), Fit(K_l) < Fit(H_l) \\ H_l(s) + v(H_l(s) - K_l), \qquad\qquad else \end{cases} \tag{20}$$

Here, $Fit(K_l)$ represents the fitness function of the hybrid leader K_l, $Fit(H_l)$ presents the objective function of the l^{th} solution, v is an arbitrary number in the range [0,1] and P specifies an integer chosen arbitrarily from the set $\{1,2\}$. Here, the hybrid leader is produced from the population based on (21).

$$K_l = W_l.H_l + W_{best}H_{best} + W_tH_t \tag{21}$$

Here W_l, W_{best} and W_t represent the participation coefficients of the l^{th} individual, optimal individual H_{best}, and randomly selected individual H_t respectively. The coefficients of participation are given by (22).

$$W_l = \frac{O_l}{O_l + O_{best} + O_t}, W_{best} = \frac{O_{best}}{O_l + O_{best} + O_t}, W_t = \frac{O_t}{O_l + O_{best} + O_t} \tag{22}$$

Here, $l \neq t, O_l$ represents the quality of the l^{th} individual, and it is calculated using (23),

$$O_l = \frac{Fit_l - Fit_{worst}}{\sum_{i=1}^{r} Fit_l - Fit_{worst}}, l \in \{1,2, \dots\dots, r\} \tag{23}$$

Here Fit_{worst} represents the fitness of the worst individual.

Equation (20) can be refined by considering the condition $Fit(K_l) < Fit(H_l)$ as shown in (24) and (25),

$$H_l(s+1) = H_l(s) + v\big(K_l + PH_l(s)\big) \tag{24}$$

$$H_l(s) = (H_l(s+1) - vK_l)/((1 + vP)) \tag{25}$$

Applying (25) in (19),

$$H_l(s+1) = \frac{H_l(s+1) - vK_l}{(1+vP)}(1+D) - DH_y(s) \tag{26}$$

$$H_l(s+1) = \frac{(v.K_l)(1+D) + D.H_y(s)(1+v.P)}{(D - v.P)} \tag{27}$$

Equation (26) is the intermediate equation and (27) is used to update the location of the l^{th} individual in the iteration $(s+1)$.

iii) Omnivore: If an omnivore is a consumer selected at random, it can consume the producer or other highly energetic consumers. This behavior is expressed as in (28):

$$H_l(s+1) = H_l(s)D.\Big(u_2.\big(H_l(s) - H_1(s)\big)\Big) + (1-u_2).\Big(H_l(s) - H_y(s)\Big),$$
$$l \in [3, \dots .r] \tag{28}$$

Here, u_2 indicates a random number with a value in [0, 1] and $y = randi([2l-1])$.

e. Decomposition: It is a significant task that enables the smooth working of the ecosystem and is crucial in producing nutrients for the producers. The process of decomposition can be modeled mathematically based on a decomposition parameter and weight variables. The location of the individuals is adapted based on the above factors and is expressed as in (29),

$$H_l(s+1) = H_l(s) + L\big(nH_m(s) - O.H_l(s)\big), \qquad l = 1, \dots .r \tag{29}$$

Where in $L = 3k, k \sim N(0,1)$

$$n = u_3.rand([1\ 2]) - 1$$
$$O = 2.u_3 - 1$$

u_3 represents a random number ranging in [0, 1].

f. Feasibility assessment: Once the positions of individuals are modified, the individual with maximal fitness is regarded as the optimal solution, and the location of the member is modified using (29).

g. Termination: The algorithmic stages are carried out again till the maximum number of iterations is reached. The HLAEO algorithm's pseudocode is presented in Algorithm 1.

An optimal individual H_{best} gives the selected CH and by incorporating the HLBO algorithm with the AEO algorithm, the HLAEO algorithm attains the best solution with high global convergence and minimal complexity.

Algorithm 1: Pseudocode of the HLAEO algorithm

Set an ecosystem H with r members
Input: population dimension r, maximal iteration S
Begin
Calculate the fitness using (8)
Find the optimal solution H_{best}
While $(\boldsymbol{s \leq S})$ **do**
//Production//
Determine the solution using (12) for the producer H_1
//Consumption//
For members H_l $(l = 2,\ldots,r)$
//Herbivore//
If $\boldsymbol{rand < 1/3}$
Modify the solution based on (17)
// Carnivore //
Elseif $1/3 \leq rand \leq 1/3$
Modify the solution based on (27)
// Omnivore //
Else
Modify the solution based on (28)
Endif
Endif
Determine fitness using (8)
Modify H_{best}
//Decomposer//
Use (29)
Determine fitness with (8)
Modify H_{best}
End while
Return H_{best}

5 Routing Using the HLAEO Algorithm

Effective routing techniques can also be used to manage energy consumption, reducing the amount of energy that nodes use while transmitting data. In a WSN network, routing controls the best use of energy. The information is aggregated by the sensor nodes, and then it is sent to the BS via the CH that has been chosen. The route that data must take is decided upon after the CH is chosen. Here, the HLAEO algorithm is used to determine the optimal path to be used for data transmission.

Solution Encoding

The HLAEO algorithm is used to illustrate the routing problem, and each solution indicates the nodes that route the data to the CH. Figure. 2 describes the solution encoding used in the HLAEO algorithm, which determines the best route based on the nodes' fitness.

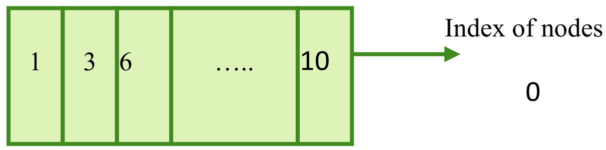

Figure. 2 Solution encoding for routing using the HLAEO algorithm

Each answer in this case corresponds to a node, and the solution is shown as a vector form where each element represents the index of a node. In this case, the dimension of the encoded solution is assumed to be $1 \times a$, where a is the total number of nodes.

Fitness Function

Taking into account the fitness function that is calculated using parameters such as delay, distance, energy, and LLT, the optimal path is identified. Here, the ideal path is represented by the maximal fitness, which should have the least amount of delay and distance, the maximum amount of energy, and LLT. The fitness function that determines the optimal path is as in (30).

$$Fit_1 = \frac{1}{4}\left[E + \left(1 - dt_{pw}\right) + \left(1 - \delta_{pw}\right) + LLT\right] \tag{30}$$

Here, E represents the residual energy in the p^{th} node, dt_{pw} presents the distance between the p^{th} node and the w^{th} node. Further, δ_{pw} is the delay incurred during data transmission to the w^{th} node from the p^{th} node. LLT represents the LLT of the link amidst the p^{th} and w^{th} nodes.

6 Results and Discussions

This section compares the suggested approach with two base algorithms, HLBO and AEO, and verifies it through several MATLAB simulation experiments. All sensor nodes of varying network sizes were dispersed at random throughout the monitoring region to prevent the experimental results from becoming contingent. The average of the trial results was then calculated.

Experimental Set-up

The HLAEO technique is validated through simulations using MATLAB environment. The experimentation is conducted with three test cases –

Case 1: Total number of nodes = 50

Case 2: Total number of nodes = 100

Case 3: Total number of nodes = 150.

Dataset Description

The energy performance of the HLAEO technique is evaluated using the Air Quality Data Set (Vito, 2008). This dataset includes 9358 instances of averaged responses collected hourly from a 5-metal oxide semiconductor chemical sensor array in an Air Quality Chemical Multisensor Device. The period of observations was from March 2004 to February 2005. A co-located reference certified analyzer was used to provide ground truth concentrations on an hourly basis for Nitrogen Dioxide (NO2), Total Nitrogen Oxides (NOx), Benzene, Non Metanic Hydrocarbons, and Carbon Monoxide (CO).

Evaluation Measures

1. Network Energy

Improving energy utilization, or maximizing the network lifetime with limited energy, is one of the major goals of WSNs for energy-constrained applications. The variation in each node's residual energy can be represented by the Energy Variance (EV). The energy distribution among all nodes in the network is represented by the remaining energy when the first node dies. The network's energy efficiency increases with more balanced residual energy, and its lifetime increases as well.

Network energy was evaluated across three test scenarios with different network sizes. Figures 3, 4, and 5 demonstrate an even energy distribution among nodes for Cases 1, 2, and 3 respectively. In all three cases, the HLAEO algorithm exhibits slightly lower energy consumption variability compared to the HLBO and AEO algorithms. This is likely due to HLAEO's capability to select an optimal set of CHs, facilitating data transmission through energy-efficient paths to the BS. Energy consumption fluctuations are highest when the first node fails and then decrease to zero as more nodes within the network fail.

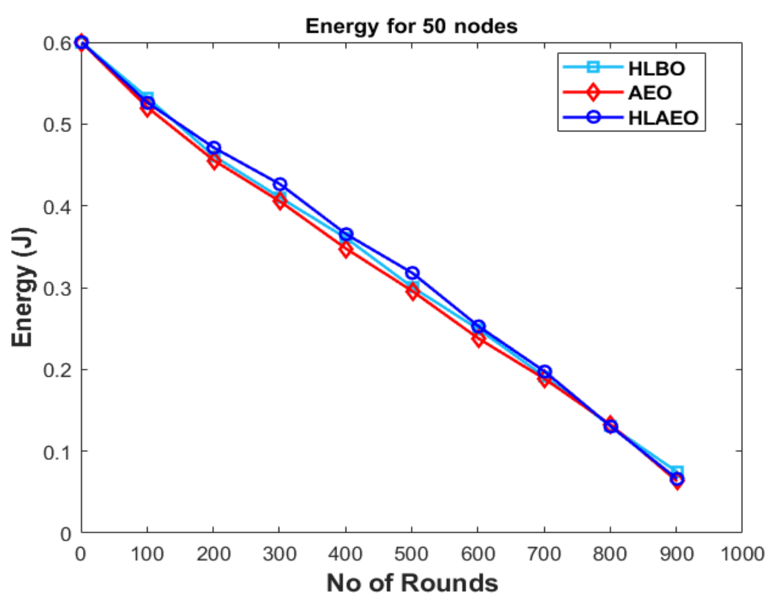

Figure 3: Residual Energy for Case 1

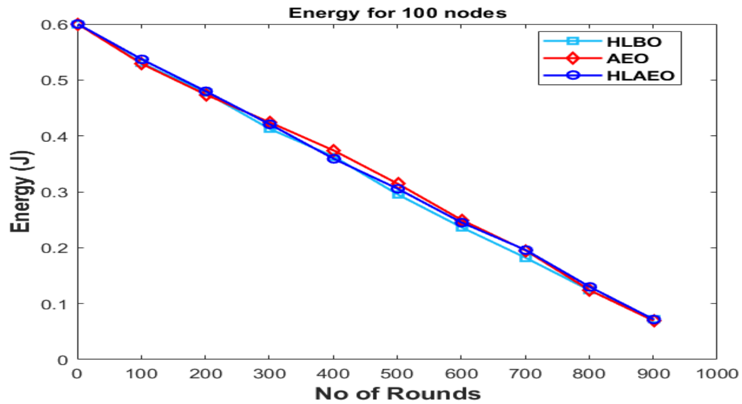

Figure 4: Residual Energy for Case 2

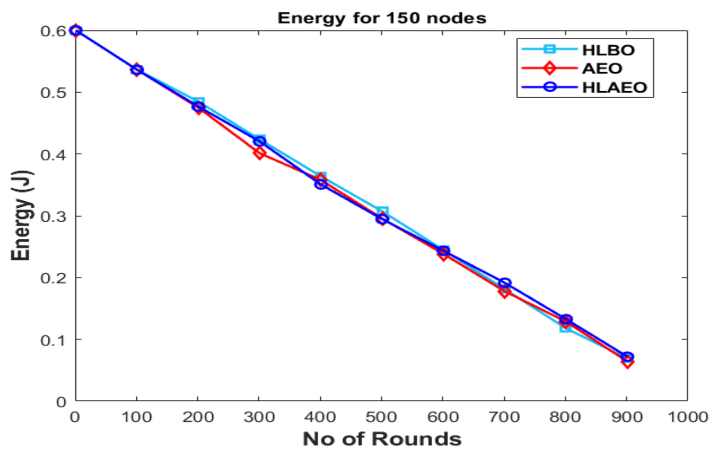

Figure 5: Residual Energy for Case 3

Alive Nodes

"Alive nodes" refers to the number of nodes that can take part in the routing operation. The number of live nodes for three distinct network sizes is used to validate the performance of the suggested HLAEO. The suggested HLAEO framework displays more living nodes than the HLBO and AEO algorithms, as seen in the Figures 6, 7, and 8. This is a result of the optimization model that was applied while choosing CHs.

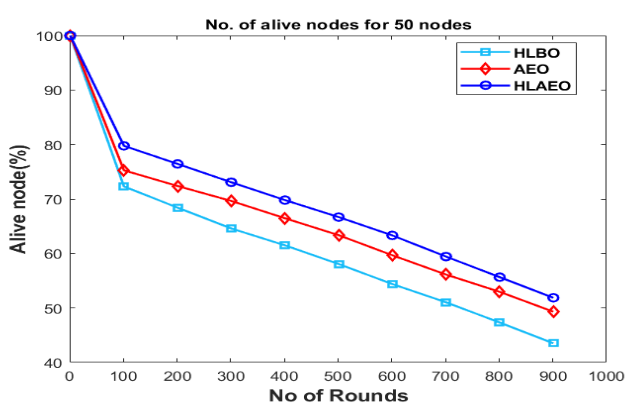

Figure 6: Alive Node Percentage in Case 1

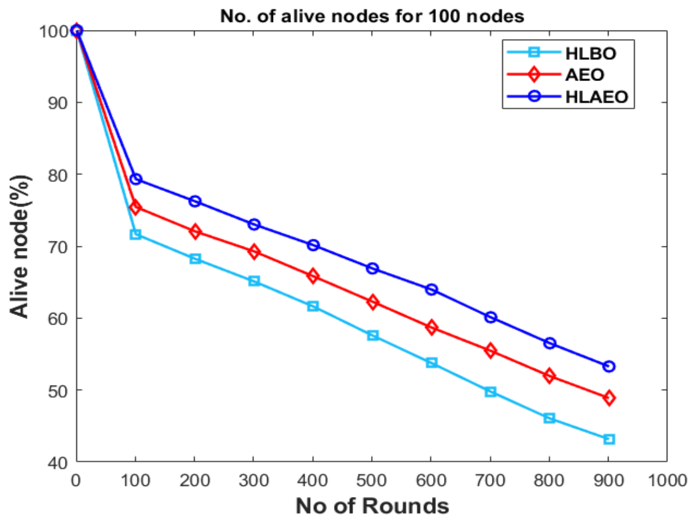

Figure 7: Alive Node Percentage in Case 2

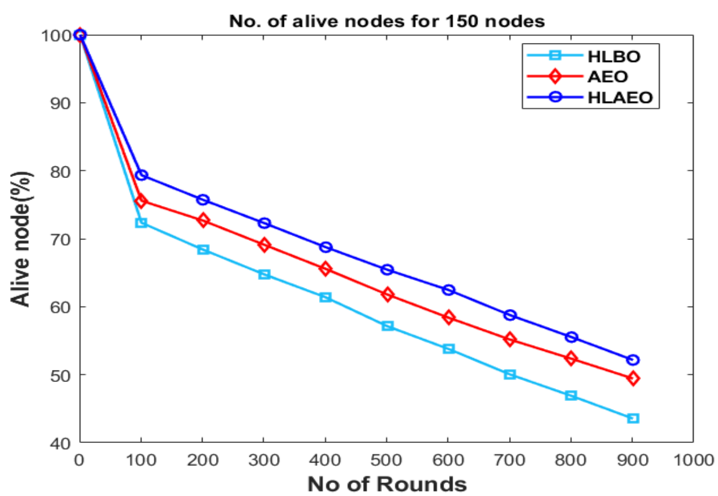

Figure 8: Alive Node Percentage in Case 3

From the simulation results, it can be seen that the proposed HLAEO algorithm performed better in terms of energy utilization, delay and prediction error. HLAEO offers reduced energy consumption thus enhancing the network lifetime. The algorithm is also validated for its scalability and thus making it well-suitable for the real-time WSN implementations.

7 Conclusion

Energy conservation during data transmission is an important issue in WSNs. A novel approach to achieve an extended network lifetime is presented in this paper. The proposed HLAEO algorithm assures energy efficient routing through proper CH selection. Leader-based optimization is used for CH selection. The algorithm is validated for its performance through various performance indicators of the network. HLAEO considers the advantages of both HLBO and AEO and thus assuring optimal path between source and the destination. HLAEO considers the dynamic nature of the network conditions and adapts accordingly. Simulation results show that the proposed HLAEO offers a better energy efficiency and hence enhances the network lifetime.

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