HIWAEO: Hybrid Improved Whale Artificial Ecosystem Optimization Algorithm based Energy-Efficient Routing Protocol for Wireless Sensor Network

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Abstract

Wireless Sensor Network (WSN) is a resource constraint network that utilizes more energy for transmitting and receiving the data. Hence energy efficiency is the vital issue faced by the WSN. Besides the packet routing process consumes more energy than the other processes. Moreover, the working of WSN is based on the battery life span of sensor nodes. Thus the constrained energy source affects the life span of the network battery. To tackle this issue, we proposed a novel method known as the Hybrid Improved Whale optimization-based Artificial Ecosystem optimization method (HIWAEO). This enhances the energy efficiency of the WSN and thereby improves the routing of the network. The energy-efficient WSN can be obtained by selecting optimal cluster head (CH) and forward nodes. To select the optimal CH the proposed method estimates the fitness function which includes node degree, space between the sensor nodes and space between the CH and base station (BS), residual energy, and node centrality. This estimated fitness function arranges the sensor nodes based on their increased energy and distance from the BS and the best node is chosen as the CH. Henceforth to obtain the routing efficiency the forward nodes are selected based on their residual energy and distance. The performance of the proposed method is analyzed with the other existing approaches for three conditions of BS alignment and concluded that our proposed method outperforms all the other approaches.

Keywords: Improved Whale optimization, Improved Artificial Ecosystem Optimization, WSN, fitness function, node degree, routing, and energy efficiency.

1. Introduction:

The design of an energy-effective wireless sensor network integrated with an efficient routing system[1] has recently become a leading field for research. The sensor is a system used to sense the physical as well as environmental conditions of pressure, heat, light, fluid level, etc. The output of the sensor is mostly an electrical signal that can be forwarded to the controller for further processing via radio frequency [2]. Meanwhile, the wireless sensor network is a network of devices that can gather information via wireless connections. The information is transmitted to other networks through multiple nodes. Besides, it is a self-configuring
network system that is composed of enormous cheap micro sensor nodes. Moreover, it also connects different sensor technologies, embedded computing technology, modern network and wireless communication technology, and distribution information processing technology, and so on.

The WSN possesses several features like self-configurable routing, wireless, the capacity of regeneracy, etc. The applications of WSN include environmental monitoring, health care, health monitoring field, industrial applications, etc [3], [4]. However, the WSN exhibits some of the shortcomings like limited power, energy, and battery lifetime, and also it is arduous to replace the battery regardless of its lifetime. Subsequently, the failure in one node also makes the WSN inoperable. Therefore it is very much needed to improve the lifetime of the network with the designing of energy-efficient routing protocols based on WSN [5], [6]. The period before a certain proportion of nodes dies determines the life of the network, including the time until the initial node dies. Dramatically, the stability of the network decreases after the death of the first node.

The life of the network is effectively extended by improving energy efficiency and managing the energy usage of the nodes. Dividing the nodes into several clusters and expanding the network life using hierarchical clustering protocols. The cluster head is the main node in the network and the member node captures data collections. Communication with the respective cluster head is an important requirement of member nodes, which consumes less energy with the shortest distances. Optimal cluster head selection is the major aim of the clustering protocols in which the energy consumption of nodes is balanced by rotating the cluster head among all nodes. Hence we proposed a novel energy-efficient routing protocol method known as a Hybrid Improved Whale optimization-based Improved Artificial Ecosystem optimization algorithm to enhance the energy efficiency of the wireless sensor networks. The contribution of our proposed HIWAEOA work is enclosed below,

- The hybrid IWAEO algorithm is composed of both an improved Whale Optimization algorithm and an improved Artificial Ecosystem Optimization algorithm
- The proposed algorithm is exploited to enhance the optimal selection of CH by enhancing the convergence speed and exploration capacity of the utilized algorithms
- The ranking of sensor nodes is made by estimating the fitness function such as residual energy, space between the sensor nodes and between the Ch and base station, and node degree.
- The ranking of nodes is utilized to select the optimal CH and to select the forward nodes. The forward nodes are selected based on the residual energy the node holds and the distance between the node and BS.
- The energy-efficient routing protocol can be obtained by selecting the optimal CH and also the forward nodes

The remainder of this work is organized as; section 2 elucidates the literature survey of the proposed work. The formulation of the proposed HIWAEOA is performed in section 3. The system model is illustrated in section 4. Moreover, the proposed methodology is explained in section 5, which also deliberates the ranking phase by estimating the fitness
function. The experimental analysis of the proposed work is depicted in section 6. Further, we concluded our work in section 7.

2. Review of Related works:

A novel Dynamic Energy Efficient Routing (DEER) protocol was proposed by Haque et al. [7] to satisfying multiple constraints such as throughput maximization, node failure, delay, and energy consumption minimization. Further, the message flow, maximum network lifetime, and message delivery were guaranteed. The realistic channel model evaluates the performance of the DEER model thereby improving session lifetime. This method is unsuitable for energy harvesting-based sensor networks. The Extended-OCER (E-OCER) with Optimized Cost Effective and Energy Efficient Routing Protocol (OCER) was proposed by Kaur et al. [8]. For selecting the most optimal route, the multi-objective cost function with path loss, link reliability, and residual energy parameters are optimized by applying the Genetic Algorithm (GA). The distance between any two sensor nodes is reduced by applying a multi-hop approach. For sending the data from a given node to the sink, the required reliability value is maintained with the energy-efficient routing protocols. The energy efficiency is enhanced but it considers more complex network scenarios such as different network accountability.

Liu et al. [9] proposed a low-energy adaptive clustering hierarchy for wireless sensor networks. The average energy and residual node energy of networks are considered using improved energy-efficient (IEE) LEACH protocol. The sensor energy consumption is minimized to achieve satisfactory performance. A new threshold has been used for CHs in the selection of sensor nodes using the IEE-LEACH process. This protocol substantially minimizes the energy consumption of WSNs with poor system reliability when compared to some existing routing protocols. Clustered-Based Energy Efficient Routing (CBE2R) protocol was introduced by Liu et al. [10] to prolong the battery power of the nodes and control node mobility. The powerful static courier nodes with CBE2R prolong the battery power and sea surface to the seabed on various layers deploys it. The comparative results are tested using the energy-efficient DRP, EMGGR, and REEP with CBE2R. Hence, it provides higher performance results but it required better energy-efficient protocols.

The fuzzy logic tools with energy-efficient routing protocol were proposed by Jain et al. [11] to enhance network lifetime. The multi-hop route to the base station with an intelligent selection of CHs is established by an energy-efficient routing protocol. The experimental results demonstrate higher throughput and network lifetime using fuzzy logic tools with energy-efficient routing protocol while compared to the MH-EEBCDA, OCM-FCM, and FD-LEACH methods but this model required a secure network. Energy Efficient Clustering and Shortest-Path Routing Protocol (EECSRP) was suggested by Walter et al. [12] for to Wireless Sensor Networks (WSNs) assistance in which it ensures the high packet transmission ratio with minimal delay, network overhead minimization, high packet transmission ratio with minimal delay ensuring and network lifetime extending. The gradient-oriented demand routing between source and destination is evaluated with the implementation of RSS-based network partitioning. Based on recent well-known current techniques, this EECSRP accomplishes higher performance with a poor network lifetime.
3. Formulation of Hybrid Improved Whale Artificial Ecosystem Optimization Algorithm

In this section, we first initialize both the improved Whale Optimization Algorithm and improved Artificial Ecosystem Optimization algorithm and henceforth combined both the algorithm to enhance the optimized energy-efficient cluster head selection and routing protocol.

3.1 Artificial Ecosystem Optimization (AEO)

AEO[13] is a modern metaheuristic algorithm focused on the flow of energy in the earth's ecosystem. An ecosystem is a group of living organisms that live and interact with each other on Earth. This algorithm considers three stages of living beings like creation, consumption, and decomposition that are the three unique characteristics of living organisms. Green plants are used in the first stage of creation; the second stage involves animals used by producers to acquire energy, and the third stage is the decomposer used by both creators and consumers to feed them. Exploiting this behavior the first stage of the AEO algorithm is used to sustain the balance between the exploitation and exploration and the second stage enhances the exploration and the third stage is used to improvise the exploitation of the AEO algorithm. This algorithm considers only one creator and decomposer and all other individuals are taken as consumers.

3.1.1 Creator

The creator of this stage is arbitrarily chosen among the individual who initiates the search ($I_{arb}$) space and the individual who is best among all ($I_b$). The creator used to update the decomposer and also the upper and lower constraints of search space. However, it also guides the other individuals to search for their locations. Thus it helps to sustain the balance between the explorative and exploitative search. Numerically this stage can be expressed as,

$$I_i(t + 1) = (1 - \alpha)I_m(t) + \alpha a_{arb}(t)$$  
(1)

$$\alpha = (1 - t Max.\ Iter)a_i$$  
(2)

$$I_{arb} = a(UP - LW) + LW$$  
(3)

The number of initial population is denoted as $m$, $Max.\ Iter$ is used to denote the maximum number of iterations. ‘$a_i$’ is used to indicate the arbitrary number between $[0, 1]$. $a$ is the vector representation of $a_i$ and hence lies between 0 and 1. $\alpha$ represents the coefficient of linear weighting and the upper and lower constraints are denoted as UP and LW correspondingly.

3.1.2 Consumption

This stage is exploited to improvise the exploration of the algorithm [13]. Moreover, it updates the individual solution by analyzing the energy levels. The searching method and the exploration stages are honed by exploiting the concept of Levy flight. The Levy flight is a random walk that can be used to search for food. Sometimes the length of the steps is
increased to enhance the optimization of search to attain the global optimum. Hence it can be expressed as,

$$L = \frac{1}{2} f_1$$

$$f_1 \approx N(0,1), \quad f_2 \approx N(0,1)$$

Here, $N(0,1)$ is the normal distribution with zero mean and unit standard deviation. Thus by exploiting various hunting behaviors the consumer can hunt food with the help of the consumption factor. Generally, the consumers are of three kinds: herbivores, carnivores, and omnivores [14]. The consumers are classified as any one of the above kind arbitrarily. The selected herbivores can be expressed numerically as,

$$L \approx \frac{1}{2} [f_1] \quad (4)$$

The numerical expression for the selected carnivores is given as,

$$I_j(t + 1) = I_j(t) + L \left( I_j(t) - I_i(t) \right), \forall i \in (2, \ldots, n)$$

However, the selected omnivores can be expressed as,

$$I_j(t + 1) = I_j(t) + L \left( r_2(1 - r_j)(I_j(t) - I_j(t)) + r_j(I_j(t) - I_j(t)) \right), \forall i \in (2, \ldots, n); \quad j = \text{arbitrary}[2i - 1]$$

### 3.1.3 Decomposition

To enhance the exploitation of AEO this decomposition stage is been deployed. This stage involves three coefficients such as $D$, $e$, and $w$ to update the individual solutions and thereby select the best solutions from entire solutions. Where $D$ is a factor and $e$ and $w$ are the two variables used to represent the weights. Moreover, the position of each individual is upgraded to the newest position by utilizing the decomposer variable $I_n$ and the decomposer factor $D$ along with the two-weighted variables $e$ and $w$. Hence it can be expressed as,

$$I_i(t + 1) = I_i(t) + D \left( e I_i(t) - w I_i(t) \right), \quad i = 1, \ldots, n$$

$$D = 3g, \quad g \approx N(0,1)$$

$$e = r_3 \text{arbitrary}[12] - 1$$

### 3.1.4 IAELO

The AEO needs enhancement in the consumption stage since the classification of animals into herbivores, carnivores, and omnivores is an arduous process [15]. Therefore to hone the performance of AEO we exploited the sine-cosine algorithm [24] which can be used to generate the best possible solution by moving forwards and backward. Hence the improved version of the AEO algorithm can be written as,

$$r_i = 2 - X_t \times \left( \frac{2}{\max(X_t)} \right)$$
\[ r_3 = (2 \times pi) \times \text{arb}(0,1) \] (13)

The current iteration can be denoted as \( X_t \), and the maximum number of iterations can be indicated as \( \text{max } X_t \). The \( r_1 \) and \( r_2 \) denote the arbitrarily selected numbers lie between 0 and 1.

\[
I_i(t+1) = \begin{cases} 
I_i(t) + r_1 \times \sin(r_1) \times L \times (I_i(t) - I_j(t)) \cdot r_3 < 0.5 \ i \in [2, \ldots, n] \\
I_i(t) + r_1 \times \cos(r_1) \times L \times (I_i(t) - I_j(t)) \cdot r_3 > 0.5 \ i \in [2, \ldots, n] 
\end{cases}
\] (14)

\[
I_i(t+1) = \begin{cases} 
I_i(t) + r_1 \times \sin(r_1) \times L \times (I_i(t) - I_j(t)) \cdot r_4 < 0.5 \ i \in [3, \ldots, n] \\
I_i(t) + r_1 \times \cos(r_1) \times L \times (I_i(t) - I_j(t)) \cdot r_4 > 0.5 \ i \in [3, \ldots, n] \\
j = \text{arb}[2i-1] 
\end{cases}
\] (15)

\[
I_i(t+1) = \begin{cases} 
I_i(t) + r_1 \times \sin(r_1) \times L \times \left( r_2 (I_i(t) - I_j(t)) + (1 - r_2) (I_i(t) - I_j(t)) \right) \cdot r_4 < 0.5 \ i \in [3, \ldots, n] \\
I_i(t) + r_1 \times \cos(r_1) \times L \times \left( r_2 (I_i(t) - I_j(t)) + (1 - r_2) (I_i(t) - I_j(t)) \right) \cdot r_4 > 0.5 \ i \in [3, \ldots, n] \\
j = \text{arb}[2i-1] 
\end{cases}
\] (16)

### 3.2 Improved Whale Optimization algorithm (IWOA):

This section explains the Improved Whale Optimization Algorithm (IWOA) procedures.

#### 3.2.1 Whale Optimization Algorithm (WOA):

The social behavior of humpback whales is characterized using a whale optimization algorithm (WOA) [16]. The WOA utilizes a ransom candidate solution set in which it enhances the candidate solution position and three rules are used to update the positions.

**i) Prey Encircling:**

Equation (17) update the candidate solution position \( \vec{Z}(k+1) \).

\[
\vec{C} = \left| \vec{D} \cdot \vec{Z}^*(k) - \vec{Z}(k) \right| \] (17)

\[
\vec{Z}(k+1) = \vec{Z}^*(k) - \hat{\vec{B}} \cdot \vec{C} \] (18)

Therefore, the best candidate solution in the current generation is \( \vec{Z}^* \). Equation (19) and (20) calculates \( \hat{\vec{B}} \) and \( \vec{C} \).

\[
\hat{\vec{B}} = 2 \hat{\vec{a}} \cdot \hat{\vec{n}} - \hat{\vec{a}} \] (19)

\[
\vec{C} = 2 \hat{\vec{n}} \] (20)

Hence, the vector \( \hat{\vec{a}} \) randomly tends to the interval \([0, 1]\) and it linearly decreased from 2 to 0 respectively.

**ii) Prey searching:**
The prey encircling and prey searching has similar procedures but \( Z^* \) is used for prey searching. Equations (21) and (22) select the random candidate solution \( Z_{random} \).

\[
\begin{align*}
\bar{C} &= |\bar{D} \cdot Z_{random} - Z(k)| \tag{21} \\
\bar{Z}(k+1) &= Z_{random}(k) - B \cdot \bar{C} \tag{22}
\end{align*}
\]

During the exploration stage, the searching for prey is used and the global search is performed using WOA.

\[\text{(iii) Spiral updating position:}\]

During the exploitation stage of WOA, the spiral updating position and prey encircling are utilized. Equation (23) updates the individual position updating.

\[
\bar{Z}(k+1) = \bar{C} \cdot e^{at} \cdot \cos(2\pi t) + \bar{Z}^*(k) \tag{23}
\]

The distance among distance best solution and \( k^{th} \) candidate solution is \( \bar{C} = |\bar{Z}^*(k) - \bar{Z}(k)| \).

3.2.2 Improved Whale Optimization Algorithm (IWOA):

The above section describes the steps involved in WOA. Nevertheless, the premature convergence and exploration ability of WOA is improved using the Differential Evaluation algorithm (DE). Author [17] presented easy use of a population-based algorithm called Differential Evolution (DE). The crossover and mutation operators performed to generate new individuals. If it is fitter than the corresponding agent then the parent is replaced by its offspring. In this work, the mutation of DE integrates the whale optimization algorithm is called Improved Whale Optimization Algorithm (IWOA) [18]. The exploration and exploitation stages of IWOA are changed using a new parameter as search mode. Equation (24) adjust the \( \gamma \).

\[
\gamma = 1 - \frac{t}{t_{max}} \tag{24}
\]

Here, the maximum number of generations is \( t_{max} \) and the current generation is \( t \). Where \( \eta \) is minimized over time from 1 to 0. While doing exploration as time increases, the initial generation is explored by allowing the individuals.

\[
Y_k(j) = \begin{cases} 
\bar{\chi}_j + random(0,1) \times (\bar{\lambda}_j - \bar{\chi}_j) & \text{if } Z_k(j) < \bar{\chi}_j \\
\bar{\lambda}_j - random(0,1) \times (\bar{\lambda}_j - \bar{\chi}_j) & \text{if } Z_k(j) < \bar{\lambda}_j 
\end{cases} \tag{25}
\]

According to the \( j^{th} \) dimensions, the upper and lower bounds are \( \bar{\chi}_j \) and \( \bar{\lambda}_j \). The random number between 0 and 1 is \( \text{random} \). The IWOA contains an easy and simple outline. The selection method of DE and WOA are similar. The best fitness is selected using the maximum number of generations \( M_g \).
In order to increase the convergence speed and exploration capacity to select the optimum cluster head, to minimize the energy consumption and routing distance, we are hybridizing both IWOA and IAEO for our proposed work. The proposed hybrid IWAEOA helps to acquire the energy-efficient routing protocol for the wireless sensor network. Figure 1 shows the schematic diagram of our proposed HIWAEOA approach.

### 3.3 Hybrid IWAEOA

In order to increase the convergence speed and exploration capacity to select the optimum cluster head, to minimize the energy consumption and routing distance, we are hybridizing both IWOA and IAEO for our proposed work. The proposed hybrid IWAEOA helps to acquire the energy-efficient routing protocol for the wireless sensor network. Figure 1 shows the schematic diagram of our proposed HIWAEOA approach.

### 4. System Model

This section elucidates the network energy model and its settings of our proposed WSN model.

#### 4.1 Network Model

The network model [19] of this proposed method is employed in a 150×150 square meter area. This includes two kinds of sensor nodes: advance nodes and normal nodes. The battery efficiency of advanced nodes is better than the normal nodes. Each node possesses a unique network ID and the base station is positioned at the center of the employed area. However,
the initial energy, processing, and communication ability of all sensor nodes are similar and
thus show the homogeneity feature of sensor nodes. Subsequently, with the aid of received
signal strength, the node itself estimates the distance between the destination and its own.
Also detects its own residual energy. Besides, the nodes directly link the base station for
forwarding the data as well as to receive the transmission power according to the estimated
distance. Further, the base station supplies unlimited power and energy to the sensor nodes.
Fig 2 illustrates the network model of the WSN.

Fig 2: Framework of clustered WSN

4.2 Energy consumption model

Our proposed method utilizes the first-order energy model [7] which is illustrated in fig 3.
The consumption of energy is high in wireless sensor networks since there are several energy
degrading systems in them. The energy consumption of the transmitter and receiver can be
mathematically expressed as shown below,

Consumption of energy at the transmitter side of the sensor nodes,

\[
\xi_{\text{Trans}}(m,h) = \begin{cases} 
    m \times \xi_{\text{elec}} + m \times \xi_{\text{fs}} \times h^2 & \text{if } h \leq h_0 \\
    m \times \xi_{\text{elec}} + m \times \xi_{\text{amp}} \times h^2 & \text{if } h > h_0 
\end{cases}
\]  

(26)

Consumption of energy at the receiver side can be expressed as,

\[
\xi_{\text{Rec}} = m \times \xi_{\text{elec}}
\]  

(27)

Where \( \xi_{\text{Trans,elec}} \) determines the amount of energy dissipated per bit at the transmitter side
and \( \xi_{\text{Rec,elec}} \) indicates the energy dissipated per bit at the receiver side. Moreover, the distance
between the sensor node and its respective CH can be denoted as \( h \). \( \xi_{\text{elec}} \) can be used to
evaluate the cost of circuit energy while forwarding or receiving one bit of data, \( h_0 \) is the
threshold distance, and can be evaluated as below,
The coefficients of free space and multipath of the taken amplifiers are correspondingly denoted as, $\varepsilon_{fs}$ and $\varepsilon_{amp}$. Besides, these coefficients are completely based on the amplifier used on the transmitter side [23].

\[ h_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{amp}}} \]  \hspace{1cm} (28)

Consider that the distance between the sensor node and its respective CH ($h$) is less than the threshold distance $h_0$, then the free space energy model is exploited and if it is greater than the $h_0$, the multi-path energy model is exploited. Further, our model exploits the infinite compressibility method to compress the accumulated data in CH from its sensor nodes to a single packet of fixed length.

5. Proposed methodology

This selection elucidates the proposed methodology to select the optimal energy-efficient routing protocol for the wireless sensor network. To acquire the energy-efficient routing protocol, the estimation of the fitness function is necessary. Hence we estimate the fitness function utilizing the proposed Hybrid IWAEO algorithm.

5.1 Ranking Phase of Proposed HIWAEO Algorithm

The ranking phase of our proposed method can be performed by evaluating the fitness function. The fitness function of the proposed method is to estimate the optimal CHs among all the sensor nodes. This can be obtained by evaluating node degree, node centrality, and space between the neighbors, space between the base station and sensor nodes, and residual energy. Here, the node degree is defined to choose the CH with the least number of normal nodes in order to sustain the nodes for the upcoming iterations. Besides, the energy consumption of the nodes can be reduced by choosing the best optimal CH [28]. This can be acquired by minimizing the space between the neighboring nodes and the space between the nodes and the BS. Meanwhile, the inclusion of dead nodes or broken or useless nodes can be circumvented by estimating the residual energy. These fitness functions are defined in the following section.

- **Node Degree**
The ranking phase is the important stage to arrange the CH based on the increasing sensor nodes to attain the energy-efficient routing protocol. To arrange the CH it is necessary to evaluate the node degree for each CH. The best optimal CH can be selected based on the CH that holds the least number of sensor nodes since CH with the least number of sensor nodes sustain more energy than the CH with more and hence it can be used for future performance. Therefore, the node degree [20] can be defined as the number of nodes that the respective CH holds and can be expressed as,

$$ND = \sum_{l=1}^{L} SN_l$$  \hspace{1cm} (29)$$

Where is $SN_l$ the number of sensor nodes held by $CH_l$.

**Space between the sensor nodes**

The energy consumption of nodes increased with the transmission space between the nodes. Hence the optimal CH selection can be obtained by evaluating the space among the nodes and thereby minimizes the consumption of energy [21]. Thus the space between the sensor nodes along with the respective CH can be determined as,

$$DS = \sum_{l=1}^{L} \sum_{c=1}^{L_c} dis(SN_l, CH_c) / L_c$$  \hspace{1cm} (30)$$

Here, $dis(SN_l, CH_c)$ is used to determinethe space between the sensor $l$ and CH$c$,and sensor nodes that are under the CH$c$ are indicated as $L_c$.

**Space between CH and BS**

If the selected optimal CH is located far away from the BS, then it consumes more energy, hence is arduous to obtain the energy efficiency [21]. Therefore, it is a must to choose the CH which is positioned nearer to the BS to minimize energy usage. The distance between the CH and BS can be determined as,

$$DB = \sum_{c=1}^{L_c} dis(CH_c, BS)$$  \hspace{1cm} (31)$$

Here, the term $dis(CH_b, BS)$ is used to determine the distance between the Cluster head $CH_c$ and BS.

**Node Centrality**

The node centrality can be defined as how the optimal CH is placed centrally from the adjacent nodes and can be determined as,

$$NC = \sum_{l=1}^{m} \sqrt{\frac{\sum_{c=1}^{\text{Network Dimension}} dist^2(l,c)/n(l)}}$$  \hspace{1cm} (32)$$

The neighboring nodes of the selected optimal $CH_l$ can be denoted as $n (l)$. This can be used to minimize the space between the CH and the other sensor nodes.
Residual energy

The elimination of dead or unused or broken nodes is predominantly important for the optimal CH selection. Hence we estimate the residual energy. Residual energy [4] is defined as the energy possessed by the nodes after receiving or transmitting the data while performing the transmission process. It can be expressed as,

\[ RE = \sum_{l=1}^{L} \frac{1}{RE_{CH_l}} \tag{33} \]

The above equation \( RE_{CH_l} \) denotes the residual energy of the \( l^{th} \) cluster head.

Thus the best CH can be selected by exploiting the above-mentioned fitness function. Some of the advantages of selecting the optimal CH are, (i) increases the network life span, (ii) lowering the energy consumption while transmitting the information from sensor nodes to the respective BS, (iii) enhances the reliability, and (iv) minimization of latency. Following the selection of optimal CH, it is necessary to assign sensor nodes for the selected CH. Our proposed HIWAEO algorithm-based method can be used to allocate the sensor nodes to the respective CH by utilizing the potential function that is expressed below.

\[ P_{SN} = z \times \frac{Energy(CH_c)}{Dist(SN_i, CH_c)} \tag{34} \]

The potential of the sensor node can be represented by \( P_{SN} \); the space among the cluster head and sensor nodes are represented by \( Dist(SN_i, CH_c) \); \( z \) is the proportionality constant; the residual energy of the respective CH can be denoted as \( Energy(CH_c) \). Meanwhile, the assignment of sensor nodes to the cluster can be performed based on the distance and also with the maximum potential. Suppose, if two or more CH exhibits the same distance, then the sensor node with higher energy can be assigned to the corresponding CH.

5.2 Proposed HIWAEO Algorithm based Energy efficient routing protocol

The energy consumption model illustrated in the system model section indicates that the energy consumption of the sensor nodes is exponentially increased with the increases in transmission distance [22]. Consequently, if the selected optimal CH transmits directly data to the BS then the process will consume more energy. Due to this reason, the CH which is located far away from the base station will discard its transmission due to its large consumption of energy [22]. Hence it is necessary to reduce the energy consumption of CH and maintain the load balance between the CH and clusters in order to attain the energy-efficient WSN. Therefore our proposed HIWAEO algorithm carefully selects the forwarding nodes to reduce energy consumption [26]. The selected forwarding nodes possess higher residual energy than the other sensor nodes to enhance the packet delivery ratio and minimize the packet loss percentage. This can be achieved by choosing nodes with higher waiting time and can be expressed as,
The residual energy of an energized sensor node can be represented as $E_{t}$. $S$ denotes the total sum of cluster heads. However, the initial energy of the $CH$ of cluster $c$ can be denoted as $E_{0}(CH_{c,j})$. $E(CH_{c,j})$ denotes the residual energy of the particular cluster head.

6. Simulation setup:

The network lifetime is affected via three main parameters such as network size, base station location, and the number of nodes. We set various scenarios of different sizes considering these factors, which are described in Table 1. The simulation parameters used in this work are delineated in Table 2.

| Different Situations | Parameters | | |
|----------------------|------------|---|---|
| Area | Location of the base station | Number of sensors |
| Situation 1 | 150 $\times$ 150 $m^2$ | 250 $\times$ 250 $m^2$ | 350 $\times$ 350 $m^2$ |
| Situation 2 | (75, 75) | (0, 0) | (350, 500) |
| Situation 3 | 150, 250, 350 | 150, 250, 350 | 550 |

| Table 2: List of implementation parameters |
| Parameters | Ranges | | |
| Percentage of cluster heads | 5% | | |
| Initial energy | 0.5 J | | |
| Control packet size | 200 bits | | |
| Data packet size | 4000 bits | | |
| $\varepsilon_{amp}$ | 0.0013 pJ/bit/m$^4$ | | |
| $\varepsilon_{fs}$ | 10 pJ/bit/m$^2$ | | |
| $\varepsilon_{fs}$ | 5 pJ/bit/m$^4$ | | |

6.1 Evaluation metrics:

The simulation analysis is performed using the aspects of network throughput, network stability period, and network total residual energy and network lifetime [25, 27], which are compared using the proposed HIWAEO algorithm with existing methods such as DEER [7], OCER [8], IEE-LEACH [9] and CBE2R [10] respectively.

6.2 State-of-art results:
Fig 4 shows the performance of network lifetime with respect to situation 1. The proposed protocol outperforms better outputs than other methods in terms of network lifetime. The proposed protocol contains a higher lifetime in situation 1 with 150, 250, and 350 sensors. The BS is located in the center area in which the scale of situation 1 is small. The clustering effect is a major factor affecting the protocol performance. The optimized clustering and cluster heads are selected with a better network lifetime.

![Network lifetime performance](image)

**Fig 4**: Performance of network lifetime with respect to situation 1

The performance of stabilization time with respect to situation 1 is delineated in Fig 5. When compared to other methods, the proposed protocol outperforms better network stability performance in situation 1 with various node densities as shown in Fig 5. The proposed protocol will balance the network energy consumption, hence, the network stability of the proposed model is optimal than the other five methods. Based on situation 1, the proposed protocol demonstrates better reliability requirements.

![Stabilization time performance](image)

**Fig 5**: Performance of stabilization time with respect to situation 1

The throughput performance with respect to situation 1 is delineated in Fig 6. During the working time of the network, the throughput performance with respect to situation 1 is seen from Fig 6 and more data packets are received from the base station. The intra-cluster
communication stage introduces a pooling control mechanism according to the idle/busy nodes. The network throughput is increased in order to create the best use of the time slot.

**Fig 6**: Performance of throughput with respect to situation 1

**Fig 7**: Performance of entire energy to situation 1, (a) in terms of 150 sensors, (b) in terms of 250 sensors, and (c) in terms of 350 sensors
The performances of entire energy to situation 1 in terms of 150, 250, and 350 sensors are described in Fig 7 such as Fig 7(a), Fig 7(b), and Fig 7(c). Three different node densities with situation 1 are clearly seen from figure 7(a) – 7(c). Compared to other protocols, the proposed protocol with its residual energy is higher. Finally, the energy efficiency is improved as well as it effectively balances the network energy consumption.

Fig 8: Performance of lifetime with respect to situation 2

Fig 9: Performance of stabilization time with respect to situation 2

Fig 8 explains the performance of a lifetime with respect to situation 2. There are five protocols are simulated in situation 2. The corner field places a base station in situation 2 compared with scenario 2. We still consider 150, 250, and 350 sensors as for the number of sensor nodes. The proposed protocol delivers a better network lifetime compared with other methods. Create the cluster heads location more disperse and this is due to the proposed method select the cluster heads. The path between both base stations and each cluster head is determined carefully. The performance of stabilization time with respect to situation 2 is discussed in Fig 9. A better network stabilization time is obtained using the proposed method. An optimal cluster head is selected based on the proposed protocol. Hence, the proposed
protocol prolongs the stable working time compared to the other four protocols. The high-reliability requirements and is more appropriate for situations.

![Graph showing performance of throughput with respect to situation 2](image1)

**Fig 10:** Performance of throughput with respect to situation 2

![Graph showing performance of entire energy to situation 2 for 150 sensors](image2)
![Graph showing performance of entire energy to situation 2 for 250 sensors](image3)
![Graph showing performance of entire energy to situation 2 for 350 sensors](image4)

**Fig 11:** Performance of entire energy to situation 2, (a) in terms of 150 sensors, (b) in terms of 250 sensors, and (c) in terms of 350 sensors
The performance of throughput with respect to situation 2 is delineated in Fig 10. The better network throughput present in the proposed protocol. When compared to the existing protocols, the proposed method achieves higher network throughput with higher network lifetime results. Based on the proposed protocol, the pooling scheme is established in an intra-cluster communication stage and the base station receives more data packets due to higher network lifetime. Finally, the network throughput is enhanced as well as it creates full utilization of the time slot.

![Fig 12: Performance of total energy for situation 3](image)

The performances of entire energy to situation 2 in terms of 150, 250, and 350 sensors are described in Fig 11 including Fig 11(a), Fig 11(b), and Fig 11(c). Three different node densities with situation 1 are clearly seen in Figures 11(a) to 11 (c). The total remaining energy metrics performed with the help of the proposed method. The energy efficiency is improved as well as the network energy consumption is effectively balanced using the proposed protocol and it delivers optimal results than other protocols such as DEER [7], OCER [8], IEE-LEACH [9], and CBE2R [10].

The performance of total energy with respect to situation 3 is delineated in Fig 12. When compared to the existing algorithms, the higher total remaining energy is obtained using the proposed HIWAEO algorithm. From each cluster head to the base station, an optimal path is determined using the proposed HIWAEO algorithm.

7. Conclusion

This paper proposed a Hybrid Improved Whale Artificial Ecosystem Optimization (HIWAEO) algorithm for Wireless Sensor Network (WSN) in which the fitness function calculates the residual energy, distance between the sensor node, and the base station, and energy consumption thereby the network lifetime gets increased. The three main parameters such as network size, base station location, and the number of nodes affect the network lifetime and we set various scenarios of different sizes considering these factors. The comparative analysis is validated via the proposed HIWAEO algorithm with existing methods such as DEER, OCER, IEE-LEACH, and CBE2R. The proposed HIWAEO
algorithm contains higher network lifetime, throughput, and minimum energy consumption in situations 1, 2, and 3 with 150, 250, and 350 sensors.

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**Authors’ contributions**

RRD agreed on the content of the study. RRD and TS collected all the data for analysis. RRD agreed on the methodology. RRD and TS completed the analysis based on agreed steps. Results and conclusions are discussed and written together. Both author read and approved the final manuscript.

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