# Deep Learning and Evolutionary Model for Energy Efficient Node Localization in WSN

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***Abstract- Being aware of the nodes positions is a key issue in order to locate precisely the sensor node, localization is very important information about sensor nodes in wireless sensor network (WSNs). Hence, the precision improvement is a significant issue that allows an effective data transmission between sensor network (SN) in order to save their energy and extend the network lifetime. In this work, propose and implement a new mechanism for routing. In this work node localization is performed using Improved recurrent neural network (IRNN). Once the localization algorithm has detected the location of nodes with unknown position, the proposed mechanism selects effectively the next-elected CH to reduce the energy dissipation of sensor nodes using mutation chicken swarm optimization, which leads to an extension of the network lifetime. The main advantages of the proposed mechanism are three folds: the first is to minimize the position error of nodes and reduces the error localization average. The second is to increase the number of packets transmitted to the next hop cluster head (CH) based on the localization algorithm. The third one is to, reduce the energy consumption of nodes and then extends the network lifetime using an efficient selection of next hop CH. The obtained simulation results show that the proposed mechanism outperforms the existing solutions in terms of energy consumption, execution time (localization time) and localization error, similarly for the number of the packets transmitted to the base station. Experimental results show the effectiveness of the proposed model in terms of packet delivery ratio, energy consumption, execution time and localization error.***

***Indexed Terms- Deep Learning, Energy -Efficient, Wireless Sensor Network (WSNs), Improved Recurrent Neural Network (IRNN), Chicken Swarm Optimization (CSO)***

## I. INTRODUCTION

WSNs are made up of multiple sensor nodes, and a substantial number of them have been developed in remote and inaccessible areas. Data is collected via sensor nodes. Wireless radio interferences connect nodes and also connect them to the base station [1,2]. In fact, the nodes send data collected from the environment to the base station in a single-hop or multi-hop fashion [3]. Sensor nodes are capable of performing a variety of tasks. In other words, simple nodes may only monitor physical phenomena, whereas complex nodes may collect data using a variety of sense techniques such as acoustic, optical, and magnetic [4]. WSNs have numerous uses in the Internet of Things (IoT), healthcare, environmental monitoring, agricultural, military, and other fields.

The main limitation of WSNs is the limited power of the sensor nodes, which are powered by tiny batteries are represented in the Figure.1. Furthermore, in many applications, they are usually generated at random employed in severe environments where human interaction is essentially non-existent, making it impossible to recharge their batteries [5]. Furthermore, because they operate in a hostile environment, the sensor nodes are prone to failure's are distinct from regular networks in that they have various restrictions such as restricted resources, a lack of central management, dangerous communications, and so on [6]. As a result, using typical routing algorithms in these networks is not advised [7].

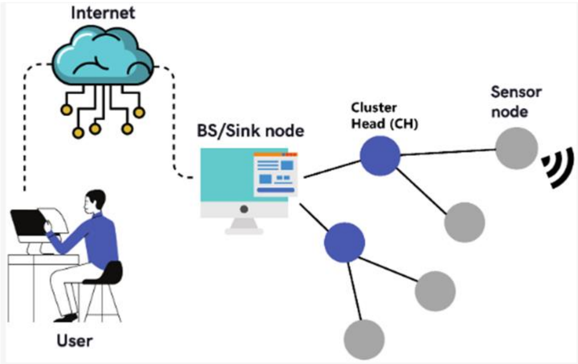

Figure 1. Typical Wireless Sensor Network Elements

Several routing strategies have recently been proposed to reduce energy usage and increase network performance. One of the primary issues in WSNs is energy-aware routing between nodes [8]. Several routing systems attempt to reduce the energy consumed for data packet transmission in order to reduce network energy consumption and improve network lifetime [9]. The majority of routing algorithms are data-centric and employ attribute-based addressing approaches as well as location awareness [10,11]. An efficient routing system should ensure numerous factors, including scalability, energy economy, and low control overhead [12,13].

It formulates multipath routing as a linear programming problem with the goal of maximizing the duration until the first sensor node runs out of energy. Knowing the positions of the nodes is critical in order to correctly locate the sensor node; localization is critical information about sensor nodes in wireless sensor networks (WSNs). As a result, accuracy improvement is an important issue that enables effective data transfer between sensor networks (SN) in order to save energy and lengthen network lifetime. To overcome these problems, a multipath routing for homogeneous WSNs is proposed. The purpose of proposing the routing method is to decline energy consumption and balance load, which results in improved network lifetime. Also, we intend to reduce packet loss rate. The proposed routing method includes 3 phases: clustering network nodes, discovering the paths between CHs, and maintaining the paths. The simulation results improve the network lifetime, reduces the packet delivery ratio between source and destination, and reduces the energy consumption for the better results.

## II. LITERATURE REVIEW

Goyat et al [14] suggested a technique termed energy-efficient localization for precise localization in Wireless Sensor Networks (WSN), and then proceeded with three steps. To begin, the beacon nodes use extra tone requests and reply packets via the media access control (MAC) layer to discover their one-hop neighbour nodes. Second, the found one-hop unknown nodes are split into two groups: those with direct communication and those with indirect communication for energy efficiency. In direct communication, source beacon nodes send information directly to unknown nodes, whereas in indirect communication, a common beacon node is chosen for communication, which minimizes overall energy consumption during transmission. Finally, a correction factor is introduced, and localised unknown nodes are promoted to helper nodes in order to reduce localization mistake. Various simulations are run and compared with current algorithms to assess the efficiency and effectiveness of the new algorithm.

Kagi and Mathapati [15] proposed the range-based localization strategy by an optimization-assisted deep learning model introduces a new localization model. The proposed effort is divided into two key phases: (a) training and (b) localisation. The trained Deep Neural Network (DNN) uses measured distance-based parameters such as "Angle of Arrival (AoA) and Received Signal Strength Indicator (RSSI)" to pinpoint the location of the unknown node. To improve localization accuracy, the weight of the DNN is modified using a novel hybrid optimisation approach known as the Lion-Assisted Firefly approach (LAFA) model. The proposed LAFA combines the Lion Algorithm (LA) and the Firefly Algorithm (FF). Finally, the proposed work is evaluated in terms of error measures.

Chen et al [16] proposed to put forward energy-efficient clustering and localization based on genetic algorithm (ECGAL), in which the fitness function is formed by residual energy, distance estimation, and coverage connection. This function certainly runs quickly. The suggested ECGAL uses less energy and increases the life of wireless networks. Finally, simulations are run to evaluate the performance of the suggested approach. The experimental findings reveal that the suggested technique approximates the unknown node position with the least amount of localization error.

Hallawa et al [17] proposed an Evolutionary algorithms (EAs) to be utilised to optimise agents' resources off-line for an energy-efficient environment mapping. The Centralised Offline Localization and Mapping (COLAM) challenge was highlighted, followed by a model to tackle it. This model also depicts a modified version of the Vietoris-Rips Complex known as the Trajectory Incorporated Vietoris-Rips (TIVR) complex as a mapping tool. Finally, test the suggested model using real-world data and present the results.

Nain and Goyal [18] proposed based on Mobility and Propagation delay prediction, suggested an energy-efficient localization approach. The system model consists of surface buoys that float on the ocean's surface, anchor nodes that float at various water depths, and ordinary nodes that are widely dispersed at various depths. The anchor node mobility prediction technique analyses and records its speed at each localization cycle. The propagation delay is then anticipated and accounted for in order to achieve exact localisation. The normal nodes perform localization using the expected speed vectors obtained from the anchor nodes. The replicated results show that the proposed strategy improves overall energy efficiency.

Umashankar et al [19] suggested the simulated Annealing technique for population vector initialization using the opposite point procedure, self-adaptive control approach by node mutation rate, crossover rate, node capacity, and cluster head allocation Methods. When compared to traditional methods, it enhances throughput, accuracy, efficiency, energy utilisation, battery recharging capabilities, and replacement operations. According to the study and comparison of the proposed method with existing methods, reducing the number of dead nodes gradually enhances the throughput and lifetime of the nodes with respect to the number of iterations.

Kaviarasan and Srinivasan [20] proposed as novel algorithm called K-Means and Modified Whale Optimisation Algorithm (KM-MWOA). Clustering algorithms are critical in determining the most energy-efficient and least delayed cluster head under these conditions. The K-means algorithm is utilised to determine the cluster head selection (CHS), and the modified whale optimisation algorithm (MWOA) is then used to transmit packets in multi-hop transmission between the CHS and the BS and choose an ideal routing. Random population seeding is performed during the global search phase to raise the standard WOA. By altering the parameters, A and b, algorithms can discover in the early phases of the search while also utilising the search space for a longer period of time in the later stages. This clustering approach allows for reduced intra-cluster communication as well as greater energy efficiency for sensor nodes. Performance indicators such as network lifetime, energy consumption, and network throughput have been realised as a result of the KM-MWOA strategy.

Poggi et al [21] proposed a unique approach for assisting decision-makers during the deployment process based on machine learning (ML) and metaheuristics (MH). To propose a new hybridised version of the "Hitchcock bird-inspired algorithm" (HBIA) metaheuristic algorithm called "Intensified-Hitchcock bird-inspired algorithm" (I-HBIA) for optimising node placements. Our fitness algorithm focuses on received signal maximisation between nodes and antennas during the optimisation phase. The machine learning "K Nearest Neighbours" (KNN) algorithm working with real measured data provides signal estimations. To demonstrate our contribution, we compared the performance of the standard HBIA algorithm and our I-HBIA approach on classical optimisation benchmarks. To assess the accuracy of signal predictions made by the KNN algorithm on various maps. Finally, KNN and I-HBIA are combined to generate efficient deployment propositions based on real measured signal in areas of interest.

Gudla and Kuda [22] presented an energy-efficient data collection approach, as well as a genetic algorithm. Identify the most energy-efficient and dependable data route in WSNs. This algorithm minimises the quantity of data transmissions, energy usage, network packet delivery latency, and network lifetime. Furthermore, simulation results confirmed the usefulness of the proposed strategy when energy consumption, network lifetime, number of data transmissions, and average delivery delay.

Ali et al [23] introduced a novel ARSH-FATI based Cluster Head Selection (ARSH-FATI-CHS) algorithm integrated with a heuristic termed Novel Ranked based Clustering (NRC) to reduce sensor node communication energy consumption while efficiently improving network LT. Unlike other population-based algorithms, ARSH-FATI-CHS dynamically shifts between exploration and exploitation of the search process during run-time to obtain a better performance-to-cost ratio and greatly increase network Life Time. During Cluster Heads (CHs) selection, ARSH-FATI-CHS takes into account residual energy, communication distance factors, and workload. To determine the performance of the WSN in terms of Life Time, ARSH-FATI-CHS is simulated and various results are generated. To demonstrate that the ARSH-FATI-CHS strategy enhances network LT by comparing our results to state-of-the-art Particle Swarm Optimisation (PSO).

## III. PROPOSED METHODOLOGY

The proposed methodology relies to detect the location node with the help of Improved Recurrent Neural Network (IRNN) [24]. Then effectively selects the Cluster Head (CH) to reduce the energy dissipation of sensor nodes using mutation Chicken Swarm optimization and leads to an extension of the network lifetime [25].

### 1.1. IMPROVED RECURRENT NEURAL NETWORK (IRNN):

This paper proposes an encoder-decoder model that combines the attention mechanism used in fund correlation prediction—improved RNN. Assuming that the predicted value of the fund correlation at time t is $y\hat{}t$, the predicted value $(x1, x2, \ldots, xt)$ is related to the value $(y1, y2, \ldots, yt-1)$ of each feature and to the output of the previous time step, which can be expressed as eq.1:

$$\widehat{y_t} = F([y_1, y_2, \ldots, y_{t-1};\ x_1, x_2, \ldots, x_t])$$

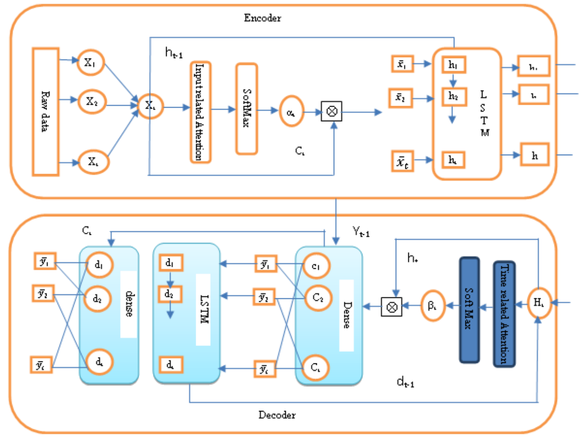

Fig. 2. Improved RNN model structure

The key difference between these model and other attention models is the simultaneous use of attention mechanisms in the encoder and decoder [26]. In the encoder, an attention-related attention mechanism is used for selecting a feature factor represented in Figure.2. In the decoder, a time-dependent attention mechanism is used to analyze the time dependence of the previous time step. In the encoder part, an attention-related attention mechanism is first used to obtain the attention value of the original fund data $x_t \in \mathbb{R}^m$ and the previous code vector $h_{t-1} \in R^n$:
As the Eq.2 and Eq.3:

$$z_t = \tanh(W_\alpha[x_t; h_{t-1}]) \quad (2)$$

$$\alpha_t = \exp(W_{z\alpha}^T \cdot z_t) \quad (3)$$

where $[x_t; h_{t-1}] \in \mathbb{R}^{m\times n}$ is the connection between the original fund data $x_t$ and the previous time step coding vector$h_{t-1}$, $W_\alpha$is the weight of the feedforward neural network, and $\alpha_t$ is the attention value. Then, the obtained attention value αt is used to rewrite the original input, obtaining the following eq.4:

$$\bar{X}_t = \sum_{i=1}^{t} \alpha_i x_i \quad (4)$$

$\bar{X}_t$ is the original fund data after using attention weighting. The LSTM network [27] is initialized using the previous time step coding vector $h_{t-1}$, and the weighted original fund data $\bar{X}_t$ are encoded using the LSTM network to obtain the code vector $h_t$ of the current time step in Eq.5:

$$h_t = LSTM(\bar{X}_t, h_{t-1}) \quad (5)$$

$$z'_t = \tanh\left(W_\beta [h_t; d_{t-1}]\right) \quad (6)$$

In the decoder section, the system uses another time-related attention mechanism to obtain the attention value of the encoding vector $h_t$ of the original fund data and the encoding vector $d_{t-1}$ of the correlation coefficient of the previous time step fund, namely as represented in Eq.6 and Eq.7:

$$\beta_t = \exp\left(W_{c\beta}.z'_t\right) \quad (7)$$

where $[h_t; d_{t-1}]$ is the connection between the original fund data encoding vector $h_t$ and the previous time step fund correlation coefficient encoding vector $d_{t-1}$, $W_\beta$ is the weight of the forward neural network, and $\beta_t$ is the attention value. $\beta_t$is used to rewrite the input code vector $h_t$ to obtain the context matrix of the original fund data $c_t$ in Eq.8:

$$c_t = \beta_t.h_t \quad (8)$$

The context matrix $c_t$ is the final encoded result of the original fund data $x_1, x_2, \dots, x_t$.

After the context matrix is obtained, the context vector $c_t$ can be concatenated with the previous time -phase fund correlation coefficient $y_{t-1}$ and encoded using a single- layer neural network describes as Eq.9:

$$\bar{y}_{t-1} = W_y[c_t; y_{t-1}] + b \quad (9)$$

Where $[c_t; y_{t-1}]$ is the connection of the context vector $c_t$ of the original fund data with the previous time phase fund correlation coefficient $y_{t-1}$, $\bar{y}_{t-1}$ is the coding result of the neural network, and $W_y$ and $b$ are the weights and offsets of the network, respectively. Then, using the previous time step encoding vector $d_{t-1}$ to initialize a layer of the LSTM network and encoding the $\bar{y}_{t-1}$ with the LSTM network, the encoding vector $d_t$ of the previous time step fund correlation coefficient $\bar{y}_{t-1}$ can be obtained as Eq.10:

$$d_t = LSTM\ (\bar{y}_{t-1}, d_{t-1}) \quad (10)$$

After obtaining the encoding result $c_t$ of the original fund data $(x_1, x_2, \dots, x_t)$ and the encoding result $d_t$of the fund correlation coefficient $(y_1, y_2, \dots\dots, y_{t-1})$, the formula is rewritten as Eq.11:

$$\hat{y}_t = F([c_t, d_t]) \quad (11)$$

Using a neural network model to fit the function F (,), the predicted value of the fund correlation coefficient $\hat{y}_t$ can be expressed as Eq.12:

$$\hat{y}_t = W_t[c_t, d_t] + b_t \quad (12)$$

Where $[c_t, d_t]$ is the connection of the context vector $c_t$ of the original fund data with the coding vector $d_t$ of the correlation coefficient of the previous time step fund, $W_t$ and $b_t$ are the weights and offsets of the neural network, and $\hat{y}_t$ is the predicted value of the correlation coefficient of the final fund.

### 3.2 CHICKEN SWARM OPTIMIZATION ALGORITHM:

The CSO simulate the chickens' movement and the behavior of the chicken swarm, the CSO can be described as follows [28]: In CSO there are many groups and each group consisting of a dominant rooster, a few of hens, and chicks. Roosters, hens, and chicks in the group are determined based on their fitness values. Roosters (group head) are the chicken that has the best fitness values. While chicks are the chickens that have the worst fitness values. The majority of the chickens would be the hens and they choose randomly which group to stay in. In fact, the mother-child relationship between the hens and the chicks is performed arbitrarily. The dominance relationship and mother-child relationship in a group will stay unaltered and updated every several (G) time steps. The flowchart of CSO is as shown in Figure 3. The movement of the chickens can be formulated below:

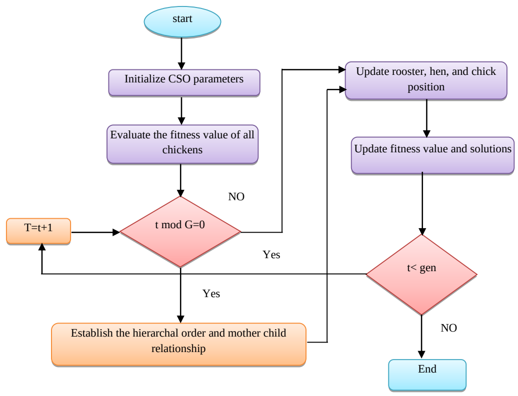


Figure.3. CSO Flow chart

1. The formula that used for the roosters' position update is given by Eq.13 and 14:

$$X_{i,j}^{t+1} = X_{i,j}^{t} * \left(1 + randn(0, \sigma^2)\right) \qquad (13)$$

Where

$$\sigma^2 = \begin{cases} 1 & if\ f_i \leq f_k \\ exp\left(\frac{f_k - f_i}{|f_i + \epsilon|}\right) & otherwise \end{cases} \qquad (14)$$

Where $k \in [1, N_r], k \neq i$ and $N_r$ is the number of selected roosters. $X_{i,j}$ represents the position of rooster number $i$ in $jth$ dimension during $t$ and $t+1$ iteration, $randn\ (0, \sigma^2)$ used to generate Gaussian random number with mean 0 and variance $\sigma^2$,ε is a constant with low value, and $f_i$ is the fitness value for the corresponding rooster $i$.

2. The formula that used for the hen's position update is given by Eq.15, Eq.16, Eq.17

$$X_{i,j}^{t+1} = X_{i,j}^{t} + S_1 randn\left(X_{r1,j}^{t} - X_{i,j}^{t}\right) + S_2 randn\left(X_{r2,j}^{t} - X_{i,j}^{t}\right) \qquad (15)$$

Where

$$S_1 = exp\left(\frac{f_i - f_{r1}}{|f_i| + \epsilon}\right) \qquad (16)$$

And

$$S_1 = exp(f_{r2} - f_i) \qquad (17)$$

Where, $r_1, r_2 \in [1, \dots, N], r_1 \neq r_2,\ r_1$ is the index of a rooster, while $r_2$ is a chicken from the swarm that can be a rooster or a hen and a uniform random number is generated by randn.

3. The formula that used for the chicks position update is given by Eq.18:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + FL\left(X_{m,j}^{t} - X_{i,j}^{t}\right), FL \in [0,2] \qquad (18)$$

Where, $X_{m,j}^{t}$ is the position of the $i^{th}$ chicks' mother. FL is a parameter which means the chick will follow its mother. The complete process is explained in Algorithm 1.

ALGORITHM 1- PSEUDO CODE FOR CSO
Define parameters such as population size (popSize), number of generations (gen), the number of roosters (Rn), the number of hens (Hn), the number of chicks (Cn) and the update time steps (G).
Step 1: Initialize the population of chicken as a matrix k;
Step 2: Calculate the fitness values for each row in k;
Step 3: While (t<gen);
Step 4: t=t+1;
Step 5: if (t % G==0)
Step 6: Divide k into three groups (rooster, hens and chicks) according to their fitness value
Step 7: else
Step 8: for i=1: k
Step 9: if (i= rooster); Update the position of rooster using Eq (4); end if
Step 10: if (i=hen); updates the position of hens using Eq (6); end if
Step 11: if (i=chick); updates the position of chick using Eq (9); end if
Step 12: Update the new solution of k
Step 13: end
Step 14: end

3.2.1. SYSTEM MODEL:
In this research work, the system model consists of a base station (BS) and the sensors (N) which maintains uniform distribution based random deployment in the coverage area. As so to enhance the network connectivity the network is filled with huge number of sensor nodes and are deployed inside the coverage area. The subsections and the hidden details of the network are described as follows.

- The network is totally static which includes the BS and the sensor nodes.

- At the initial stage, all nodes have equal initial energy.
- The BS has no energy limitations its computation energy extremely high.
- According to the coverage area and localization primary cluster head (PCH) and secondary cluster head (SCH) are chosen periodically.
- According to the transmission distance the energy is optimized by the nodes.
- In order to reduce the energy consumption, sleep and wake node concept is initiated in the network.
- Both the cluster heads are multi weighted which it maintains the variable energy level.
- The nodes have the capability to send their address details to its neighbor nodes in the network.
- The BS and PCH are placed within the transmission range in the network.

In general, one hop communication greatly affects the energy. So, p-jump is a better way. Here, the multi weight clustering will be discussed in this paper that uses load balancing in clusters in order to reduce the power consumption and to increase the energy efficiency of WSN.

### 3.2.2. ENERGY MODEL:

In our model two types of power loss is used which are free space power loss ($d^2$) and multipath fading power loss ($d^4$) and according to the transmission distance between the source and the sink the channel model is chosen [29]. In case if this distance is less than its threshold value ($d^{th}$), then it employs the free space model as a channel model or else the multipath fading model is chosen as a channel model. The energy utilization of the data based on the distance factor is mathematically given as follows as Eq.19:

$$E_{TX}(l,d) = \begin{cases} l \times E_{energy} + l \times E_{tm} \times d^2, if\ d \le d_{th} \\ l \times E_{energy} + l \times E_{am} \times d^4, if\ d > d_{th} \end{cases} \quad (19)$$

where $E_{energy}$ is a total dissipated energy of the circuit per bit, $E_{tm}$ and $E_{am}$ are the transmitter and amplifier model of the network, and $d_{th}$ is the threshold distance of the network and it is given as below in Eq.20:

$$d_{th} = \sqrt{\frac{E_{tm}}{E_{am}}} \quad (20)$$

The energy utilization of the sink is given in Eq.21:

$$E_{RX}(l) = l * Energy \quad (21)$$

### 3.2.3. ENERGY CONSUMPTION MODEL:

The energy consumption model is explained in the figure.4:

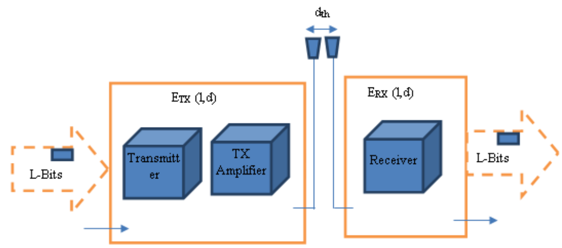


Figure.4. Energy Consumption Model

The consumed energy [30] of the transmitting node of l bits data to cluster head is mathematically expressed in Equations (22)

$$E_{non-CH} = l * E_{energy} + l * E_{tm} d_{cn-CH}^2 \quad (22)$$

Where $d_{cn-CH} = child\ node\ to\ CH\ distance$

ALGORITHM 2: CLUSTER HEAD ELECTION PHASE ALGORITHM
Input: K number of CHs, CSO parameters
Output: The indices list that includes the indices of the nodes that work as CHs.
1: Initialize the matrix X that represents population by random values from 0 to 1.
2: Repair the infeasible solutions that do not has K number of CH.
3: For each row of X, calculates the fitness value.
4: bestX= the row in X which has the corresponding to best fitness value.
5: for t=1 to t_max do
6: if (t%G==0||t==1) then
7: All the fitness values taken in the ascending order.
8: Divide X into three categories (rooster, hens, and chicks)
9: end if
10: for each row y in X do
11: if y represents a rooster then
12: Using Eq.3, update y values.
13: end if
14: if y represents a hen then
15: using Eq.4, update y values
16: end if
17: if y represents a chick then
18: using Eq.7, update y values
19: end if

20: transform y to its binary representation b using equation 13
21: Repair the infeasible solutions that do not has K number of CH.
22: update the fitness values for each row of X.
23: if a new solution is better than the previous one, update best X with the new best solution.
24: end for
25: end for

Now the consumed energy of the cluster head CH is expressed in Eq.23

$$E_{CH} = \left(l\left(\frac{n}{c} - 1\right) * E_{energy} + \frac{n}{c} * E_{con}\right) + E_{RX}(l, d) + E_{TX}(l, d_{CH-BS}) \quad (23)$$

Where $n$ is the number of alive nodes in the network, $c$ the number of clusters in the network $E_{RX}$ is the energy consumption of the cluster head, and $d_{CH-BS}$ is the base station to cluster head distance.

## IV. RESULTS AND DISCUSSION

In this section, the CSO algorithm's parameters are analyzed. Then CSO-CH are evaluated in terms of network lifetime and consumed energy against other algorithms. All experiments are conducted using MATLAB R2016b. Besides, we consider 100 nodes are randomly scattered in the region of size 100 × 100 meters square with BS at the corner, and with simulation setting provided in Table 2.

Table 2: Simulation Setting

| Parameter | Value |
|---|---|
| Network area size | 100×100 |
| Nodes | 160 |
| Initial Energy | 0.5 J |
| $E_{else}$ | 50 nJ/bit |
| Free space ε $f_s$ | 10 pJ/bit/m$^2$ |
| Multi-path $ε_m$ p | 0.00013 pJ/bit/m$^4$ |
| Do | 87m |
| $E_{DA}$ | 5 nJ/bit/signal |
| Packet size | 4000 bits |
| Percentage of CH | 0.05 |

The Performance evaluation parameters considered for comparison are: packet delivery ratio, Energy Consumption, Network Lifetime, Localization Error.

1. PACKET DELIVERY RATIO:
Packet delivery ratio measures the ratio of successfully received packets at sink to the total number of packets sent by the sources. It is calculated as eq.24:

$$PDR = \frac{number\ of\ packets\ received\ at\ sink}{total\ number\ of\ packets\ sent} \quad (24)$$

2. ENERGY CONSUMPTION:
The energy consumption measures the average energy dissipated by the node in order to transmit a data packet from the source to the sink. The same metric is used in [1] to determine the energy efficiency level of WSNs. It is calculated as follows as Eq.25:

$$PDR = \frac{number\ of\ packets\ received\ at\ sink}{total\ number\ of\ packets\ sent} \quad (25)$$

3. NETWORK LIFE TIME:
Network lifetime is the total number of rounds of the mobile sink before first node runs out of its energy

4. LOCALIZATION ERROR:
The error that presents due to the error in estimated distance during localization the unknown nodes.

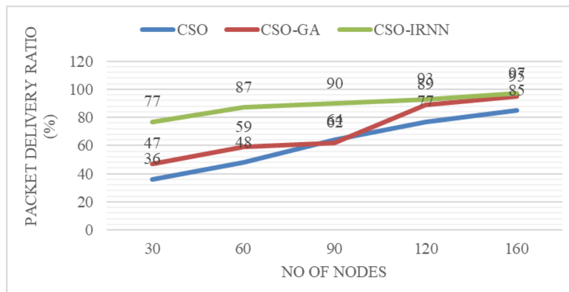


Figure Packet Delivery Ratio Results

Figure 7 displays the contrast of packet delivery ratio recital Chicken Swarm Optimization (CSO), Chicken Swarm Optimization – Genetic Algorithm (CSO-GA), Chicken Swarm Optimization -Improved Recurrent Neural Network (CSO-IRNN) grounded routing. The nodes are changing from 30 to 160 and packet delivery ratio is planned for certain nodes per seconds. From the graph it is vibrant that the CSO grounded routing due to the assortment of optimal path outdoes the other replicas with great packet delivery ratio. The proposed algorithm, reach 97(%), compare with existing algorithm reach 85(%),95(%) respectively.

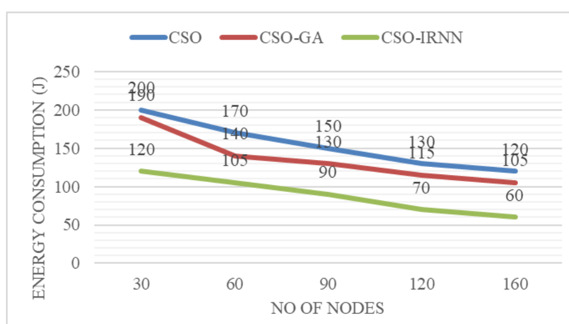


Figure Energy Consumption Results

Figure 7 displays the contrast of Energy Consumption recital Chicken Swarm Optimization (CSO), Chicken Swarm Optimization – Genetic Algorithm (CSO-GA), Chicken Swarm Optimization -Improved Recurrent Neural Network (CSO-IRNN) grounded routing. The nodes are changing from 30 to 160 and energy consumption is planned for certain nodes per seconds. From the graph it is vibrant that the CSO grounded routing due to the assortment of optimal path outdoes the other replicas with great energy consumption. The proposed algorithm, reach 120 (J), compare with existing algorithm reach 60(J),105(J) respectively.

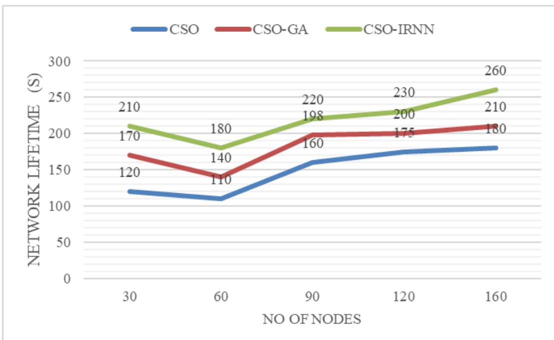


Figure Network Life Time Results

Figure 7 displays the contrast of Network Life time recital Chicken Swarm Optimization (CSO), Chicken Swarm Optimization – Genetic Algorithm (CSO-GA), Chicken Swarm Optimization -Improved Recurrent Neural Network (CSO-IRNN) grounded routing. The nodes are changing from 30 to 160 and life time is planned for certain nodes per seconds. From the graph it is vibrant that the ANFIS grounded routing due to the assortment of optimal path outdoes the other replicas with great life time. The proposed algorithm, reach 260(s), compare with existing algorithm reach 180(s),210(s) respectively.

## CONCLUSION

As a result, now that WSN is being utilised for a variety of purposes, energy consumption is always a concern. Improving energy efficiency is a main focus of our study in order to extend the network's life. They proposed an Improved Recurrent Neural Network (IRNN), in which the localization algorithm must detect the location of nodes with unknown positions, and the mechanism effectively selects the next elected cluster Head (CH) to reduce the energy dissipation of sensor nodes using mutation chicken swarm optimisation, resulting in a network lifetime extension. The distance parameters between different types of nodes in the network are then used to construct an effective fitness function. Among the criteria are the distance between the sending and receiving nodes, the distance from the next hop to the base station, and the number of hops. Finally, simulation analysis is utilised to validate the effectiveness of the strategy. Finally, the simulation experiment is used to test our method, and the findings indicate that the routing strategy given in this study performs better. In the future, when balancing energy between paths and relay nodes in both static and mobile scenarios, we will incorporate Quality of Service (QoS) attributes.

## REFERENCES

[1] Adu-Manu KS, Adam N, Tapparello C, Ayatollahi H, Heinzelman W (2018) Energy-harvesting wireless sensor networks (EHWSNs): A review. ACM Trans Sensor Networks (TOSN) 14(2):10.

[2] Yue YG, He P (2018) A comprehensive survey on the reliability of mobile wireless sensor networks: Taxonomy, challenges, and future directions. Information Fusion 44:188–204.

[3] Yousefpoor MS, Barati H (2019) Dynamic key management algorithms in wireless sensor networks: A survey. Comput Commun 134:52–69.

[4] Fanian F, Rafsanjani MK (2019) Cluster-based routing protocols in wireless sensor networks: A survey based on methodology. Journal of Network and Computer Applications.

[5] Kandris, D., Nakas, C., Vomvas, D. and Koulouras, G., 2020. Applications of wireless sensor networks: an up-to-date survey. Applied system innovation, 3(1), p.14.

[6] Hatamian M, Barati H, Movaghar A, Naghizadeh A (2016) CGC: Centralized genetic-based clustering protocol for wireless sensor networks using onion approach. Telecommunication systems 62(4):657–674.

[7] Al Aghbari, Z., Khedr, A.M., Osamy, W., Arif, I. and Agrawal, D.P., 2020. Routing in wireless sensor networks using optimization techniques: A survey. Wireless Personal Communications, 111, pp.2407-2434.

[8] Sumathi, J. and Velusamy, R.L., 2021. A review on distributed cluster-based routing approaches in mobile wireless sensor networks. Journal of Ambient Intelligence and Humanized Computing, 12, pp.835-849.

[9] Naghibi M, Barati H (2020) EGRPM: Energy efficient geographic routing protocol based on mobile sink in wireless sensor networks. Sustainable Computing: Informatics and Systems 25:100377.

[10] Verma S, Sood N, Sharma AK (2019) A novelistic approach for energy efficient routing using single and multiple data sinks in heterogeneous wireless sensor network. Peer-to-Peer Netw Appl 12:1110–1136.

[11] Sangeetha G, Vijayalakshmi M, Ganapathy S et al (2020) An improved congestion-aware routing mechanism in sensor networks using fuzzy rule sets. Peer-to-peer Netw Appl 13:890– 904.

[12] Guo, J., Karimi-Bidhendi, S. and Jafarkhani, H., 2020, June. Energy-efficient node deployment in wireless ad-hoc sensor networks. In ICC 2020-2020 IEEE International Conference on Communications (ICC) (pp. 1-6). IEEE.

[13] Aljubayri, M., Peng, T. and Shikh-Bahaei, M., 2021. Reduce delay of multipath TCP in IoT networks. Wireless Networks, 27, pp.4189-4198.

[14] Goyat, R., Rai, M.K., Kumar, G., Saha, R. and Kim, T.H., 2019. Energy efficient range-free localization algorithm for wireless sensor networks. Sensors, 19(16), p.3603.

[15] Kagi, S. and Mathapati, B.S., 2022. Optimal Trained Deep Neural Network for Localization in Wireless Sensor Network. International Journal of Computational Methods, 19(08), p.2142006.

[16] Chen, J., Sackey, S.H., Anajemba, J.H., Zhang, X. and He, Y., 2021. Energy-efficient clustering and localization technique using genetic algorithm in wireless sensor networks. Complexity, 2021, pp.1-12.

[17] Hallawa, A., Schlupkothen, S., Iacca, G. and Ascheid, G., 2017, July. Energy-efficient environment mapping via evolutionary algorithm optimized multi-agent localization. In Proceedings of the Genetic and Evolutionary Computation Conference Companion (pp. 1721-1726).

[18] Nain, M. and Goyal, N., 2022. Energy efficient localization through node mobility and propagation delay prediction in underwater wireless sensor network. Wireless Personal Communications, 122(3), pp.2667-2685.

[19] Umashankar, M.L., Anitha, T.N. and Mallikarjunaswamy, S., 2021. An efficient hybrid model for cluster head selection to optimize wireless sensor network using simulated annealing algorithm. Indian Journal of Science and Technology, 14(3), pp.270-288.

[20] Kaviarasan, S. and Srinivasan, R., 2023. Energy Efficient Based Optimized K-Means and Modified Whale Optimization Algorithm For Cluster Head Selection in WSN. Journal of Theoretical and Applied Information Technology, 101(1), pp.61-71.

[21] Poggi, B., Babatounde, C., Vittori, E. and Antoine-Santoni, T., 2022. Efficient WSN Node Placement by Coupling KNN Machine Learning for Signal Estimations and I-HBIA Metaheuristic Algorithm for Node Position Optimization. Sensors, 22(24), p.9927.

[22] Gudla, S. and Kuda, N., 2023. A reliable routing mechanism with energy-efficient node selection for data transmission using a genetic algorithm in wireless sensor network. Facta Universitatis, Series: Electronics and Energetics, 36(2), pp.209-226.

[23] Ali, H., Tariq, U.U., Hussain, M., Lu, L., Panneerselvam, J. and Zhai, X., 2020. ARSH-FATI: A novel metaheuristic for cluster head selection in wireless sensor networks. IEEE Systems Journal, 15(2), pp.2386-2397.

[24] Hu, G., Ye, Y., Zhang, Y. and Hossain, M.S., 2019, December. Improved recurrent neural networks (rnn) based intelligent fund transaction model. In 2019 IEEE Globecom Workshops (GC Wkshps) (pp. 1-6). IEEE.

[25] Osamy, W., El-Sawy, A.A. and Salim, A., 2020. CSOCA: Chicken swarm optimization-based clustering algorithm for wireless sensor networks. IEEE Access, 8, pp.60676-60688.

[26] S. Kiyono, S. Takase, J. Suzuki, N. Okazaki, K. Inui, and M. Nagata, “Unsupervised token-wise alignment to improve interpretation of encoder-decoder models,” in Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pp. 74–81, 2018.

[27] Mohanty, S.N., Lydia, E.L., Elhoseny, M., Al Otaibi, M.M.G. and Shankar, K., 2020. Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks. Physical Communication, 40, p.101097.

[28] Li, Y., Wang, S. and Han, M., 2019. Truss structure optimization based on improved chicken swarm optimization algorithm. Advances in Civil Engineering, 2019, pp.1-16.

[29] Del-Valle-Soto, C., Mex-Perera, C., Nolazco-Flores, J.A., Velázquez, R. and Rossa-Sierra, A., 2020. Wireless sensor network energy model and its use in the optimization of routing protocols. Energies, 13(3), p.728.

[30] Daanoune, I., Baghdad, A. and Ballouk, A., 2020. An enhanced energy-efficient routing protocol for wireless sensor network. International Journal of Electrical & Computer Engineering (2088-8708), 10(5).