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GENERATIVE AI-DRIVEN ELITIST RESOURCE OPTIMIZED DATA TRANSMISSION IN WSN

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Abstract

Wireless Sensor Networks (WSNs) consist of spatially distributed sensor nodes that communicate wirelessly. In this paper, a novel Generative AI driven Multi-objective Elitist Horse herd Optimization (GAI-MEHO) technique is proposed for resource efficient data transmission in WSN. The main aim of GAI-MEHO technique is to achieve high data transfer with minimal delay. The proposed GAI-MEHO technique includes two processes namely resource efficient sensor node selection and optimal route path discovery. First, GAI-MEHO technique employs a Generative AI model to examine multiple resources of sensor nodes such as residual energy, bandwidth and memory. Based on analysis, resource efficient sensor nodes are classified. After the multiple route paths are established between the sensor nodes. Followed by optimal route path discovery with minimal distance and better link connectivity is identified using Multi-objective elitist horse herd algorithm. Finally, data forwarding is carried out from the source node to the sink or base station through the optimal route path. Experimental evaluation of GAI-MEHO technique is conducted on factors such as energy drain rate, success rate, jitter, data transfer rate and average hop count.

Keywords:

Wireless Sensor Networks, Resource Efficient Data Transmission, Generative AI Model, Deep Belief Neural Networks, Segmented Regression, Optimal Route Path Discovery

1. INTRODUCTION

An energy-efficient routing approach combining a fuzzy neural network and the Combined Random Sampling Prevosti Bat Optimization algorithm was proposed in [1], aiming to improve routing performance by minimizing delay and loss while increasing throughput. However, the method did not consider the less hop count to minimize the jitter. A Federated Deep Reinforcement Learning (FDRL) model was developed in [2] for routing the high-speed data packets with minimal latency and high energy efficiency. The designed FDRL optimizes resource utilization and enhances network efficiency. However, approach failed to address the challenges related to data routing in dynamic and resource constrained environments.

A Machine Learning-based Energy Optimization Approach (ML-EOA) was designed in [3] to enhance the data transmission efficiency by increasing the data delivery ratio and minimizing the delay. However, the computational time of the data transmission was not reduced.

An integration of hybrid optimization with fuzzy neural networks were developed in [4] for efficient data transmission by minimizing the latency and stabilizing energy consumption. However, the technique did not address bandwidth availability-aware data transmission to minimize packet loss rate. Enhanced deep Q-network (EDQN) algorithm with hippopotamus optimization (HO) was developed in [5] with the aim of increasing the coverage rate by minimizing the energy consumption. But it failed to handle large-scale routing challenges in sensor networks. An energy optimization routing was carried out in [6] using improved artificial bee colony (EOR-iABC) for cluster based WSN. But, the hybrid energy saving algorithm was not used to optimize and balance CH selection through mobile sink.

An energy efficient multi-hop routing in WSN termed Taylor based Cat Salp Swarm Algorithm (Taylor C-SSA) was introduced in [7] through changing the C-SSA with Taylor series. An energy-saving routing was carried out in [8] with Adaptive Black hole Tuna Swarm Optimization (ABTSO). ABTSO method reduced the delay and increased the network lifetime. Tree-Based Forwarding Routing (TBFR) was introduced in [9] to transmit the data packets to the destination through shortest reliable path. Multi-Route Clustering Protocol Using Timeslot Transmission (MRCP-TTDPS) was introduced in [10] for path selection.

An energy-efficient anchor zone-based routing (EAZR) protocol was introduced in [11] through different anchor zone nodes. EAZR protocol partitioned the traffic among multiple nodes with minimum energy consumption. A novel geometrical-based energy-efficient routing protocol termed EVRP was introduced in [12] for cluster head selection. An energy-efficient RPL routing was introduced in [13] with optimal parent selection model. The optimal parent selection was carried out with delay, energy, link quality (LQ) and distance. A new location-aware geographic routing protocol was designed in [14] depending on Q-learning for path planning. Node Grade Factor (NGF)-centered node-disjoint multi-path routing technique was introduced in [15] for energy-efficient route selection.

1.1 NOVEL CONTRIBUTION

The major issues reviewed by the above-said existing methods are overcome by introducing the GAI-MEHO technique. The main contribution of the GAI-MEHO technique is listed as given below,

- A novel GAI-MEHO technique is introduced for improving resource efficient data transmission in WSN by including different processes sensor node classification and optimal route path selection.
- To minimize the energy drain rate and extend the network lifetime, Generative AI model includes deep belief neural networks is employed to classify the nodes based on their energy, bandwidth and memory. The segmented regression analysis these factors and provides the resource efficient and inefficient sensor nodes. These nodes are more effective for successful data delivery from source to destination.
- To minimize the jitter and increase the data transfer rate, Multi-objective elitist horse herd algorithm is applied for selecting an optimal path selection with better link

connectivity and minimal distance, less hop counts to transmit the data effectively.

- Finally, an extensive simulation is carried out to estimate the performance of our GAI-MEHO technique and other related works.

2. RELATED WORKS

Hybrid Whale-Ant Optimization Algorithm (WAOA) was introduced in [16] for energy-efficient routing in WSNs. Energy efficient scalable routing algorithm was designed in [17] depending on Hierarchical Agglomerative Clustering (ESR-HAC) for WSNs. Particle Swarm Optimization and Q-learning based Congestion Aware and Energy Efficient Routing (PSO-QLR) was designed in [18] to reduce the energy consumption and delay. Hybrid path finder-based vortex search (HPF-VS) algorithm was introduced in [19] for cluster head selection. HPF-VS algorithm was used for node location optimization with minimum energy. An improved dual-phased framework was designed in [20] for energy-efficient cluster based routing in WSNs. The designed framework addressed energy consumption issues with better network performance.

A clustering and routing algorithm was introduced in [21] depending on energy-balanced path tree for WSNs. EBPT-CRA increased the network lifetime and throughput in WSNs. A new clustering routing protocol was introduced in [22] for addressing the Traveling Salesman Problem to identify the optimal path with increased QoS efficiency. A route selection scheme was introduced in [23] to improve the reliability and data sensitivity. The node reliability was determined through evidence theory for data forwarding.

A Stacked Auto Encoder and Probabilistic Neural Network (SAEPNN) was presented in [24] to address energy consumption issues. Transfer learning technique was developed in [25] to improve the network lifetime in WSN. New energy efficient management approach was designed in [26] to optimize energy consumption in wireless sensor networks for mobile target-tracking applications. But, the time complexity was not minimized. A hybrid approach was designed in [27] with artificial bee colony (ABC) and ant colony optimization (ACO). An energy efficient fusing data gathering (EEFDG) protocol was introduced in [28] through distributed clustering and data fusion for WSN. An energy-conscious routing method was introduced in [29] to reduce the energy consumption and to increase network lifetime through clustering probability. A route selection scheme was introduced in [30] to improve the reliability score and data sensitivity.

3. METHODOLOGY

Wireless Sensor Networks (WSNs) comprise the sensor nodes with processors, battery module and wireless communication devices. The nodes gather the environmental information and send to the base station for efficient processing. WSNs are dynamic networks to enhance the capacity for processing and data transmission. Resource efficient data transmission remains a key issue in WSN. In order to address these issues, GAI-MEHO technique is introduced for finding the resource efficient sensor nodes and optimal route path discovery. Figure 1 illustrates the architecture diagram of GAI-MEHO technique for resource efficient data transmission in WSN. The GAI-MEHO techniqueinvolves two main steps namely resource efficient node selection, and optimal route path discovery. First, the number of sensor nodes is randomly distributed in the wireless network. Then the resource efficient node selection process is employed using Generative AI model to choose the sensor nodes from the network.Next, optimal route path is distinguished to ensure the proposed model utilizing the multi-objective elitist horse herd algorithm. These major processes of the proposed GAI-MEHO technique are described in the following sections.

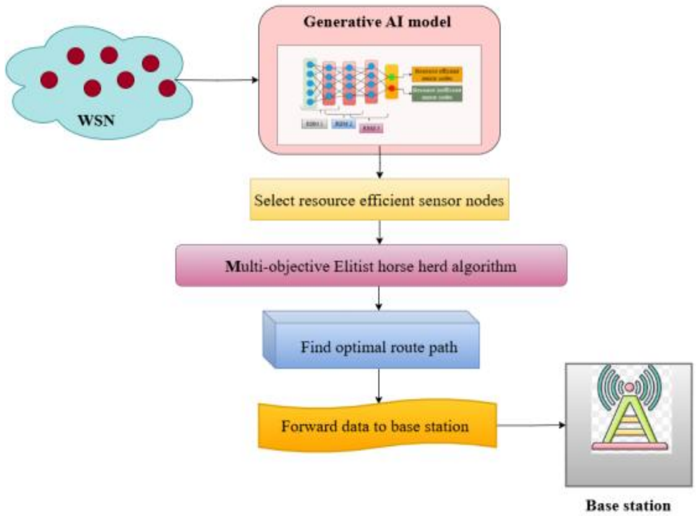

Fig.1. Architecture Diagram of GAI-MEHO technique

3.1 NETWORK MODEL

In this section, the network model of the proposed GAI-MEHO technique is presented. A WSN represented by a graph 'G=(V,E)' where 'V' denotes a sensor node $sn_i = sn_1, sn_2, sn_3,\ldots,sn_n$ and 'E' denotes a set of edges i.e. links between the sensor nodes. In WSN, the sink node or base station 'BS' act as aggregator node located in the deployment area. The source node (SN) transmits the sensed information or data packets D_1, D_2, $D_3,\ldots D_m$ to aggregator through the resource efficient sensor node and optimal route path. Here the aggregator node acts as a data collector to gather the data from the other resource efficient sensor nodes in the network.

3.2 GENERATIVE AI BASED CLASSIFICATION MODEL

The first process of GAI-MEHO technique is a resource efficient sensor node selection to extend the lifespan of the network. This contribution is achieved through the Generative AI model. Generative AI refers to artificial intelligence systems that provide novel outputs, making it useful for a wide range of innovative and analytical applications. In GAI-MEHO, Generative AI is modeled using a Deep Belief Neural Network, a type of generative graphical model capable of learning complex patterns from a large volume of input data simultaneously. The structure of Deep Belief Neural Network is shown in Fig.2. The Fig.2 shows the basic structure of a deep belief neural network for performing the classification of sensor nodes in WSN. A Deep Belief Network (DBN) utilizes the Restricted Boltzmann

Machines (RBMs), which are probabilistic neural networks composed of two primary layers such as the visible layer and the hidden layer. The visible layer takes in the input, while the hidden layer is responsible for learning the given input. Neurons in the visible layer are fully connected to those in the adjacent hidden layer, but they are connected between the layers.

As shown in Fig.2, the network architecture incorporates Restricted Boltzmann Machines (RBMs), each assigned to a specific function. The hidden layer of the RBM is used to RBM measure the resources of sensor nodes. Then it performs classification by using the estimated resources to accurately assign input data to categories, such as resource efficient sensor or resource inefficient sensor nodes. The output from each RBM layer serves as the input for the next layer, creating a hierarchical structure that facilitates efficient learning.

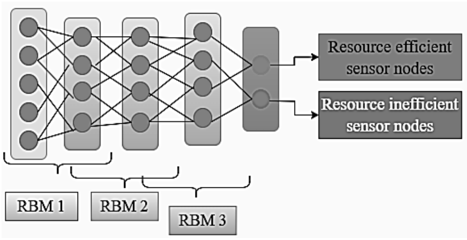

Fig.2. Structure of Deep Belief Network

Let us consider the number of sensor nodes $sn_i = sn_1, sn_2, sn_3,\ldots,sn_n$ are given to the input visible layer. The neuron in input layer is associated with a weight and included with bias 'b'. The activation probability of a neuron in the input visible layer is represented as follows,

$$Pr = A\left(\sum_{i=1}^{n} sn_i \cdot wt_i\right) + b \tag{1}$$

$$Pr_H = A\left(\sum_{i=1}^{n} sn_i \cdot wt_{ih}\right) + b \tag{2}$$

$$R(sn_i) = \{E_{Res}(sn_i), BW(sn_i), MA(sn_i)\} \tag{3}$$

Initially, all sensor nodes have same energy level. The total energy of sensor node is determined as,

$$E_C(sn_i) = E_{TX}(sn_i) + E_{RX}(sn_i) \tag{4}$$

$$E_{TX}(sn_i) = \left(E_{el(Trans)} \cdot K\right) + \left(E_{amp} \cdot DS_{Trans} \cdot D^2\right) \tag{5}$$

$$E_{RX}(sn_i) = E_{el(rec)} \cdot K_{RX} \tag{6}$$

$$E_{Res}(sn_i) = E_{TL}(sn_i) - E_C(sn_i) \tag{7}$$

The bandwidth of sensor denotes the amount of data sent over wireless network in particular time period. It is computed in terms of bits per second (bps), kilobits per second (kbps), megabits per second (Mbps) or gigabits per second (Gbps). It is formulated as,

$$BW(sn_i) = \frac{DP_{max}}{T(s)} \tag{8}$$

From Eq.(7), '$BW(SN_i)$' denotes a bandwidth of a sensor node. 'DP_{max}' symbolizes the maximum amount of data packets transferred over the network. '$T(s)$' denotes the time period in seconds.

$$MA(sn_i) = MT(sn_i) - MC(sn_i) \tag{9}$$

$$RI(sn_i) = \beta_1 \cdot R(sn_i) + c_1, \quad \text{if } R(sn_i) < T \tag{10}$$

$$RE(sn_i) = \beta_2 \cdot R(sn_i) + c_2, \quad \text{if } R(sn_i) > T \tag{11}$$

$$Y = A\left[w_{ho} \cdot h_t\right] \tag{12}$$

Input: Number of sensor nodes: $sn_i = sn_1, sn_2, sn_3,\ldots,sn_n$
Output: Classify the resource efficient sensor nodes
Begin
Step 1: Collect number of sensor nodes $sn_i = sn_1, sn_2, sn_3,\ldots,sn_n$ at the input layer
Step 2: For each sensor node sn_i
Step 3:Measure the neuron activation probability using Eq.(1) and Eq.(2)
Step 4: End for
Step 5: For each sensor node sn_i - Hidden layers
Step 6: Compute multiple resources using Eq.(3)
Step 7: Measure residual energy using Eq.(7)
Step 8: Measure bandwidth using Eq.(8)
Step 9: Measure memory availability using Eq.(9)
Step 10: Formulate segmented regression with resources using Eq.(10) and Eq.(11)
Step 11: End for
Step 12: Apply sigmoid activation function - output layer
Step 13: If (A=1) then
Step 14: sensor nodes are classified as resource efficient
Step 15: else if (A=0) then
Step 16: sensor nodes are classified as resource inefficient
Step 17: End if
End

3.3 MULTI-OBJECTIVE ELITIST HORSE HERD OPTIMIZATION TECHNIQUE

In this section, optimal route path is determined among the resource efficient sensor nodes to enhance the data transmission efficiency from source to base station in WSN. First, the multiple available route paths between the resource efficient sensor nodes and the base station are determined through beacon message broadcasting. In GAI-MEHO technique, the Zone based routing protocol is employed for selecting the most appropriate route from source to base station.

The source node (S) originates a request beacon ($reqb$) message to border nodes. Upon receiving the $reqb$ message, each border node rebroadcasts the $reqb$ message to its border nodes until reaches the destination end.

$$S \overset{reqb}{\Rightarrow} \sum_{h=1}^{r} (Bn_h \overset{reqb}{\Rightarrow} BS) \tag{13}$$

where, source node (S) transmits a request beacon '$reqb$' to the border node Bn_h to construct the route paths between the source and base station 'BS'.

$$BS \overset{repb}{\Rightarrow} \sum_{h=1}^{r} (Bn_h \overset{repb}{\Rightarrow} S) \tag{14}$$

Initialize the population of the horses (i.e. number of available route paths) in search space i.e. network.

$$RP_k = \{RP_1, RP_2, RP_3, \ldots, RP_k\} \tag{15}$$

Let us consider the coordinates source node (x_1,y_1) and the coordinates of destination node (x_2,y_2) in two dimensional spaces.

Therefore, the distance 'D' between the source and base station are computed as follows,

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{16}$$

The metric is mathematically formulated as follows,

$$RSSI_{rp} = TSSI_N \cdot g_t \cdot g_r \cdot \left(\frac{\lambda}{4\pi d}\right)^2 \tag{17}$$

where, '$RSSI_{rp}$' represent the received signal strength, '$TSSI_N$' represent the transmitted signal strength, 'g_t' and 'g_r' denotes the gain of transmitter and receiver antenna. 'λ' represent the wavelength of the signal, 'd' represent the distance between transmitter and receiver. Therefore, the fitness is measured with set of criterion as follows,

$$f = (d_{min} \wedge RSSI_{rp} > T_{RSS}) \tag{18}$$

where f denotes a fitness of the route path, T_{RSS} denotes a threshold for received signal strength, min_d indicates the minimum distance respectively.

$$Q = \begin{cases} f(RP_k) > f(RP_l), & \text{select best } RP_k \\ \text{otherwise}, & \text{select best } RP_l \end{cases} \tag{19}$$

where, Q denotes an Elitist selection result, $f(RP_k)$ denotes a fitness of the path 'k' $f(RP_1)$ denotes a fitness of route path 'l'. As a result, the fitness route path $f(RP_k)$ is higher than the fitness of other paths $f(RP_1)$. Therefore, the route path $f(RP_k)$ is selected as current best than the others in the populations. The current best horse is chosen as leader 'L' in their herd.

$$L = f(RP_k) \tag{20}$$

After selecting the current best as a leader, different behaviors such as exploration and exploitation of the horse are executed.

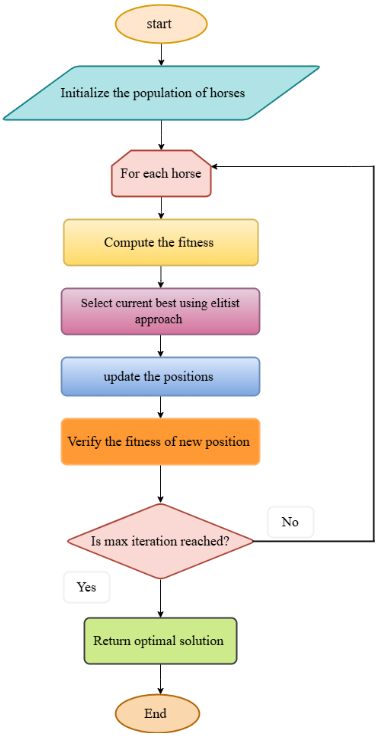

Fig.3. Flowchart of Multi-Objective Elitist Horse Herd Optimization

Algorithm 2: Multi-objective Elitist Horse herd Optimization technique

Input: Number of route paths RP_k=RP_1,RP_2,RP_3….RP_k, data packets DP_j∈DP_1,DP_2,,…DP_m

Output: Select optimal route path

Begin

Step 1:Initialize the random number H_1,H_2 ∈(0,1), maximum iteration 't_{max}'

Step 2: **Initialize the population of** route paths RP_k= RP_1, RP_2, RP_3….RP_k

Step 3:For each route path 'RP_N'

Step 4. Calculate multiple objective functions using Eq.(16) - Eq.(17)

Step 5. Evaluate the fitness using Eq.(18)

Step 6. End for

Step 7. **if** ($f(RP_k)$>$f(RP_l)$) then

Step 8: Select the current best 'P_{best}^t' using Eq.(19)

Step 9: End if

Step 10: While (t<t_{max}) **do**

Step 11: for each route path 'RP_k' in population **do**

Step 12: if the exploration phase then

Step 13: Update the positions 'P_i^{t+1}'

Step 14. Else if exploitation phase then

Step 15: Update the positions 'P_i^{t+1}'

Step16: End if

Step 17. **End for**

Step 18: Evaluate fitness 'f' for updated positions 'P_i^{t+1}'

Step 19: if $f\left(P_i^{t+1}\right) > f\left(P_{\text{best}}^{t}\right)$ **then**

Step 20: P_i^{t+1} considered as best optimal solution or optimal route path

Step 21:else

Step 22: P_{best}^t considered as optimal solution or optimal route path

Step 23: End if

Step 24: Increment t= t+1

Step 25: Go to step 10

Step 26: **End While**

Step 27: Return optimal route path

Step 28: Forward data packets DP_j to BS or sink node

End

4. SIMULATION SETTINGS

For simulation environment, 500 sensor nodes are deployed in the square dimension (1100 m* 1100 m) for resource efficient data forwarding in simulation environment. The random waypoint model is used as mobility model. In simulation scenario, Bordercast Resolution Protocol (BRP) is employed for performing the resource-efficient data transmission in WSN. BRP is a component of the Zone Routing Protocol which is a hybrid that combines proactive and reactive routing approaches.

Table.1. Simulation Parameters

Parameter	Value
Simulator	NS3
Number of sensor nodes	50, 100, 150, 200, 250, 300, 350,400,500

Initial energy of node	0.5 Joule
Network area	1100m * 1100m
Simulation time	300s
Mobility model	Random Way Point
Routing protocol	BRP
Sensor nodes speed	0-20m/s.
Data packets	100,200,300,400,500, 600,700,800,900,1000
Number of runs	10

4.1 DISCUSSION AND IMPLICATIONS

This section provides a detailed explanation of the various stages involved in the EALC GAI-MEHO technique. Initially, 50 sensor nodes are randomly distributed within a 1100×100 m² area, as depicted in Fig.4.

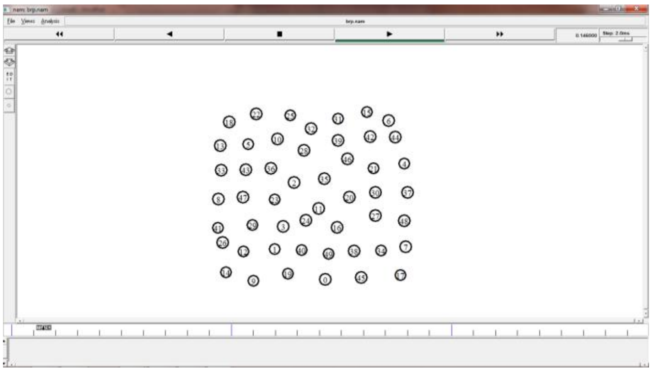

Fig.4. Sensor Node Deployments

A Generative AI model is employed to evaluate multiple resource parameters of sensor nodes, including residual energy, bandwidth, and memory. Based on this analysis, the sensor nodes are classified according to their resource efficiency as shown in Fig.6.

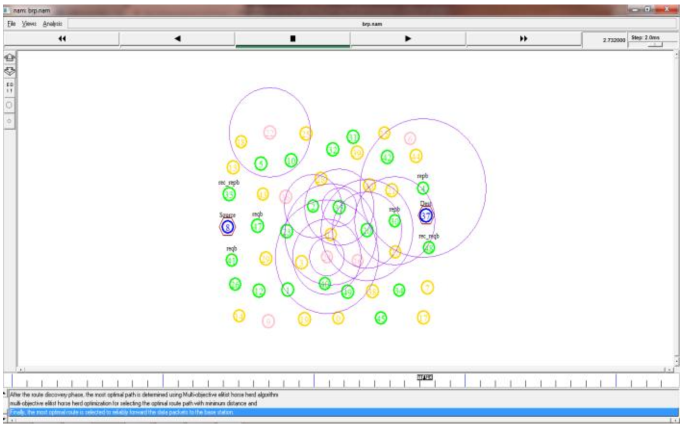

Fig.5. Multiple Route Paths

The Fig.5 illustrates the multiple route paths are established between the source and destination through the request and response beacon message distribution. From the figure, three possible route paths are identified between the source and destination, represented in green.

Fig.6. Optimal Route Path Discovery

The Fig.6 illustrates the optimal route path discovery using multi-objective elitist horse herd algorithm for selecting the most efficient communication path between a source and destination node in a WSN, represented in pink colored round.

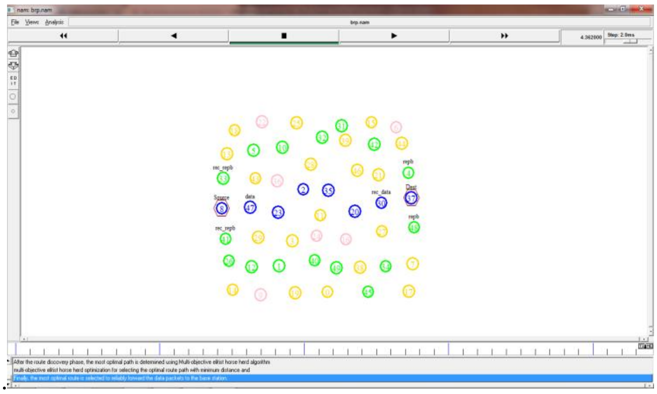

Fig.7.Data Transmission via Optimal Route Path

Once the optimal route path is discovered, data transmission is carried out through this selected path to ensure efficient and reliable communication between the source and destination nodes.

5. PERFORMANCE COMPARISON ANALYSIS

The performance of the proposed GAI-MEHO technique is compared with ERFN-CSSBO [1] and FDRL [2] using multiple evaluation metrics, such as Energy drain rate, success rate, jitter, data transfer rate and average hop count across varying number of sensor nodes and data packets.

5.1 ENERGY DRAIN RATE

It is a performance metric used to measure the rate at which sensor nodes consumes the energy for data transmission and reception over a specific period of time. It is typically expressed in joules per second (J/s). It is mathematically calculated using following formula,

$$EDR = \frac{E_{consumed}(sn)}{time(\text{sec})} \tag{21}$$

Table.2. Comparison of Energy Drain Rate

Number of sensor nodes	Energy drain rate (J/sec)		
	Proposed GAI-MEHO	ERFN-CSSBO [1]	FDRL [2]
50	8.63	9.77	12.38
100	11	12.19	15.45
150	12.87	14.21	17.07
200	13.04	15.08	19.65
250	15.34	18.36	20.41
300	17.28	19.05	22.96
350	18.77	21.62	23.45
400	22	24.36	26.32
450	24.10	27.65	29.06
500	26.42	28.36	31.63

5.2 SUCCESS RATE

It measured as the ratio of successfully delivered data packets to the total number of packets sent from source node. This is mathematically evaluated as given below.

$$SR = \frac{\sum_{j=1}^{m} DP_{succ}}{DP_j} \times 100 \quad (22)$$

Table.3. Comparison of Success Rate

Number of data packets	Success rate (%)		
	Proposed GAI-MEHO	ERFN-CSSBO [1]	FDRL [2]
100	94	92	90
200	94.5	91.5	89.5
300	95	91.66	90.6
400	94.5	92.5	90.5
500	95	92.6	91
600	94.33	92.16	90.83
700	94.71	92.14	90.71
800	95.37	92.62	90.62
900	95.77	92.88	90.66
1000	95.2	92.5	90.8

5.3 JITTER

It refers to the variation in the time delay of packet arrival in a network. It measures the delay variation of data packet transmission from source to destination. Lesser jitter indicates stable transmission and it lead to high data delivery. This is mathematically formulated as given below.

$$J = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(Del_j - \overline{Del})^2} \quad (23)$$

Table.4. Comparison of Jitter

Number of data packets	Jitter (ms)		
	Proposed GAI-MEHO	ERFN-CSSBO [1]	FDRL [2]
100	0.2	0.3	0.41
200	0.36	0.48	0.63
300	0.44	0.57	0.75
400	0.58	0.75	0.96
500	0.72	0.9	1.16
600	0.96	1.12	1.36
700	1.12	1.38	1.53
800	1.24	1.57	1.76
900	1.38	1.74	1.93
1000	1.47	1.82	2.02

5.4 DATA TRANSFER RATE

It is referred to as the speed at which the data packets is transmitted through the communication channel in a given time. Data transfer rate is mathematically estimated as given below,

$$DTR = \frac{\text{Data packets transmitted (bits)}}{time\text{(sec)}} \quad (24)$$

Table. 5.Comparison of Data Transfer Rate

Size of data packets (KB)	Data transfer rate (bps)		
	Proposed GAI-MEHO	ERFN-CSSBO [1]	FDRL [2]
100	126.6	116.7	106.6
200	176.5	153.3	142.2
300	213.6	175.6	155.8
400	346.7	226.3	185.4
500	413.6	346.3	226.6
600	585.7	423.4	355.4
700	745.6	533.3	465.6
800	876.2	668.6	563.3
900	963.5	865.3	745.1
1000	1056.3	936.6	864.7

5.5 AVERAGE HOP COUNT

The average hop count is a metric that represents the mean number of intermediate nodes (i.e. hops) a data packet transferred from the source to the destination in WSN. It reflects the average path length in terms of hops in the communication network.

$$AHC = \frac{1}{k}\sum_{h=1}^{k} hops_h \quad (25)$$

Table.6. Comparison of average hop count

Node density	Average hop count		
	Proposed GAI-MEHO	ERFN-CSSBO [1]	FDRL [2]
50	5	7	8
100	5.67	7.67	9
150	5.67	7.33	9.33
200	6.33	8.33	9.33
250	6.33	8.33	10
300	6.67	8.67	10.33
350	7	9.33	11
400	7.33	9.67	11.33
450	7.67	10.33	12
500	8	10.67	12.33

6. CONCLUSION

This paper introduces a novel AI technique called GAI-MEHO for achieving resource-efficient, data transmission in WSN. The approach begins by partitioning the sensor nodes into resource efficient or not using the Generative AI model, based on criteria such as residual energy, bandwidth and memory. Following this, optimal route path is selected for transferring the data packets, which improves routing efficiency and helps reduce delays. To determine the most efficient route from the source to the sink node, the method integrates Elitist Horse Herd Optimization. This algorithm evaluates multiple routing factor link stability, and minimum transmission distance to select the most optimal path with less number of intermediate hops for data forwarding. This optimization significantly improves data transfer rate and reduces jitter. A detailed simulation using the various performance metrics, including energy drain rate, success rate, jitter, data transfer rate and average hop count, across various number of data packets and node density. The results indicate that the GAI-MEHO technique considerably improves the delivery success rate, data transfer rate while minimizing jitter, energy drain rate as well as hop counts when compared to existing deep learning methods.

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